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Escuela de Doctorado

Programa de Doctorado en Contabilidad y Finanzas

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PhD dissertation

"High Frequency Market Microstructure: Market Quality, Informed Trading and the Limit Order Book"

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1. Introduction

1.1 Context and relevance of the research

The study of market microstructure has evolved into a critical area of financial research, particularly in the modern era of automated and high-frequency trading (HFT). Financial markets have undergone a profound transformation due to rapid advancements in trading technologies and the extensive use of complex algorithms. These developments have reshaped the fundamental mechanics of price formation, liquidity provision, and market volatility. Within this highly automated environment, informed trading plays an essential role, not only in determining market orders but also in shaping the dynamics of the limit order book (LOB). The LOB serves as a vital conduit for the transmission of market information, influencing the behavior of prices and the distribution of liquidity across the market.

The growing complexity of market microstructure, driven by the interplay between human and algorithmic trading, underscores the need for a deeper understanding of how these elements interact. In particular, the role of how new information is incorporated in such an environment has become increasingly significant, as it directly impacts market quality metrics such as volatility, liquidity, and price efficiency. This thesis aims to explore these interactions, with a focus on the Spanish equity market, a representative example of a modern, automated trading environment.

In this thesis, diverse methodologies were applied to address the hypotheses presented in Chapters 2, 3, and 4, each focusing on key aspects of financial market microstructure. These chapters employed advanced econometric techniques and high-frequency, tick-by-tick data spanning from 2019 to 2020, which includes a complete limit order book (LOB) that updates every time a new order is generated, canceled, or executed. This dataset also covers the period during the COVID-19 pandemic, providing a unique opportunity to analyze the behavior, buying and selling intentions, and consensus on value and price under crisis conditions, as well as the impact of the short-selling ban imposed in Spain, similar to other European countries.

1.2 Motivation, justification, and objectives of the research

The motivation behind this research is rooted in the critical importance of understanding the implications of different trading strategies—particularly informed trading and algorithmic (non-informed) or feedback trading—on market quality. The concept of market quality encompasses various dimensions, including volatility, liquidity, and price efficiency, all of which are fundamental to the proper functioning of financial markets. The recent financial crises, most notably the one triggered by the COVID-19 pandemic, have highlighted the vulnerabilities of financial markets, especially in periods of heightened uncertainty and extreme volatility. These crises have reignited debates around the effectiveness of regulatory interventions, such as short-selling bans, which are often implemented to curb excessive market volatility.

The first research chapter (Chapter 2) of this thesis investigates the impact of the short-selling ban imposed during the COVID-19 crisis on the Spanish equity market, with a particular focus on market quality within a high-frequency trading framework. Short-selling restrictions are a commonly employed regulatory tool intended to prevent market destabilization during periods of crisis. However, there is considerable debate regarding their effectiveness. Some argue that such restrictions help stabilize markets, while others suggest they introduce distortions that may impair market efficiency. This study seeks to clarify these issues by examining the effects of short-selling restrictions on key market quality indicators, such as realized volatility, price efficiency, and liquidity, especially in a market dominated by automated trading systems.

Chapter 3 delves into the complex interactions between the probability of informed trading, the distribution of beliefs within the LOB, liquidity and market volatility. This analysis is conducted using an event-based clock rather than a calendar-based one, allowing for a more accurate reflection of how information is generated and impacts the market throughout the trading day. Understanding these dynamics is crucial for comprehending the broader implications of informed trading on market behavior, particularly how informed investors shape market liquidity and contribute to price discovery processes. Thus, the objective of this chapter is threefold: first, it aims to analyze the impact of informed trading on consensus within the LOB and its effects on liquidity; second, the paper seeks to shed light on the dynamics of market volatility by examining the relationship between informed trading, belief consensus in the LOB, and market volatility itself; finally, the third objective is to assess whether the slope of the LOB can complement or even surpass the VPIN regarding the predictive power the slope as compared to that of VPIN. The insights derived from this analytical process are indispensable for the formulation of strategies that are aimed at augmenting market efficiency and stability by means of fostering the involvement and activities of informed traders.

To enhance the accuracy of this analysis, conditional volatility is modeled using the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) framework. The EGARCH model is particularly effective in capturing the asymmetric responses of volatility to new information, addressing the limitations of simpler volatility measures by reflecting the dynamic and conditional nature of market volatility throughout the day. The COVID-19 crisis, coupled with the imposition of short-selling restrictions, provided a unique context in which significant shifts were observed in how informed trading influenced market liquidity and consensus formation within the LOB.

In Chapter 4, the slope of the LOB is examined by distinguishing between its permanent and temporary components. Similar to the previous one, this analysis is also conducted under an event-based clock to better capture the real-time flow of information. The permanent component is associated with efficient information that affects long-term price formation, while the transitory component is linked to short-term fluctuations, often driven by uninformed trading, such as algorithmic liquidity provision or feedback trading. The objective of this chapter is to analyze whether the unobservable components of the slope of the LOB affect market quality measures (i.e. volatility, adverse selection costs, and liquidity) and how. Additionally, the existence of a non-contemporaneous relationship between these components and returns is explored, as well as the possible predictability of returns through the permanent and transitory components of the SLOPE. By utilizing a state-space model, this study offers a detailed analysis of how the unobservable components of the LOB slope influence market volatility, adverse selection costs, and liquidity. EGARCH modeling is again employed to account for the conditional and asymmetric nature of volatility, ensuring that the analysis more accurately reflects the true market dynamics. The insights gained from this analysis are of particular relevance to regulators and market participants seeking to enhance market stability and efficiency.

1.3 Main contributions

This thesis makes substantial contributions to the literature on market microstructure, with a particular emphasis on market quality in various contexts, including during the COVID-19 crisis. A major achievement of this work is the innovative integration of transaction-based measures with those based on trading intentions, as reflected in the slope of the Limit Order Book. This approach allows us to explore the tangle relationships between the actual trades executed in the market and the underlying buy and sell intentions captured within the LOB. By examining how these dimensions interact, we uncover the Granger causality between transaction-based market quality metrics and those derived from the LOB, providing a deeper understanding of how informed orders influence market dynamics.

Furthermore, this thesis delves into the informational content embedded within the LOB, particularly through its slope, which serves as a proxy for the consensus among market participants. We separate this slope into two unobservable components: one associated with efficient price formation, reflecting fundamental value, and the other linked to short-term fluctuations driven by liquidity-uninformed, algorithmic trading or event-driven activities. This decomposition enables us to distinguish between the permanent component that aligns with long-term, informed trading and the transitory component influenced by noise and liquidity provision activities. The detailed contributions of each research are outlined as follows:

Chapter 2: Impact of the Short-Selling Ban During the COVID-19 Crisis[1]

This research provides a rigorous analysis of how the short-selling ban during the COVID-19 crisis influenced market quality in Spain. Utilizing high-frequency data and sophisticated econometric methods, the study reveals that while short-selling restrictions may reduce intraday volatility, they also impose significant implicit costs by deteriorating price efficiency and liquidity. The findings indicate that these restrictions exacerbate the negative autocorrelation of returns and increase transaction costs for market participants. Moreover, the study uncovers that the ban asymmetrically impacts buy and sell orders, dispersing sell orders away from their fundamental value, thereby further degrading overall market quality.

Chapter 3: The role of informed trading and belief consensus in market volatility.

This research explores the tangle relationship between informed trading, the distribution of beliefs within the LOB, and market volatility. By employing Granger causality models, the analysis demonstrates how informed trading influences consensus formation within the LOB and how this consensus serves as a predictor of future volatility. The results indicate that, in large-cap stocks, informed trading tends to enhance consensus within the LOB, whereas in mid-cap stocks, a bidirectional relationship is observed between these variables. The study further identifies the LOB slope as a more potent predictor of volatility than the informed trading measure itself, suggesting that this indicator should be integrated into risk management and market regulation frameworks.

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[1] This chapter corresponds to the article published as: Ferreruela, S., & Martín, D. (2022). Market Quality and Short-Selling Ban during the COVID-19 Pandemic: A High-Frequency Data Approach. *Journal of Risk and Financial Management, 15*(7), 308. https://doi.org/10.3390/jrfm15070308

Furthermore, the consensus within the LOB is compared with the Volume-Synchronized Probability of Informed Trading (VPIN) (Abad & Yagüe, 2012; Easley et al., 2012) to assess whether the consensus offers similar or enhanced predictive capacity. This comparison is key because the consensus within the LOB accounts for the complete information from the trading intentions of market participants, rather than solely the transactions executed in the market. This broader perspective could provide a more comprehensive and accurate understanding of market dynamics and potential future movements.

Chapter 4: Analysis of the components of the Slope of the Limit Order Book through a state-space model: Impact on the market.

In the third research chapter, a state-space model is employed to decompose the LOB slope into its permanent and transitory components, providing a nuanced analysis of how each component affects market volatility, adverse selection costs, and liquidity. The permanent component, associated with efficient information, contributes to price stabilization and liquidity enhancement, reflecting the fundamental value derived from informed trading. In contrast, the transitory component, driven by uninformed algorithmic trading or event-driven activities, is found to increase volatility and reduce market depth. This decomposition offers a more sophisticated understanding of how different trading activities impact market quality, laying a solid foundation for future research and regulatory initiatives in financial markets.

1.4 Methodology of the research

In this thesis, diverse methodologies were applied to address the hypotheses presented in Chapters 2, 3, and 4, each focusing on key aspects of financial market microstructure. These chapters employed advanced econometric techniques and high-frequency data to explore issues related to liquidity, volatility, and price efficiency in the Spanish equity market.

Chapter 2:

The analysis in the first research chapter is based on high-frequency data that includes messages from the limit order book (LOB) and transactions of ordinary shares traded on the Spanish market's electronic platform. This data, provided by BME MarketData, covers 184 days divided into four-time windows: pre-pandemic, pandemic crash, short-selling ban, and de-escalation. The sample consists of 35 stocks that are part of the IBEX 35 index, subdivided into quartiles by market capitalization.

For each stock and each level of the LOB, information was collected on quotes, the number of visible orders at each level, and the book's depth. Each executed trade was perfectly matched with the LOB messages and changes, allowing for a snapshot of the LOB each time it was updated with a message. Given that the first and last minutes of the trading day are critical to the study, all messages and order data from the pre-auction and auction periods were included in the analysis.

The measures used in the study were categorized into three groups:

Group 1 focused on algorithmic trading and high-frequency trading (HFT) proxies. Due to the absence of specific HFT labels in the Spanish market data, the Algorithmic Trade Indicator provided by MiFID II was used to identify orders submitted by trading algorithms. Additionally, indirect proxies for HFT activity, such as the number of messages per second, per trade, changes in the mid-price, and the number of trades, were calculated. These metrics were defined based on previous literature, particularly the work of Hendershott et al. (2011), to estimate HFT activity in markets without explicit HFT labels.

Group 2 addressed liquidity measures by calculating market quality indicators on an intraday basis. These include the daily traded volume, bid-ask spread, relative spread, and market depth. The Amihud illiquidity ratio was also adapted to a trade-by-trade level, providing a robust measure of market liquidity. The intraday analysis allowed for a more precise evaluation of liquidity by revealing the depth available for trade at all price levels throughout the day, rather than focusing solely on the top-level prices of the order book at specific points in time.

Group 3 evaluated volatility and price efficiency parameters, such as the slope of the LOB. This analysis adapted the method of Næs and Skjeltorp (2006) to examine the symmetry in the deterioration on both sides of the order book. Realized volatility was calculated at one-minute and 30-minute frequencies to provide consistency in the analysis of price efficiency. Additionally, the difference-in-differences (DID) technique was employed to evaluate the impact of the short-selling ban on market volatility, comparing the treated group (IBEX 35 stocks) with a control group (VDAX).

Chapter 3:

The second research chapter focuses on determining the level of informed trading using the Volume-Synchronized Probability of Informed Trading (VPIN) measure, as described by Easley et al. (2012). This methodology relies on the imbalance between buy and sell orders, emphasizing volume information over price data to capture the toxicity of order flow in high-frequency trading environments. The process began by defining the volume bucket size as one-fiftieth of the average daily volume in 2019, excluding auction periods, to ensure consistency and mitigate the impact of extreme values.

Liquidity measures such as the relative spread (RS) and the depth of the Limit Order Book (LOB) were used as key indicators. These measures provide a comprehensive view of market liquidity, with RS serving as a proxy for external liquidity and LOB depth reflecting internal market liquidity. Furthermore, while the slope of the LOB has traditionally been treated as a bi-dimensional measure of liquidity provision (Kempf & Mayston, 2008), this study delves deeper by interpreting it as a proxy for the dispersion of beliefs or the level of price consensus among market participants within the order book, following the approach of Næs and Skjeltorp (2006). Specifically, a higher value of the LOB slope indicates greater consensus on the asset's price, as trading volumes are concentrated near the current price level rather than being dispersed across a wide range of prices. This concentration suggests that market participants have similar expectations about the asset's value, leading to a tighter clustering of limit orders around the prevailing price.

This perspective is grounded in the extensive literature on heterogeneous beliefs models, which emphasize how differing investor perceptions can influence market dynamics (Varian, 1985; Harris & Raviv, 1993; Scheinkman & Xiong, 2004). Varian (1985) posits that divergence of opinion in complete markets can lead to reduced asset prices due to increased uncertainty. Harris and Raviv (1993) explain that differences of opinion among investors drive trading volume, as each investor acts on their own private information or beliefs. Scheinkman and Xiong (2004) further highlight how speculation driven by heterogeneous beliefs can lead to overpricing of assets, particularly when short-sale constraints are present.

Moreover, Chiarella and He (2003) demonstrate that the interaction between different belief systems can complicate the stability of market equilibria, with traders' learning processes significantly affecting price dynamics. Brock and Hommes (1998) illustrate that heterogeneous beliefs can lead to chaotic market behavior, emphasizing the nonlinear dynamics arising from differing trader expectations. Hommes (2005) reviews various models incorporating heterogeneous beliefs and underscores the importance of strategy switching among agents, which can lead to emergent market phenomena. Calvet et al. (2018) discuss the implications of aggregating heterogeneous beliefs in asset pricing and risk-sharing contexts, arguing that the presence of diverse beliefs allows for a more nuanced understanding of market behavior and asset pricing mechanisms. Vácha et al. (2009) further explore how the interactions of agents with differing beliefs can explain observed market behaviors such as volatility clustering and fat tails in return distributions.

By interpreting the LOB slope as a measure of beliefs dispersion, this study contributes to the understanding of how differing perceptions among investors impact liquidity provision, volatility, and overall market quality. Specifically, it examines whether informed orders can exist within the limit order book, challenging the common assumption that informed trading is primarily associated with market orders used to swiftly capitalize on private information. This approach involves analyzing the possible presence of informed limit orders and their relationship with the LOB slope, as well as assessing whether a greater dispersion of beliefs (reflected in a lower LOB slope) is associated with higher levels of informed trading, as measured by VPIN.Volatility measures were estimated through the absolute value of bucket returns, capturing immediate price fluctuations associated with trading activity. As a robustness measure, an (EGARCH) model was applied to capture conditional volatility and account for asymmetries and volatility clustering inherent in financial time series (Engle & Gallo, 2006; Chkili et al., 2014). This allowed for a detailed evaluation of volatility dynamics and their impact on market quality.

To analyze causality and impulse responses, a Vector Autoregression (VAR) model was implemented, incorporating variables such as VPIN (its CDF), relative spread, LOB depth, and the LOB slope. This model provided a robust framework for understanding the non-contemporaneous relationships between informed trading, the dispersion of beliefs as measured by the LOB slope, liquidity, and volatility in a high-frequency trading environment. Granger causality tests were conducted within the VAR framework to determine the directionality of influence among these variables (Hamilton, 1994). Additionally, contingency tables were used, following the approach of Easley et al. (2012), to compare the distribution of beliefs in the LOB with informed trading levels and their prior effect on volatility. This comprehensive analysis offers new insights into the interplay between informed trading, order book consensus, and market volatility.

Chapter 4:

In the third research chapter, a methodology was developed to analyze the slope of the limit order book (LOB) from the perspective of its permanent and transitory components, using a state-space model with unobserved components. This distinction between components allows for a deeper understanding of long-term influences, which encapsulate fundamental changes in asset price formation based on new and relevant information, versus short-term influences, attributed to non informed-based algorithmic trading.

The permanent component is attributed to efficient information, assuming that a permanent change in the LOB slope reflects the absorption of new information into the market. This approach is consistent with the logic of market efficiency, where the informed component of the LOB slope adjusts permanently, while trading activity exploiting this information is transitory. In contrast, the transitory component captures short-term dynamics associated with temporary liquidity imbalances or trading operations driven by algorithms not based on new information. To model these components, a non-stationary local level model was adopted for the permanent component, allowing for abrupt adjustments or jumps in its level, as opposed to the traditional random walk models that suggest gradual changes.

The analysis was further enhanced by employing state-space models, integrating the Kalman filter to generate optimized and objective estimates of latent components. The LOB slope was modeled as the sum of a non-stationary permanent component and a stationary transitory component. This approach enables capturing the dynamics of informed positions that affect value perception and (efficient) price in the long term, while temporary fluctuations reflect liquidity provision and noise-based trading.

EGARCH models were employed to analyze the volatility of both the permanent and transitory components of the LOB, providing a detailed assessment of the inherent volatility dynamics, consistent with models like Kyle (1985), which emphasize how equilibrium prices adapt to asymmetric information among traders, reflecting the incorporation of information into prices, independent of noise trading. Additionally, OLS regression models were developed to study the influence of the LOB slope components on market quality metrics such as return volatility, VPIN, and market depth, with controls for dummy variables and quoted spread, allowing for precise analysis within the IBEX 35.

In Chapters 3 and 4, the conditional volatility estimated through the EGARCH (1,1) model is used as a proxy for volatility due to its superior capability to capture the dynamics of volatility, especially in environments where volatility varies over time with information and economic shocks (Chkili et al., 2014; Engle & Gallo, 2006). The EGARCH model is particularly valuable for modeling asymmetries in volatility responses to shocks, capturing the leverage effect, where volatility increases more in response to negative news, a phenomenon well-documented in financial markets (Sanusi, 2017; Thurner et al., 2010). This model also allows for precise incorporation of temporal structure information, which is crucial in an event-driven context, such as the one in this study where an event-time clock is used instead of a calendar clock, allowing for a more accurate capture of volatility dynamics around specific events (Gallo & Velucchi, 2008; Chkili et al., 2014). While simple methods, such as utilizing the absolute value of return residuals or daily returns as a proxy for volatility, have their limitations—including the failure to capture conditional and asymmetric nature (Giles, 2008)—EGARCH overcomes these issues by providing a more comprehensive and accurate estimation of future volatility expectations and asymmetries (Zheng et al., 2014).

In this study, the EGARCH (1,1) model is employed both as a robustness test when volatility is the dependent variable and as a control variable in models analyzing market microstructure quality. Using EGARCH as a dependent variable enables a more robust validation of results by capturing temporal and asymmetric volatility dynamics, which is crucial for accurate market response analysis (Behmiri & Manera, 2015). When used as a control variable, it offers a precise tool for controlling volatility effects on variables such as liquidity, bid-ask spread, or market depth, ensuring the reliability of microstructure quality analysis (Zheng et al., 2014; Giles, 2008).

The combined use of the EGARCH (1,1) model and the event-time clock is preferred in this case study, as it not only mitigates heteroscedasticity and reduces volatility clustering but also effectively models the residual volatility dynamics, providing a robust framework for capturing complex market behaviors and improving the accuracy of volatility predictions.

In conclusion, the methodologies employed in this thesis provide a robust and detailed framework for analyzing market microstructure, utilizing high-frequency data and advanced econometric models. These approaches offer a deep understanding of how informed trading, liquidity, and volatility interact in a complex and evolving market environment, contributing significantly to the literature on financial markets and providing valuable insights for both regulators and market participants.

1.5 Thesis structure

This thesis is structured around three main research chapters, each addressing critical aspects of market microstructure and market quality measures:

Chapter 2: Investigates the impact of short-selling restrictions during the COVID-19 crisis on the Spanish equity market, using a high-frequency approach to assess volatility, liquidity, and price efficiency.

Chapter 3: Explores the relationships between the probability of informed trading, the belief distribution in the LOB, and volatility, with a particular focus on how these factors interact during periods of high uncertainty, such as the COVID-19 crisis.

Chapter 4: Applies a state-space model to analyze the permanent and transitory components of the LOB slope, providing a deeper understanding of how these factors affect market stability, volatility, and liquidity.

Each of these chapters significantly contributes to the understanding of market microstructure, offering new perspectives on how different forms of trading, particularly informed trading, affect market quality. These contributions have important implications for economic theory as well as regulatory practice, providing a solid foundation for future research and policy decisions in the field of financial markets.

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2. Market quality and short selling ban during the COVID-19 pandemic. A high frequency data approach

Abstract

The recent emergence of COVID-19 and the subsequent short selling restriction (SSR) imposed on some equity markets provides us with a unique framework to analyze the effects of this kind of measures on market quality in the context of increasingly automated equity markets. We contribute to the literature by analyzing the microstructure and quality parameters of the Spanish equity market during COVID-19 and SSR. We study four subperiods: pre-crisis, turmoil, SSR, and first de-escalation periods by means of a tick-by-tick dataset and the complete limit order book (LOB). We observe the following impact of the SSR on the constituents of IBEX 35®: (1) The SSR did comply partially with its aim at an intraday level regarding volatility, but liquidity was reduced; (2) liquidity deterioration affected more the sell than the buy side of the LOB; (3) high frequency activity (HFT) diminished during SSR reinforcing volatility; (4) negative effects on liquidity and HFT diminished and disappeared as the ban was lifted; (5) HFT unidirectionally Granger causes 1-min realized volatility while the natural logarithm of the slope of the LOB bidirectionally Granger causes 1-min realized volatility.

Keywords: short-selling restriction; high frequency activity; market efficiency; liquidity; volatility; slope of the limit order book.

2.1 Introduction

The prevalence of algorithmic trading (AT) and high frequency activity (HFT) in particular, has increased significantly in recent years (Baron et al. 2019; Borch 2016; Cvitanic and Kirilenko 2012;Dall'Amico et al. 2019;Golub, Keane, and Poon 2012; Hasbrouck and Saar 2013; Jovanovic and Menkveld 2012). Financial literature has thoroughly studied market quality parameters and their relationship with AT and HFT, although inconclusive findings have been reached regarding volatility, liquidity, price efficiency, and transaction costs related to HFT's impact and behavior (Virgilio 2019). If one conclusion can be drawn it is that technology and new AT and HFT trading strategies significantly affect market microstructure

(O'Hara 2015). This paper aims to jointly analyze the main quality parameters of the constituents of the Spanish equity index IBEX 35 and relate them to changes in the microstructure in several market situations at a high frequency level of activity.

MiFID II clearly establishes what can be considered AT and HFT in a market. Specifically, AT is described as "trading in financial instruments where a computer algorithm automatically determines individual parameters of orders such as whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission, with limited or no human intervention, and does not include any system that is only used for the purpose of routing orders to one or more trading venues or for the processing of orders involving no determination of any trading parameters or for the confirmation of orders or the post-trade processing of executed transactions" (Article 4(1)(39) of MiFID II); while HFT is defined as "an AT technique characterized by: (a) infrastructure intended to minimize network and other types of latencies, including at least one of the following facilities for algorithmic order entry: co-location, proximity hosting or high-speed direct electronic access; (b) system-determination of order initiation, generation, routing or execution without human intervention for individual trades or orders; and (c) high message intraday rates which constitute orders, quotes or cancellations" (Article 4(1)(40) of MiFID II).

The turmoil in the financial markets created by the COVID-19 shock is a unique opportunity to analyze the effects of interventionist policy measures over said market quality parameters in the context of increasingly automated markets. During the first wave of the COVID-19 crisis, the European Securities Market Authority (ESMA) prompted six European authorities to ban short selling in the most liquid shares. In Spain, Comisión Nacional del Mercado de Valores (CNMV) imposed the prohibition of short selling over liquid stocks on March 17, 2020, in accordance with Articles 23 and 24 of Regulation (EU) No. 236/2012 of the Short Selling Regulation in those inventories that involve the creation or increase of a net short position on the Spanish shares admitted to trading in the Spanish trading venues. The decision was implemented due to "extreme volatility taking hold of European securities markets, including those based in Spain, their performance in the context of the situation arisen as a result of the virus COVID-19 and the risk of disorderly trading taking place in the following weeks" (CNMV, 2020). On 17th March 2020, a proposed emergency measure introduced by CNMV under Articles 20(2)(a) and (b) of Regulation (EU) No 236/2012 (ESMA70-155-9556), subsequently imposed long-term exchange-wide short selling ban effects, which started on 18th March 2020 and was lifted on 18th May 2020 as market conditions improved. Short selling adds liquidity and benefits price discovery (Massa, Zhang, and Zhang 2015; Sobaci, Sensoy, and Erturk 2014; Feng and Chan 2016;Wang, Lee, and Woo 2017). However, it is still controversial if these restrictions with naked short selling actually reduce financial risks, through the reduction of the volatility of returns, introducing factual confidence in markets.

The period of exogenous shock due to the COVID-19 and the ban on short selling in the Spanish stock market is an eligible one to analyze the impact of these kind of measures on market quality, and to assess whether the ban complied with its objectives or not. The increased prevalence of AT and HFT and its impact on market microstructure makes it necessary to revisit the consequences of short selling restrictions, since previous results may not be valid in current markets. Although the Spanish equity market is still not labelled as a HFT venue, it provides low latency infrastructures, co-location services and direct access to algorithms, which make it a suitable place to study the effects of SSR on market microstructure and quality in the context of modern, highly automated markets.

The main aim of this paper is to analyze different market quality measures and the prevalence of HFT on the IBEX 35 constituents during four different subperiods: the pre-pandemic period, the initial market turmoil due to the COVID-19 pandemic, the short selling ban window and, finally, the first phase of de-escalation. We contribute to the literature by analyzing the microstructure and quality parameters of the Spanish equity market during the emergence of COVID-19 and the subsequent SSR by means of a unique dataset including tick-by-tick changes of the LOB. The data, containing twenty levels of the positions of the LOB, allow to detect the changes at the microstructure level and shed some light on the impact generated by SSR with low latency infrastructures and co-location services. Buy, sell, modify and cancellation orders arrived at the LOB can be perfectly linked to executed trades. Proxies based on message traffic have been used to identify AT and HFT by academics, industry bodies, trading venues and regulators. We use the number of messages per $100 of trading volume along with message-to-trade ratios as a proxy of high frequency activity (Hendershott, Jones and Menkveld 2011). We revisit liquidity measures, price efficiency and volatility. Finally, we test for panel data Granger causality between realized 1-min volatility with a high frequency proxy, and the natural logarithm of the slope of the LOB.

More precisely, we provide research on a tick-by-tick basis about the message flow in the Spanish market from the pre-pandemic period to the first stage of de-escalation. Specifically, this paper identifies (1) prevalence of high frequency activity with indirect approaches as messages-to-trade ratios, messages per second, changes in the midpoint price different from zero (Bouveret et al. 2014); (2) changes in market quality across COVID-19 periods, either before or after the SSR, from 18th of March to 18th of May 2020; and finally (3) we analyze whether short sellers act as essential information intermediaries enhancing the information environment in normal and "extreme" times, as pointed out by Marsh and Paine (2012) in relation to the 2008 financial crisis, studying whether short selling restriction impacts on the symmetric deterioration of the elasticity of the LOB. Therefore, we formulate the following hypotheses:

Hypothesis 1. *The effectiveness of short sale constraints in reducing extreme volatility is low, consistent with most previous literature.*

Hypothesis 2. *Market quality deteriorated during the SSR period.*

Hypothesis 3. *Short selling bans drastically reduce high frequency activity, based on Granger causality.*

Hypothesis 4. *Deterioration was non-symmetric in the ban period; it was worse in the sell side of the LOB.*

Hypothesis 5. *High frequency activity and the slope of the LOB Granger cause realized volatility.*

HFT prevalence features are among others (1) Low-zero inventory at the end of the day in HFT firms, (2) Smaller size per trade, as pointed out by Menkveld (2013) and Cvitanic and Kirilenko (2010). (3) Existence of co-location services or low latency infrastructures, (4) High message traffic per trade and per order. Extant HFT literature bases proxies on message traffic, which should be increased if HFT activity increases (Hendershott, Jones and Menkveld, 2011). Specifically, these types of measures used as indirect proxies by Brogaard et al. (2015, 2017); Boehmer, Fong, and Wu (2018); Brogaard, Hendershott, and Riordan (2013), and Friederich and Payne (2012, 2015).

The interaction between high-message-ratios mainly due to HFT, has affected microstructure parameters at the intraday level compared to daily basis. Brogaard, Hendershott, and Riordan (2019) concluded that the more limit orders the better price discovery but more volatility and adverse selection costs. This should be considered due to partial impact explained by high frequency activity. Due to the expansion of AT and high frequency AT (HFT), MiFID II / MiFIR imposes certain obligations on trading venues to protect the integrity and quality of the market. Co-location services, Market Maker activities, capacity and resilience of systems and Order-to trade-ratio are some of those. Trading venues are required to have systems that allow the limitation of the proportion of unexecuted orders that can be entered into the system by each participant. In the case of the Spanish stock market, the entry into force of the MiFID II directive on January 1, 2018, meant that it was no longer mandatory to reveal the broker code behind each order. Therefore, no detailed information about the companies that operate or participate in high-frequency trading as their main line of business is available from the market. However, a low-frequency infrastructure (SMART SIBE) was established in 2012. Although no member was registered as an HFT proprietary business, since April 16, 2012, the latency dropped to less than 1 millisecond. ESMA Economic Report (Bouveret et al., 2014) presented an overview of HFT activity from different approaches, such as HFT flags and lifetime orders, in which the Spanish stock market had a twenty percent of the value traded by HFT back in 2013, according to the latter, although no HFT-flag was available. Investment banks activity was 59% of the total value traded, of which 22% was HFT. In terms of the number of trades (orders) their activity accounted for 62% (70%) of the total number, of which 20% (27%) was HFT.

With regard to the private information behind Spanish HFTs and ATs, it seems appropriate to specify that algorithmic trading orders are usually based on the evolution of market parameters, more than on the information leakage related to macroeconomic fundamentals. These are orders that do not need to be managed by the broker, on the contrary, it is the system itself that is responsible for managing them internally, according to the algorithm and the parameters chosen by the trader. Without intending to present an exhaustive list, some typical variables included in the algorithms are the following: VWAP (Volume Weighted Average Price), TWAP (Time Weighted Average Price), POV (Participate on Volume), SOR-Best price or SOR-MAX Volume.

Huhtilainen (2017) and Losada López and Martínez (2020) pointed out that banning short selling is not an effective tool (or at least it is limited) for containing extreme price volatility, improving liquidity (bid-ask spread) and obtaining better results in the Amihud illiquidity ratio. Diamond and Verrecchia (1987) find that short sellers are informed traders that provide price efficiency, so prohibiting their activity will potentially prevent information from reaching the market. However, the former loss of depth is not significantly due to the ban rather than to country premia, on a daily basis. Our results indicate that the Amihud ratio throws greater coefficients on a trade-by-trade basis, and not significant due to the SSR period. Our results are consistent with prior theoretical and empirical work (European Securities and Markets

Authority 2022), as the COVID-19 short-selling bans are associated with more pronounced liquidity deterioration on large stocks.

According to Brogaard, Hendershott, and Riordan (2017), liquidity and price efficiency improved due to low-frequency trading during the 2008 short-selling ban and deteriorated by high-frequency trading due to unfavorable selection of limit orders, avoiding low-frequency trading in periods of short selling restrictions. We emphasize that high-frequency messages by trade (our proxy to HFT) decreased significantly during SSR on the venue, but liquidity did not improve relative to the rest of the periods. Losada López and Martínez (2020) in accordance with the main strand of the literature, find that the SSR had a very negative impact on bid-ask spreads and depth in IBEX 35® constituents, but Amihud illiquidity ratio is not significantly due the ban. Siciliano and Ventoruzzo (2020), on the other hand, assert that liquidity (spread and Amihud illiquidity ratio) deteriorated with the ban in 2020.Regarding the provision of liquidity in the market in a high frequency world, there is a branch of the literature focused on the measurement of order flow toxicity (the expected loss from trading against better informed counterparties) headed by the papers by Easley, de Prado, and O'Hara (2011; 2012) and their VPIN measure. According to these authors, providing liquidity in a HF environment introduces new risks: when order flows are balanced, HF traders earn tiny margins on massive numbers of trades, but when order flows become unbalanced, they face the prospect of losses due to adverse selection. Therefore, order flow toxicity can cause market makers to leave the market, triggering illiquidity. However, the accuracy of the VPIN measure as an estimator of toxicity has been questioned by Andersen and Bondarenko (2014a, 2014b, 2015), although these papers have been subsequently refuted in turn by Easley, López de Prado, and O'Hara (2014). This debate about the measurement of the existing risk does not erase the fact itself, that is, order toxicity (as measured by the existence of imbalances in the LOB) can lead to a notable decrease in liquidity. Recently, the VPIN measure has been also used to assess whether HFTs are responsible for extreme price movements, observing that they reduce their trading prior to price jumps, while low frequency traders remain as the main market participants when jumps take place (Prodromou and Westerholm 2022). Informed trading has been the object of study in the FX market, where it has been observed that there is a certain intraday momentum effect due in part to informed investors (Gençay and Gradojevic 2013), who, in order not to reveal their positions, could concentrate their trades at the times of greatest volume (usually the opening and the closing, due to the well-known U-shape in intraday trading volume) (Elaut, Frömmel, and Lampaert 2018). These studies have been replicated in the S&P500, concluding that the intraday momentum effect holds (Gao et al. 2018) but disappears during the COVID-19 pandemic shock (Hossain et al. 2021). However, on the one hand, the conclusions of FX studies are not 100% applicable to stock markets given the special characteristics of the former (trading is more decentralized and opaque in the FX market, and trades can occur around the clock as opposed to fixed opening and closing hours, as pointed by D'Souza (2007)). On the other hand, although all HFT trading is sometimes considered to be informed, there are different levels of informativeness, as Benos and Sagade (2016) pointed out: HFTs who pursue strategies that require the use of aggressive trades are most informed, as opposed to passive HFTs who more likely act as market-makers.

Price efficiency in this pandemic crisis could be treated in a different context compared to other short sales restrictions due to suggested disinformation or incomplete information, even in efficient markets, since the situation of a new disease that generates a global pandemic reduces the real information and its incorporation, worsening the price efficiency, according to the European Securities and Markets Authority of 15 April 2020 (ESMA 2020).

With regard to the symmetry of the impact of short selling restriction (SSR) over the buy and the sell side of the LOB, Marsh and Payne (2012) found that the impairment was symmetrical to financial stocks, affecting the buy and sell sides of the order book equally during the 2008/2009 financial crisis in the UK, while Duong et al. (2008) found that the buy side of the LOB is more informative than the sell side. Our results reflect a more dispersed (concentrated) order-quantity in the sell (buy) side of the LOB during the short-selling restriction period, stronger in small companies than in large capitalization stocks. Consistent with Duong et al. (2008) we find dispersion of beliefs about asset values and the slope of the buy side of the book looks more informative than the sell side (Pascual and Veredas 2006).

The slope of the LOB, raised by Næs and Skjeltorp (2006), describes how the quantity supplied in the order book changes as a function of prices. This measure relates depth with the number of orders and quantity at both sides of the LOB. According to the authors, the flatter (steeper) the slope, the more widely distributed (concentrated) the volumes in the order book are. Also, the volatility-volume relationship (negative related to slope) increases due to dispersion of beliefs partially informed by the slope of the LOB. In addition, the authors claim that this measure has informative influence as endogenous variable explaining volume, trades and price autocorrelation. Duong et al. (2008) find out that the slope of the buy side of the LOB is more informative compared to the sell side of the LOB in the Australian Stock Exchange (ASX). The slope of the LOB, considers the average of the slopes on the demand and supply side. We approach this relationship from the point of view of comparing both slopes (demand and supply) as a ratio in each period. Goldstein and Kavajecz (2004) evidenced a negative relation among the shape of the LOB and volatility in NYSE during October 1997 turbulent period.

The remainder of the paper is organized as follows: section 2 gathers extant literature on market quality and the effects of the COVID-19 pandemic shock, section 3 describes the data, and the measures applied in the research; section 4 presents the main results obtained; some and finally, section 5 concludes.

2.2 Literature review

The COVID-19 pandemic has had a great impact, affecting practically all sectors, levels of society and countries in the world. This pandemic has developed very differently from previous health threats, having spread rapidly until it was declared a global pandemic in mid-March 2020. Government attempts to counteract the effects of the pandemic have included measures to limit the severe impacts of COVID-19 throughout the world, the most striking being lockdowns, but without forgetting other movement restrictions, including learning from home or working from home for non-essential businesses or services, as well as banning crowds and establishing fiscal stimulus.

The fact that it is a relatively recent shock has not been an obstacle for the generation of a plethora of research papers focused on this period, however, the literature is still limited since there are several questions yet to be identified and explored on the financial effects of the COVID-19 pandemic. In this literature review we are going to focus on those papers which scope is the impact of the shock caused by the pandemic on market efficiency. For an extensive and systematic review of the early literature on the impact of COVID-19 on markets, see Anggraini, Utami, and Wulandari (2022).

With respect to liquidity, mixed results have been obtained when analyzing what happened in different markets. On the one hand, most of the studies have detected a worsening of liquidity measures in practically all the markets under analysis: for example, Haroon and Rizvi (2020), using a sample of emerging markets find that an increase in the number of confirmed coronavirus cases is associated with deteriorating liquidity in financial markets. Foley et al. (2022), using data from North America, Europe and Australia, claim that there are negative liquidity impacts most pronounced for stocks most exposed to HFT market makers. However, Chakrabarty and Pascual (2022) observe a drop in liquidity in assets belonging to the S&P500,

although less pronounced in those assets more actively traded by AT. Other papers pointing in this direction are Damien (2021), Tissaoui et al. (2021) or Priscilla, Hatane, and Tarigan (2022). On the other hand, authors as Marozva and Magwedere (2021) have observed an improvement in liquidity in the capital market, with a negative relationship between illiquidity measures and COVID-19, more prevalent in developed markets than in the emerging ones.

The recent pandemic also had a negative effect on volatility in the market. Research papers around the world show an increase in volatility coinciding with the outbreak of the pandemic ((Ali, Alam, and Rizvi 2020; Barro et al. 2020; Chowdhury, Khan, and Dhar 2022; Chowdhury et al. 2022; David, Inacio, and Tenreiro Machado 2020; Mishra and Mishra 2021; Sheraz and Nasir 2021; Uddin et al. 2021)). Gao, Ren, and Umar (2021) find that the impact of COVID-19 on the stock market showed a significant leverage effect in both the U.S. and China, imposing a stronger effect on the stock market volatility when it was already high. (Engelhardt et al. 2020) note that, in spite of the negative impact of the pandemic, stock markets' volatility is significantly lower in high-trust countries. Some studies have tried to identify the origin of this volatility, such as the dissemination of news about the health crisis (Alzyadat, Abuhommous, and Alqaralleh 2021; Mishra and Mishra 2021), activities that facilitate mobility and economic shocks (Egger and Zhu 2021), fear (Li et al. 2021) and the implementation of mobility restriction measures (Chowdhury, Khan, and Dhar 2021; Hunjra et al. 2021). Ftiti, ben Ameur, and Louhichi (2021) also found that market sentiment toward the pandemic had significant effects on stock price volatility.

The impact of the pandemic could be summed up in a notable decrease in market efficiency, as pointed out by authors such as (Dias et al. 2020; Hong, Bian, and Lee 2021) or (Ozkan 2021). Our paper contributes to the existing literature by uncovering the information buried in the intraday data about the changes in market quality in various subperiods (including a short selling ban), through the application of relevant measures and taking into account the activity of HFT and AT.

2.3 Materials and methods

For conducting the research shown in this paper, tick-by-tick data bases are used, both containing messages from the LOB and data on the transactions of ordinary shares traded on the electronic platform of the Spanish market. The original data has been supplied by BME MarketData. The analysis period covers 184 days, divided into four time-windows: pre-pandemic (W0) from November 20th, 2019, to January 20th, 2020; pandemic crash (W1) from

January 21st, 2020, to March 17th, 2020; short selling ban (W2) from March 18th, 2020, to May 18th, 2020; de-escalation (W3) from May 19th, 2020, to July 13th, 2020. The temporary ban on short sales concerning 13th of March is considered partial and not included in the period because it was not extensively informed further than that day. The sample consists of 35 stocks that are constituents of IBEX 35®, subdivided into quartiles by market capitalization on December 19th, 2019.

The LOB data, provided by BME DATA FEED Services, include the twenty best quotes, both bidding and asking, which are updated every time a new message is sent to the market (i.e. a limit order, a market order, a cancellation or an order modification). For each level of the LOB and for each stock, there is information about the quotes, the number of visible orders at each quote level, and the depth. Each executed trade can be perfectly joined with the limit book order messages and changes. A unique sequence number is generated every time a buy, sell, cancellation or modification order message reaches the Spanish Stock Exchange Interconnection System (SIBE), allowing us to have a snapshot of the LOB every time it is updated with a message. In this way, we relate the number of messages arriving at the SIBE to each executed trade. No information about hidden depth and iceberg orders is available in the data. Because the first and last minutes are key for our study, all messages and order data from the pre-auction and auction periods have been included in the study.

Group 1 measures: Algorithmic data and High Frequency Trading proxies.

An accurate identification of HFT presence is challenging to achieve; no unique or easy method can accurately estimate the percentage of HFT activity, apart from, of course, labelled data. Since the implementation of MiFID II in 2018, BME DATA FEED Services provides detailed information about the LOB and transactions, but it does not include HFT labels in data. However, another label (AlgorithmicTradeIndicator) reveals whether the trade was submitted by a trading algorithm. In this paper, indirect proxies have been calculated due to the fact that flagged HFT labelled data do not exist in the Spanish market.

Regarding some indirect HFT metrics, we consider, as MIFID II further defines under Article 19 of Commission Delegated Regulation (EU) 2017/565, high message intraday rate "as the submission, on average, of any of the following: ("(a) at least 2 messages per second with respect to any single financial instrument traded on a trading venue; (b) at least 4 messages per second with respect to all financial instruments traded on a trading venue"; where only messages concerning financial instruments for which there is a liquid market are to be included in the calculation." The limit is defined at firm activity, so as we do not have broker's data, we will analyze changes in the number of messages per second and per executed trade over periods as in previous literature.

Infrastructure requirements were implemented in the Spanish stock venue in 2012 with the Smart SIBE, which complies with one of the HFT and AT requirements that is using co-location and proximity services to minimize latency (see U.S. Securities and Exchange Commission, 2010). At a microstructure level, high frequency data, message traffic flow, and message-to-trade ratios are fundamental to include in the Spanish market quality study. We have to highlight that these high frequency activity proxies cannot be taken purely as an indicator of HFT, although the imprint of this activity on said measures is definitely observable. We analyze changes on average trade size, messages sent per second, messages per trade, mid-price changes on the LOB and number of trades. Additionally, we use Hendershott et al. (2011) combined number of messages per €100 of trading volume along with message-to-trade ratios as an indirect approach of HFT activity. In all the cases high frequency activity increases these measures and vice versa, except in the case of average size, where prevalence of HFT trades usually reduces the quantity of stocks in each trade.

Firms generating message traffic of more than two messages per second or 75,000 messages per trading day are HFT firms if they also fulfil the other criteria of the HFT act. Jovanovic and Menkveld (2012) define HFT firms as intermediaries with high volume traded and near to zero intraday and overnight inventories. As it is not mandatory to disclose the broker code, the average end of the day inventories of brokers cannot be calculated. The measures presented below are indirect proxies for high-frequency activity, which are calculated per transaction and on a tick-by-tick basis with LOB messages. Then, they are averaged by asset and day to obtain daily series that cover the entire analysis period. We have contrasted non-normal distribution medians of algorithm trading, average size per trade, messages per second, mid-price changes different from zero, number of executed trades and number of messages per €100 traded on the complete LOB. These measures are defined on equations 1 to 6.

$$ALGO\_TR_i = 100\ x\ (orders\ submitted\ by\ a\ trading\ algorithm/orders\ submitted)_i \quad (1)$$

$$AVGSIZE = \ (Traded\ volume/\#Executed\ trades)_i \quad (2)$$

$$MESSAGES\_SEC_i = \ (\#messages\ sent\ to\ LOB/\#seconds\ of\ trading\ day)_i \quad (3)$$

$$MESSAGES_{TRADE}(HFT)_i = \ (\#messages\ sent\ to\ LOB/\#trades)_i \quad (4)$$

$$MIDPRICE\_CHANGES_i = (\#changes\ in\ midpoint\ price\ different\ of\ zero)_i \quad (5)$$

$$MESSAGES\_€100_i = \#messages\ sent\ to\ LOB/100\ euro\ traded \tag{6}$$

Group 2 measures: Liquidity measures.

Market quality measures revisited in this paper are calculated on an intraday basis. Liquidity is one of the most important market parameters (Ma, Anderson, and Marshall 2018)**.** The measures considered at an intraday, high frequency, level include direct and indirect approaches extant used in the literature: average volume as the daily-traded volume; bid-ask spread calculated as the difference between the best buy price and the best-selling price over the midpoint; relative-spread as spread divided by midpoint-price; or depth (as the average between the accumulated stocks at the twenty best buy and sell prices). We also obtain liquidity measures as Amihud illiquidity ratio on a trade-by-trade basis. The liquidity measures taken into account are shown in equations 7 to 10.

$$AVGVOL_i = Average\ traded\ volume\ in\ a\ day_i \tag{7}$$

$$SPREAD_i = Best\ ask\ price_i - Best\ bid\ price_i \tag{8}$$

$$RELATIVE\ SPREAD_i = 2\ x\ SPREAD\ _i/(Best\ ask\ price_i + Best\ bid\ price_i) \tag{9}$$

$$Depth_i = (Accumulated\ ask\ orders\ (20\ levels)\ _i + Accumulated\ bid\ orders\ (20\ levels)_i)/2 \tag{10}$$

We have calculated Amihud (2002) illiquidity measure adapting from daily to trade-by-trade level, as the ratio of absolute stock trade-by-trade return to the volume in euros obtained from each trade. The original Amihud illiquidity measure is calculated on a daily basis, comparing close to previous day close to calculate the absolute return compared to the volume in USD. It is not necessary to apply revision due to the case of a trade-by-trade basis, as open price and prior-close price are coincident (Barardehi et al. 2019). The mean of the daily data of each stock is used as input of the constituents of the quartiles-period panel. For the rest of the test, the average across IBEX 35® constituents is used.

$$AMIHUD_{i,trades} = \frac{1}{N_{trades,i}} \sum_{s=1}^{N_{trades}} \left\{ \frac{|return_{i,trade}|}{€volume_{i,trade}} \right\} \tag{11}$$

where, at an asset level (i), $N_{trades,i}$ is the number of executed trades, $return_{i,trade}$ is the realized return in each trade, $€volume_{i,trade}$ is the volume in euros consumed in each trade.

We contrast out average-pairwise verification among stocks, considering the non-normal distribution of data. Non-parametric mean with t-test with two paired samples and median test with ranked signed Wilcoxon verification test (Wilcoxon 1945) is used. Changes between the four periods have been calculated on a tick-by-tick/trade basis, otherwise frequency has been specified in the labels.

Literature on the EU short selling restriction period linked to COVID-19 usually measures the bid-ask spread using daily (end of the trading day) data. Therefore, our analysis of the full order book at a high frequency level can provide a deeper insight of liquidity by revealing the depth available for trade at all price levels throughout the day, rather than focusing on just the prices at the top of the book at one specific point in time. The combination of higher frequency data of the LOB, orders, volumes, and prices across the whole LOB, can uncover even more precise liquidity information.

Group 3: Volatility and price efficiency measures

The first of the price efficiency indicators that have been identified is the slope of the LOB. We adapt it to analyze the symmetry in the deterioration on both sides of the order book. We analyze the daily average relation between the ratio of the slope of the demand side and the supply side in the visible order book. We processed each of the steps described in Næs and Skjeltorp (2006) as in equations (12), (13) and (14).

$$DE_{i,t}^{S} = \frac{1}{N_B}\left\{\frac{v_1^B}{\left|p_1^B/p_0^B - 1\right|} + \sum_{t=1}^{N_B}\frac{v_{t+1}^B/v_t^B - 1}{\left|p_{t+1}^B/p_t^B - 1\right|}\right\} \tag{12}$$

$$SE_{i,t}^{S} = \frac{1}{N_A}\left\{\frac{v_1^A}{p_1^A/p_0^A - 1} + \sum_{t=1}^{N_B}\frac{v_{t+1}^A/v_t^A - 1}{p_{t+1}^A/p_t^A - 1}\right\} \tag{13}$$

$$SLOPE_{i,t} = \frac{1}{N_i}\sum_{s=1}^{N_i}\left\{\frac{SE_{i,t}^{S} + DE_{i,t}^{S}}{2}\right\} \tag{14}$$

where $SE_{i,t}^{S}$ ($DE_{i,t}^{S}$) is the average slope of the sell (buy) side. N_A (N_B) is the total number of ask (bid) prices or tick levels, containing orders. Let $t = 0$ denote the bid-ask midpoint. p_0^A and p_0^B is the bid-ask midpoint and $t = 1$ represents the best quote with volume. Finally, v_1 is the natural logarithm of accumulated total share volume at each level t.

The average slope of the day is calculated following equation (15) where N_i is the number of exchanges or snapshots on the LOB for each asset.

$$ELOB_{i,t} = \frac{1}{N_i}\sum_{s=1}^{N_i}\left\{\frac{DE_{i,t}^{S}}{SE_{i,t}^{S}}\right\} \quad (15)$$

We present equation (15) where we estimate the average of the ask side (SE) divided by the average of the bid side (DE) for each snapshot change of the complete LOB and take the daily ratio (ELOB) to compare the slope of both sides of the LOB. This will highlight the changes between price concentration or dispersion on the ask side compared to those on the bid side, giving us information about the symmetry deterioration or improvement of the limit order book. The novelty of applying these measures using intraday data is of interest because the use of daily data could hinder the HFT activity due to the low-zero inventory at the end of the day of HFT firms.

Regarding volatility, we revisited parameters such as realized volatility at one-minute frequency, realized volatility at 30-minute frequency and price autocorrelation to add consistency to the price efficiency analysis. We calculate realized volatility as the standard deviation of returns for each frequency studied. We have calculated realized volatility of returns for 1-minute (RVol_1m) and 30-min (RVol_30min) periods. If prices were efficient according to the efficient market theory, the 1-min realized volatility scaled to 30 minutes (multiplying it by $\sqrt{30}$), should be the same as (or close to) 30-min realized volatility, equation (16). Following Úrsula and Palou (2015) we used the coefficient between 30-minute volatility and scaled 1-min volatility as in equation (16) as an additional price efficiency intraday measure. Again, looking only at daily changes in volatility may hide HFT activity as it was the case in the liquidity measures, so the use of intraday data could be of help to avoid the loss of information.

$$COEF\_VOL_{i,t} = \frac{\sqrt{30}\cdot\sigma_{1\,min}}{\sigma_{30\,min}} \quad (16)$$

$$AUTOCORR = \ first\ order\ return\ autocorrelation\ in\ 1\ min\ frequency \quad (17)$$

According to price efficiency theories, ideally this ratio should be around one, and non or residual first-order return autocorrelation should exist, reflecting a random walk. The greater the volatility coefficient ($COEF\_VOL_{i,t}$) and the first-order return autocorrelation ($AUTOCORR$) the less efficient prices are. In low frequency data, return or prices are unpredictable, following a random walk. In high frequency data, Roll (1984) demonstrated that the noise component of prices generates a negative autocorrelation in price changes. We calculate 1-min frequency autocorrelation.

Seasonality in intraday dynamics exists and is well revised in financial literature. Effects on variables under high frequency data vary depending on the interval chosen. Patterns can be found in the distribution of both intraday returns and main market quality measures as liquidity and volatility. Autocorrelation or co-movements generate “U”-shaped or inverted “J” patterns as noted byMartens, Chang and Taylor (2002),Hua and Li (2011),or Tian and Guo (2007) among others; Kottaridi, Skarmeas, and Pappas (2020) pointed out that the intraday pattern is more pronounced in specific days of the week in the case of returns and volatility. During the COVID-19 period, although the "U"-shape persisted, Kubiczek and Tuszkiewicz (2022) pointed out that private investors operated more, decompensating the usual distribution of the percentages of data during the day that usually exist at the opening and close of the trading day.

These patterns, and also their causes, vary between different markets. In the case of equity markets, Ozenbas (2008) noted that in different regions as US or EU, changes in the rules, (such as call auctions or the extension of trading hours) affect the shape of the distribution. Eaves and Williams (2010) assert that the timing of privately informed traders cannot be the source of intraday patterns in the Tokyo Grain Exchange. Seasonality (both intraday and day-of-the-week) despite being caused by different events, can be observed in the increasing volatility and liquidity in auctions and in the first hours of trading, thus allowing informed investors to use those periods of the day to operate their volumes as pointed by Gençay et al. (2015).

Data can be de-seasonalized to focus on the dynamics around average behavior, as in Bińkowski and Lehalle (2018), taking the natural logarithm to symmetrize the distribution and eliminate the seasonal component, thus obtaining closer to normal distributions. However, applying this correction to our data still results in non-normal distributions. Our objective being to contrast whether the representative measures are significantly different during each period studied, we applied the Wilcoxon Mann Whitney-test with the medians of the intraday values as a central measure of the day including the whole data. The original data were used because the research methodology is to determine the differences in the central tendency of the non-parametric distributions between periods. These (median) data series are also the ones regressed in the last part of the study.

To control for the day-of-the-week effect, we run the following dummy regression to understand the impact of the day of the week on all the measures considered, including Monday in the intercept.

$$Measure_{i,t} = \beta_0 + \beta_1 T + \beta_2 W + \beta_3 Th + \beta_4 F + \varepsilon_{i,t} \quad (18)$$

where T is a dummy variable that takes value 1 when the weekday is Tuesday and 0 otherwise, W is a dummy variable that takes value 1 when the weekday is Wednesday and 0 otherwise, Th is a dummy variable that takes value 1 when the weekday is on Thursday and 0 and F is a dummy variable that takes value 1 when the weekday is Friday and 0 otherwise. According to the results (available upon request for clarity reasons) no significant day-of-the-week effect is found in the majority of the measures. Only Friday is significant at a 5% level in Algorithmic Trading and Volume. In the case of the number of messages, Thursday becomes significant, and finally, Wednesday and Thursday are significant in the case of autocorrelation. The remaining measures do not present any day-of-the-week effect.

We have included the daily data of VDAX index as the implied volatility of the German option market. Implied volatility is an expectation of volatility, the variability that market makers believe the underlying will have in the next 30 days. The German market was one of the markets where the SSR was not established. The data of the 35 constituents of IBEX 35® group and the securities that are part of the IBEX 35® index (equally weighted) are considered as a treated group (by the restriction) and the VDAX is considered as a control group. They are treated as similar groups with respect to price and return characteristics during the periods under study.

The difference in differences (DID) technique is applied, disaggregating the uncertainty measured by the realized volatility in (1) that caused by the restriction of short sales and (2) the underlying one by the period of base agitation. We calculated the difference in differences as (Group treated after restriction minus Group treated before restriction) subtraction (Control group after restriction minus Control group before restriction). This DID draws out the difference caused by the treatment, in this case the SSR. The data were provided by Bloomberg.

The proxy of the impact of the SSR on volatility measure is therefore estimated through the DID technique between the treated group and VDAX (scaling down daily data to 1-min frequency data). We extract the difference of the partial realized-volatility cause due to SSR because of the COVID-19 and other causes comparing to VDAX as control group, due to the fact that the German market was a venue where no restriction on short selling was implemented.

We know that there are several pitfalls to make the Spanish 1-min realized-volatility perfectly comparable with VDAX used as German volatility proxy. The validity of this methodology (DID) is based in the assumption that the trend in control group (VDAX) approximates what would have happened in the treated (banned) group in the absence of that treatment.

$$Realized\_Vol = \beta_0 + \beta_1 D^{post} + \beta_2 D^{Tr} + \beta_3 D^{Post} D^{Tr} + [\beta_4 X] + \varepsilon \tag{19}$$

where D^{post} is a dummy variable that takes value 1 when the ban is in force and 0 otherwise, D^{Tr} is a dummy variable that takes value 1 if the stock belongs to the treated group (Spain) and 0 otherwise and $\boldsymbol{X}$ is the control variables vector (VDAX).

To conclude the study of the HFT prevalence, liquidity, volatility and price efficiency measures, we estimate the contribution of each period under study to the aggregate sample period coefficient for each measure by running a fixed effects (Hausman test) panel model, including dummy variables for each of the four subperiods (W0, W1, W2, and W3). We include a constant and 4 periods rather than leaving constant as the basis. The model we used with panel least squares (fixed effects), is as follows:

$$Measure_{i,t} = \beta_0 + \beta_1 W0_{i,t} + \beta_2 W1_{i,t} + \beta_3 W2_{i,t} + \beta_1 W3_{i,t} + \varepsilon_{i,t} \tag{20}$$

Panel data Granger causality

Panel data are composed of each measure for the median of the daily distribution of intraday data of the 35 IBEX constituents, from 20/11/2019 to 14/07/2020, with 5740 total observations. The existence of cross-sectional dependency in panel data tends to produce biased estimations. The causality process we have driven distinguishes two cases. (1) We use VAR vector error correction when endogeneity among variables is expected in the study and (2) DH Test, (Dumitrescu and Hurlin 2012). The process is as follows: (1) Testing for the existence of unit root and the stationarity in level and first order differences of variables (Hadri unit root). (2) Finding the optimal lag minimizing Information criteria (Akaike or Bayesian). (3) Testing for cointegration in case of non-stationarity in level and same order of integration. (4) Testing Granger Causality and analyzing VECM model for impulse responses on the short run.

DH test solves long panel issues and deals with the empirical issue of cross-sectional dependence, computing p-values established on a bootstrap method. In the case where the optimal number of lags through minimizing Akaike or Bayesian cannot be used, the maximum number of lags authorized by EVIEWS is used. We study panel data Granger causality between

BAN dummy (takes value 1 if the SSR is in effect, and 0 otherwise) and the natural log of the number of trades to test the causality of the decrease in trades by short selling restrictions.

2.4 Results

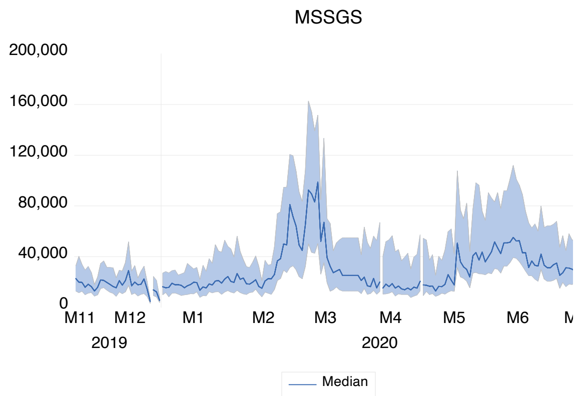
First of all, we present the results for the difference in relative medians between the daily series for the different periods, to see how the different parameters considered evolved throughout the subperiods under study. As a statistical test, we have applied Wilcoxon test (medians). The results for the total sample and for the four quartiles of IBEX 35® shares according to market capitalization are shown. The significance level of the differences is indicated.

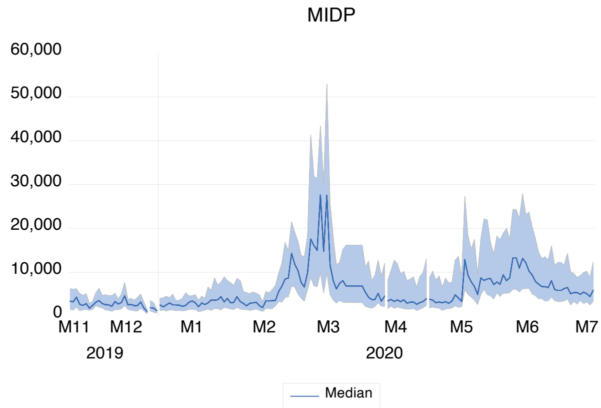
High frequency activity

We start by assessing the prevalence of AT and HFT on periods W0, W1, W2 and W3. The results are shown on Figure 2.1 and Table 2.1 MSSG_S, MSSG_T and MIDP increased during the COVID crisis period W1 from pre-COVID period W0, something that could be interpreted as a rise in the prevalence of AT and HFT in the Spanish market. The increase rates (all significantly different from zero) on MSSG_S, MSSG_T, MIDP and MSSG_100 were 75.90%, 6.04%, 102.63% and 28.13% respectively. At the same time, the number of trades increased by 68.69% in IBEX 35® constituents. The results are more pronounced in those stocks with higher market capitalization (Q4).

We highlight the following findings for the SSR period, W2 (and the variation between COVID crisis W1 and short selling ban period W2). We find that indirect proxies tend to decrease, in line with the results of Brogaard (2010), who pointed out that HFT activity stops in banned venues. The changes from the pre-COVID period W0 to the short selling ban period W2 (from the COVID crisis W1 to the short selling ban period W2), on MSSG_S, MSSG_T, MIDP and MSSG_100 were the following (all significant except for the decrease in messages per trade from W0 to W1): 7.91% (-38.65%), -4.69% (-10.12%), 66.91% (-17.63%) and 33.66 (4.31) respectively. The number of trades changed at a (significant) rate of 21.37% (-28.05%) in IBEX 35® constituents. The results are more significant for those stocks with higher market capitalization (Q4), see Table 2.1. We find that pre-COVID period W0 directly compared with SSR period W2, showed increased speed on MSSG_S, MIDP as well as MSSG_100. The difference between COVID crisis W1 and SSR period W2 yields results where high frequency activity decreased or stopped. In the fourth period under study, when SSR was lifted, MSSG_S, MSSG_T and MIDP, all of them proxies of the high frequency activity, reappeared compared to pre-COVID period W0 (variation between SSR period W2 and de-escalation W3 is also shown). The increase rates (all significant) on MSSG_S, MSSG_T, MIDP and MSSG_100 were 95.69% (114.09%), 17.16% (25.29%), 36.09% (51.65%) and 58.09% (53.96%) respectively. Additionally, the number of trades increased by a significant 71.15% (69.34%) in IBEX 35 constituents.

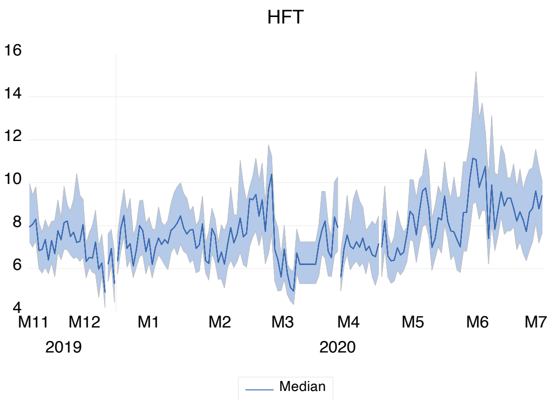
Figure 2.1 Evolution of the values of the different proxies of high frequency activity

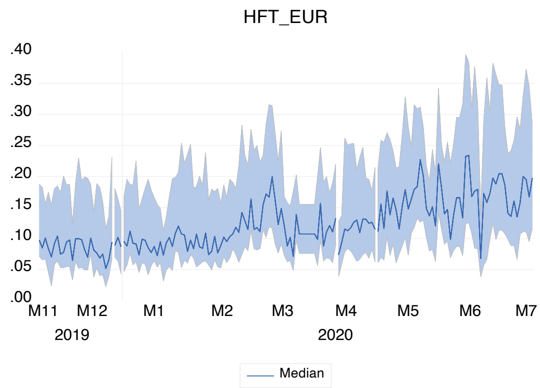




(**a**) Messages sent per trading second on average.

(**b**) Number of changes in mid-price different from zero.





(c) Number of messages per trade.

(d) Messages per 100 euro traded.

Figure 2.1 This figure shows the evolution of the values of the different proxies of high frequency activity used in this paper between November 20th, 2019, and July 13th, 2020. More precisely, (a) shows the number of messages sent per trading second on average; (b) presents the number of changes in mid-price different from zero; the number of messages per trade can be seen on (c) and (d) corresponds to the number of messages per 100 euro traded.

Table 2.1. Algorithmic data and High Frequency Trading proxies.

Panel A. Algorithmic data and High Frequency Trading proxies.

Measures		% Algo Tr	Avg Size	Messages/sec	Messages trade (HFT)	Mid-price changes	#_trades	Messages_€100
Pre_covid W0	*IB*	71.892	441.986	0.571	7.100	2,505.000	2,255.000	0.087
Covid crash W1		73.028	402.232	1.004	7.529	5,076.000	3,804.000	0.112
Short Selling Ban W2		72.454	502.345	0.616	6.767	4,181.000	2,737.000	0.117
De-escalation W3		68.377	408.680	1.225	8.801	7,293.000	4,115.000	0.167
Pre_covid W0	*Q4*	75.841	539.405	0.998	6.710	3,958.000	4,375.000	0.045
Covid crash W1		77.023	458.254	1.788	6.948	9,724.000	7,368.000	0.064
Short Selling Ban W2		76.574	529.740	1.653	6.322	11,229.000	7,403.000	0.064
De-escalation W3		73.369	430.040	2.296	8.613	11,772.000	7,852.000	0.091
Pre_covid W0	*Q3*	69.867	383.641	0.796	7.456	3,622.500	2,676.500	0.075
Covid_crash W1		70.909	351.761	1.694	8.097	8,388.000	5,314.500	0.099
Short_Selling_Ban W2		70.092	519.319	1.435	7.546	10,156.000	4,765.500	0.097
De_escalation W3		68.243	406.606	2.092	9.485	13,566.500	5,990.000	0.155
Pre_covid W0	*Q2*	73.010	561.486	0.521	6.855	2,224.000	2,145.000	0.099
Covid_crash W1		74.229	516.710	0.857	7.512	4,123.000	3,332.000	0.117
Short_Selling_Ban W2		71.618	562.891	0.542	6.699	3,354.000	2,537.000	0.143
De_escalation W3		66.501	413.067	1.096	8.681	6,399.000	3,888.000	0.197
Pre_covid W0	*Q1*	67.857	338.089	0.288	7.390	1,232.000	1,123.000	0.205
Covid_crash W1		68.379	330.296	0.418	7.549	2,214.000	1,841.000	0.229
Short_Selling_Ban W2		67.384	409.503	0.263	6.910	1,512.000	1,135.000	0.210
De_escalation W3		61.832	391.942	0.564	8.658	3,364.000	1,922.000	0.324

Table 2.1. Panel A of the table presents the median values for the algorithmic data and high frequency trading proxies for the four periods under study, for all the IBEX 35 constituents and each of the size (capitalization) quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest capitalization stocks.

Table 2.1 Algorithmic data and High Frequency Trading proxies. (Cont.)

Panel B. Changes in median: Algorithmic data and High Frequency Trading proxies.

Changes %		Algo Tr	Avg Size	Messages/sec	Messages trade (HFT)	#_trades	Messages_€100
W1-W0		1.58 ***	-8.99 ***	75.90 ***	6.04 ***	68.69 ***	28.13 ***
W2-W0		0.78	13.66 ***	7.91 ***	-4.69 ***	21.37 ***	33.66 ***
W3-W0	*IB*	-4.89	-7.54	114.57 ***	23.96	82.48 ***	91.71 ***
W2-W1		-0.79 ***	24.89 ***	-38.65 ***	-10.12 ***	-28.05 ***	4.31 **
W3-W1		-6.37 ***	1.60 ***	21.99 ***	16.90 ***	8.18 ***	49.62 ***
W3-W2		-5.63 ***	-18.65 ***	98.84 ***	30.06 ***	50.35 ***	43.43 ***
W1-W0		1.56 ***	-15.04 ***	79.08 ***	3.53 ***	68.41 ***	42.59 ***
W2-W0		0.97 ***	-1.79 ***	65.57 ***	-5.79 *	69.21 ***	43.40 ***
W3-W0	*Q4*	-3.26 ***	-20.28 ***	130.03 ***	28.36 ***	79.47 ***	105.01 ***
W2-W1		-0.58	15.60 ***	-7.54 ***	-9.01 ***	0.48 ***	0.57 *
W3-W1		-4.74 ***	-6.16 **	25.45	23.98 ***	6.57	43.78 ***
W3-W2		-4.19 ***	-18.82 ***	38.93 ***	36.25 ***	6.07 ***	42.97 ***
W1-W0		1.49 **	-8.31 ***	112.76 ***	8.58 ***	98.56 ***	32.96 ***
W2-W0		0.32	35.37 ***	80.24 ***	1.20	78.05 ***	29.66 ***
W3-W0	*Q3*	-2.33 ***	5.99 **	162.65 ***	27.21 ***	123.80 ***	107.56 ***
W2-W1		-1.15 **	47.63 ***	-15.28 ***	-6.80 ***	-10.33 *	-2.48
W3-W1		-3.76 ***	15.59	23.45 ***	17.15 ***	12.71 **	56.11 ***
W3-W2		-2.64 ***	-21.70 ***	45.72 ***	25.70 ***	25.70 ***	60.07 ***
W1-W0		1.67 ***	-7.97 ***	64.39 ***	9.58 ***	55.34 ***	18.13 ***
W2-W0		-1.91 ***	0.25 ***	3.93 ***	-2.28 **	18.28 ***	44.48 ***
W3-W0	*Q2*	-8.92 ***	-26.43	110.19 ***	26.64 ***	81.26 ***	22.31 ***
W2-W1		-3.52 ***	8.94 ***	-36.78 ***	-10.82 ***	-23.86 ***	22.31 ***
W3-W1		-10.41 ***	-20.06	27.87 ***	15.57 ***	16.69 **	69.33 ***
W3-W2		-7.15 ***	-26.62 ***	102.26 ***	29.59 ***	53.25 ***	38.45 ***
W1-W0		0.77 *	-2.31	44.87 ***	2.15 *	63.94 ***	11.93 ***
W2-W0		-0.70	21.12 ***	-8.60 ***	-6.49	1.07 **	2.68 ***
W3-W0	*Q1*	-8.88 ***	15.93 ***	95.69 ***	17.16 ***	71.15 ***	58.09 ***
W2-W1		-1.45	23.98 ***	-36.91 ***	8.46 **	-38.35 ***	-8.26
W3-W1		-9.57 ***	18.66 ***	35.08 **	14.69 ***	4.40	41.24 ***
W3-W2		-8.24 ***	-4.29 ***	114.09 ***	25.29 ***	69.34 ***	53.96 ***

Table 2.1. Panel B shows the changes in the median of the variables from one subperiod to the others for each of the size quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

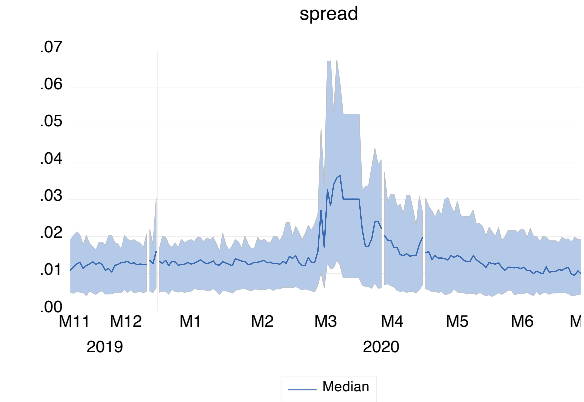
Liquidity

The results regarding the liquidity measures are shown in Figure 2.2 and Table 2.2. Panel A of Table 2.2 shows absolute results, while Panel B contains the growth rates of the medians between the four periods. The evolution shown in Figure 2.2 allows to observe an anomalous behavior of the spread, the relative spread, and the depth in the months of March and April 2020. We obtain results consistent with the descriptive results of Losada López and Martínez (2020) regarding the bid-ask spread and the Amihud (2002) illiquidity ratio, which increases drastically during the SSR period.

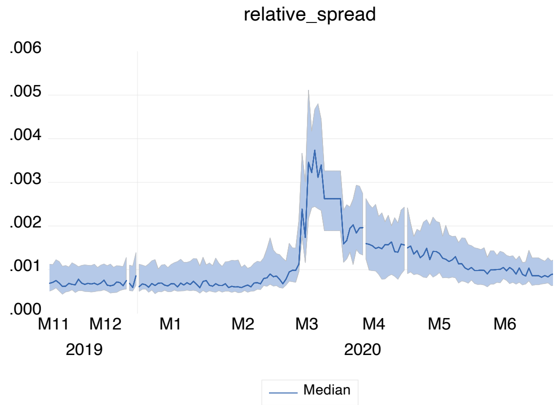
We observe that the shock created by COVID-19 increased illiquidity ratio medians from pre-COVID W0 to the short selling ban period W2 by 87.13%. We compared changes between periods and found that Amihud illiquidity ratio (intraday) increased by a significant 70.27% from COVID-19 shock W1 to short selling ban period W2, decreasing by – 40.21% when the SSR was lifted in de-escalation W3 (view Figure 2.2). Therefore, according to this measure, liquidity decreased during the SSR, something that could be expected given the role as liquidity providers that has been often assigned to short sellers. We have to remark that although Losada López and Martínez (2020) descriptive results are aligned to these, they followed a methodology similar to Arce and Mayordomo (2016) and pointed out that Amihud ratio would have been even higher without the ban. Changes at the quartile level by market capitalization are more pronounced in the extreme quartiles (Q4 and Q1) (see Table 2.2).

With regard to the bid-ask spread and the relative spread, the main results are those related to the change in medians between COVID W1 and short selling ban period W2, with an increase of 34.96% of the median spread (135.92% of the median relative spread). The subsequent decrease of – 36,88% (-45,95%) when SSR was lifted in de-escalation W3 can be highlighted as well. The median of the spread (relative spread) fell (increased) by -9,47% (44,93%) when comparing pre-COVID W0 to de-escalation W3, meaning that liquidity has not yet recovered the pre-COVID levels (in terms of relative spread). More precisely, the spread increased by 34.96% during the SSR. These results are aligned with others as Boehmer and Wu (2013) in the US market and Helmes, Henker, and Henker (2010) in the Australian market during the effects of the 2008 financial crisis. We need to highlight this quoted spread as an implicit cost to investors. Traders who want to trade quickly, buy at higher prices and sell at lower prices than those willing to wait for others to trade with them, bearing this spread cost on each trade. In an increasingly automated intraday environment, this cost should be taken into consideration by regulators, as it might be affecting different types of market participants unequally. Changes at the quartile level by market capitalization are extremely differentiated at the Q2 and Q1 ends, (see Table 2.2).

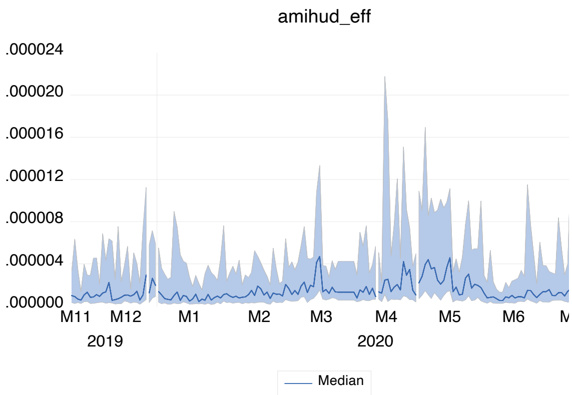
Figure 2.2. Liquidity measures during the periods under study.



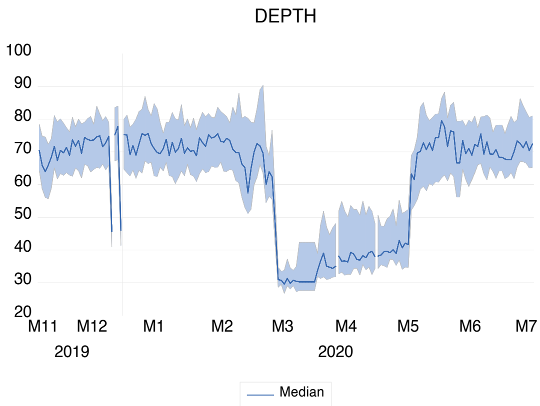
(**a**) Spread on the top of the LOB.



(**b**) Relative spread as spread to midprice.



(**c**) Amihud ratio by trade.



(**d**) Depth.

Figure 2.2 Liquidity measures during the periods under study. Median and 1st and 4th quartiles range are shown (a) Spread on the top of the LOB. (b) Relative spread as spread to midprice. (c) Amihud by trade. (d) Depth of the complete level of LOB.

The depth of the LOB was reduced by a significant 46.29% from W2 to W1 while it only increased by 3.08% during the COVID-19 shock period, W2. Depth rapidly recovered pre-COVID levels as soon as the ban was lifted. It is clear that the depth decreased significantly during the ban period, leading to higher liquidity costs, consistent with Hypothesis 2.

Table 2.2. Liquidity measures.

Panel A. Median values for the liquidity measures

Liquidity		Avg Vol	Spread	Relative Spread	Depth	Amihud (trades)
Median				%		x 1,000,000
Pre_covid W0	*IB*	894,028.000	0.013	0.068	70.736	1.010
Covid_crash W1	*IB*	1,461,954.000	0.013	0.077	68.555	1.110
Short_Selling_Ban W2	*IB*	1,205,918.000	0.018	0.183	36.819	1.890
De_escalation W3	*IB*	1,382,215.000	0.011	0.099	70.598	1.130
Pre_covid W0	*Q4*	2,335,742.000	0.013	0.042	78.601	0.378
Covid_crash W1	*Q4*	3,482,542.000	0.013	0.051	79.911	0.459
Short_Selling_Ban W2	*Q4*	3,658,708.000	0.014	0.091	48.341	0.879
De_escalation W3	*Q4*	3,217,618.000	0.012	0.064	81.125	0.688
Pre_covid W0	*Q3*	937,541.500	0.014	0.058	70.576	0.378
Covid_crash W1	*Q3*	1,749,269.500	0.015	0.062	69.189	0.482
Short_Selling_Ban W2	*Q3*	1,664,479.500	0.019	0.144	40.510	0.743
De_escalation W3	*Q3*	1,626,919.500	0.013	0.078	73.550	0.484
Pre_covid W0	*Q2*	1,245,738.000	0.010	0.078	71.835	1.680
Covid_crash W1	*Q2*	1,666,171.000	0.010	0.091	68.891	1.650
Short_Selling_Ban W2	*Q2*	1,445,547.000	0.020	0.192	35.091	3.100
De_escalation W3	*Q2*	1,540,680.000	0.010	0.111	67.870	1.930
Pre_covid W0	*Q1*	392,815.000	0.013	0.133	63.480	2.980
Covid_crash W1	*Q1*	572,274.000	0.016	0.148	60.694	4.400
Short_Selling_Ban W2	*Q1*	463,558.000	0.022	0.308	32.986	6.290
De_escalation W3	*Q1*	755,178.000	0.014	0.176	61.047	3.120

Table 2.2. Panel A of the table presents the median values for the liquidity measures considered in the four periods under study, for all the IBEX 35 constituents and each of the size (capitalization) quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest capitalization stocks.

Table 2.2 Liquidity measures (Cont.).

Panel B. Changes in median: Liquidity measures.

%		Avg Vol	Spread	Relative Spread	Depth	Amihud (trades)
W1-W0		63.52 ***	6.27 ***	13.66 ***	-3.08 ***	9.90
W2-W0		34.89 ***	43.42 ***	168.14 ***	-47.95 ***	87.13 ***
W3-W0		54.61 ***	-9.47 ***	44.93 ***	-0.20	11.88 *
W2-W1	*IB*	-17.51	34.96 ***	135.92 ***	-46.29 ***	70.27 ***
W3-W1		-5.45 ***	-14.81	27.52 ***	2.98 ***	1.80 **
W3-W2		14.62 ***	-36.88 ***	-45.95 ***	91.75 ***	-40.21 ***
W1-W0		49.10 ***	3.49 ***	20.52 ***	1.67	21.43
W2-W0		56.64 ***	12.77 ***	114.15 ***	-38.68 ***	132.54 ***
W3-W0		37.76 ***	-5.84 ***	49.76 ***	3.21 ***	82.01 ***
W2-W1	*Q4*	5.06	8.97 ***	77.69 ***	-39.69 ***	91.50 ***
W3-W1		-7.61	-9.01 **	24.27 ***	1.52 ***	49.89 ***
W3-W2		-12.06	-16.50 ***	-30.07 ***	68.32 ***	-21.73 ***
W1-W0		86.58 ***	4.53 **	5.65 ***	-1.97	27.51
W2-W0		77.54 ***	36.52 ***	146.19 ***	-42.60 ***	96.43 ***
W3-W0		73.53 ***	-4.47 ***	32.85 ***	4.21	28.04
W2-W1	*Q3*	-4.85 ***	30.60 ***	133.04 ***	-41.45	54.05 ***
W3-W1		-6.99 ***	-8.61	25.75 ***	6.30	0.41
W3-W2		-2.26 *	-30.02	-46.04 ***	81.56 ***	34.81 ***
W1-W0		33.75 ***	0.00 ***	16.45 ***	-4.10 ***	-1.79
W2-W0		16.04 ***	100.00 ***	145.15 ***	-51.15 ***	84.52 ***
W3-W0		23.68 ***	0.00 ***	41.58 ***	-5.52 ***	14.88 **
W2-W1	*Q2*	-13.24 ***	100.00 ***	110.51 ***	-49.06 ***	87.88 ***
W3-W1		-7.53 ***	0.00 ***	21.58 ***	-1.48 ***	16.97 **
W3-W2		6.58 ***	-50.00 ***	-42.25 ***	93.41 ***	-34.74 ***
W1-W0		45.69 ***	24.47 ***	11.30 ***	-4.39 ***	47.65
W2-W0		18.01 ***	74.05 ***	131.55 ***	-48.04 ***	111.07 ***
W3-W0		92.25 ***	6.71 ***	32.30 ***	-3.83	4.70
W2-W1	*Q1*	-19.00 ***	39.84 ***	108.05 ***	-45.65 ***	42.945 ***
W3-W1		31.96 *	-14.27	18.88 ***	0.58 ***	-29.09
W3-W2		62.91 ***	-38.69 ***	-42.86 ***	85.07 ***	-50.40 ***

Table 2.2. Panel B shows the changes in the median from one subperiod to the others in the liquidity measures, for all the IBEX 35 constituents and each of the size (capitalization) quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest capitalization stocks. *, **, and *** represent statistical significance of the Wilcoxon test at the 10%, 5%, and 1% levels, respectively.

Volatility

We run the difference in differences test with the realized volatility of returns for 1-minute (RVol_1m) as treated group, considering short selling ban as the treatment, and 30-day option-intrinsic volatility VDAX as control group due to the fact that no ban was implemented in the German market. Once VDAX has been scaled down to a 1-min frequency proxy of non-banned market volatility, the results show that without short selling ban, 1-minute realized volatility of the Spanish market would have been even greater than it had been. Therefore, we can infer that the SSR has in fact helped to reduce volatility during the period, in line with the findings of Losada López and Martínez (n.d). The SSR reduced the 1-min level volatility by a 37.83% in an intraday basis compared with the expected realized volatility extracted from DID with VDAX (see Table 2.3).

Table 2.3 Volatility. Difference in differences.

1-min volatility measures	No SSR period	SSR period W2
VDAX (1-min scaled)	0.002026	0.041990
(RVol_1m)	0.000957	0.001184
(RVol_1m) without SSR*	0.000957	0.003130

Table 2.3. Volatility measures. The first column shows values previous to the short selling restriction, and the second column shows the results for the restriction period. The data shown in the last row is the 1-min realized volatility median of the 35 constituent stocks of IBEX 35 if no ban had been imposed.

Table 2.4 1-min realized volatility.

Panel A. Median values for the volatility measures.

Volatility		Realized_vol_1min
Pre_covid W0	*IB*	0.001
Covid_crash W1		0.001
Short_Selling_Ban W2		0.001
De_escalation W3		0.001
Pre_covid W0	*Q4*	0.000
Covid_crash W1		0.001
Short_Selling_Ban W2		0.001
De_escalation W3		0.001
Pre_covid W0	*Q3*	0.001
Covid_crash W1		0.001
Short_Selling_Ban W2		0.002
De_escalation W3		0.001
Pre_covid W0	*Q2*	0.001
Covid_crash W1		0.001
Short_Selling_Ban W2		0.001
De_escalation W3		0.001
Pre_covid W0	*Q1*	0.001
Covid_crash W1		0.001
Short_Selling_Ban W2		0.002
De_escalation W3		0.001

Table 2.4. Panel A of the table presents the median values for the volatility measures considered in the four periods under study, for all the IBEX 35 constituents and each of the size (capitalization) quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest capitalization stocks.

Table 2.4 1-min realized volatility (Cont.)

Panel B. Changes in median: 1-min realized volatility.

%		Median change
W1-W0	*IB*	47.67 ***
W2-W0		165.41 ***
W3-W0		106.27 ***
W2-W1		79.73 ***
W3-W1		39.68 ***
W3-W2		-22.28 ***
W1-W0	*Q4*	41.39 ***
W2-W0		187.92 ***
W3-W0		117.90 ***
W2-W1		103.64 ***
W3-W1		54.11 ***
W3-W2		-24.32 ***
W1-W0	*Q3*	48.27 ***
W2-W0		191.97 ***
W3-W0		110.13 ***
W2-W1		96.92 ***
W3-W1		41.72 ***
W3-W2		-28.03
W1-W0	*Q2*	42.81 ***
W2-W0		159.68 ***
W3-W0		106.93 ***
W2-W1		81.84 ***
W3-W1		44.90 ***
W3-W2		-20.31 ***
W1-W0	*Q1*	43.74 ***
W2-W0		123.11 ***
W3-W0		92.71 ***
W2-W1		55.22 ***
W3-W1		34.07 ***
W3-W2		-13.63 ***

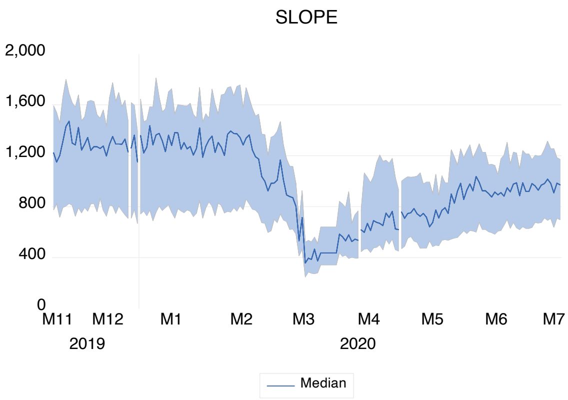
Panel B of the table shows the changes in the median from one subperiod to the others in the volatility measures, for all the IBEX 35 constituents and each of the size (capitalization) quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest capitalization stocks. *, **, and *** represent statistical significance of the Wilcoxon test at the 10%, 5%, and 1% significance levels, respectively.

These results are not consistent with Hypothesis 1, but it is important to highlight that the median of (RVol_1m) increased from W0 to W1, during the turmoil of the COVID period, and increased even more from W1 to W2 by 79.73%, accumulating a growth of 165.41% from the beginning of the studied period (see Table 2.4). We stress that during the SSR period, while IBEX did recover less than a third part of the drawdown on February 19th, 2020, the German market had recovered more than two third parts of its (see Table 2.3). These findings are especially relevant for policy makers since, despite the fact that a measure such as a restriction on naked short selling may have a certain positive impact on volatility, reducing the latter at the cost of increasing transaction costs (spread), reducing liquidity, etc., might in the end damage investors.

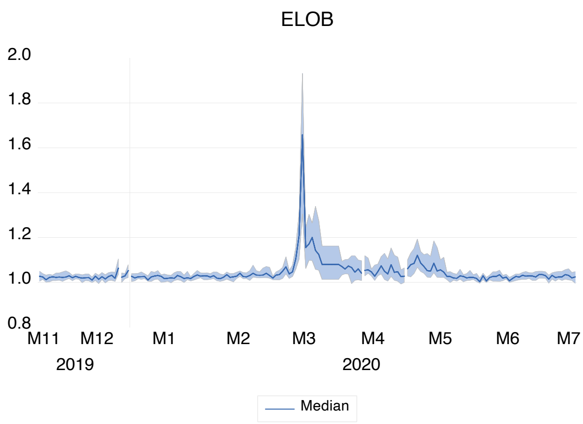
Price efficiency

As Næs and Skjeltorp (2006) pointed out, the slope of the limit order book (Equation (14)) can be used as a proxy for disagreement among investors. A steeper slope indicates concentrated intentions around price. We computed the components of the slope of the LOB, to compare the impact of the SSR on the slope of each side of the book. We compare the buy side slope (DE) with the sell side slope (SE) rather than averaging them, and look at the coefficient between them, as in equation (15). If this coefficient growths on average, the slope of the buy (sell) side increases (decreases), indicating more (less) dispersion of converge price to value in the sell (buy) side, what is consistent with Hypothesis 4.

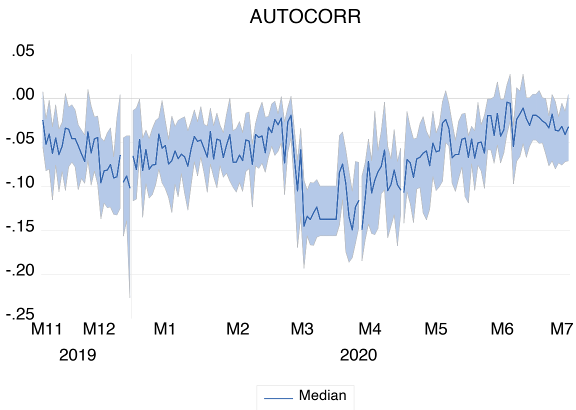
Figure 2.3 Efficiency measures



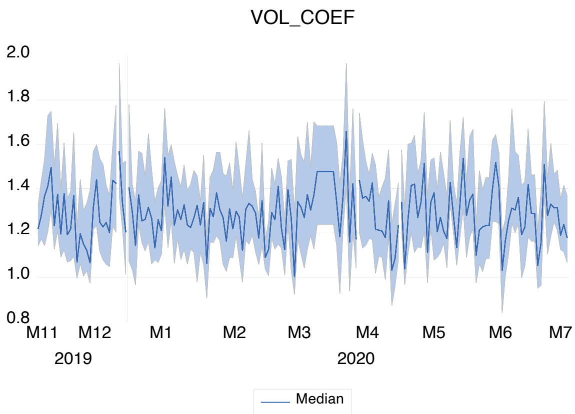
(**a**) Slope of the complete LOB.



(**b**) Relative spread as spread to midprice.



(**c**) 1-min return autocorrelation.



(**d**) Volatility Coefficient.

Figure 2.3. Efficiency measures during the periods under study. Median and 1st and 4th quartiles range are shown (a) Slope on the complete snapshot LOB. (b) ELOB. Relation among buy and sell slopes of the complete LOB. (c) 1-min first-order return autocorrelation. (d) Coefficient of scaled 1-min realized volatility divided by 30-min realized volatility.

We use the ratio to analyze the symmetry of the impact on the LOB on the different periods under study. Our findings are that ELOB medians from pre-COVID W0 to COVID crisis W1 or from pre-COVID W0 to de-escalation W3 did not change significantly. These ELOB results explain that in periods without SSR, ELOB has been symmetrically maintained on both sides of the LOB. However, the SLOPE itself decreased by -12.63% from W0 to W1. If we look at the changes from pre-COVID W0 to selling ban period W2, ELOB (SLOPE) raises (decreases) by 3,90% (-54,50%), while from COVID-19 shock W1 to short selling ban period W2 the ELOB (SLOPE) increased (decreased) by 3,05% (-47,92%). It is interesting to note that, when the SSR was lifted in de-escalation W3, the trend in the changes reversed and the ELOB (SLOPE) decreased (increased) by – 3,69% (57,04%). However, looking at the four quartiles, the size of the coefficients is not homogeneous, with bigger changes in lower capitalization stocks (Q2 and Q1), as shown in Table 2.4. We can conclude that during the ban period, the orders on the sell side were more dispersed than those on the buy side of the LOB, meaning that the buy side was more informative (Table 2.4 and Figure 2.3).

Table 2.5 Price efficiency measures.

Panel A. Median values for the price efficiency measures

Price Efficiency		Autocorrelation 1 min	Slope	Elob	Vol_coef_1m_30m
Pre_covid W0	*IB*	-0.061	1,282.29	1.023	1.28
Covid_crash W1		-0.053	1,120.38	1.032	1.26
Short_Selling_Ban W2		-0.103	583.50	1.063	1.32
De_escalation W3		-0.035	916.34	1.024	1.28
Pre_covid W0	*Q4*	-0.086	1,740.22	1.018	1.23
Covid_crash W1		-0.067	1,529.51	1.023	1.20
Short_Selling_Ban W2		-0.093	1,059.28	1.046	1.21
De_escalation W3		-0.044	1,329.84	1.019	1.19
Pre_covid W0	*Q3*	-0.049	1,454.90	1.024	1.28
Covid_crash W1		-0.047	1,308.47	1.033	1.27
Short_Selling_Ban W2		-0.100	723.95	1.044	1.34
De_escalation W3		0.000	1,021.12	1.026	1.28
Pre_covid W0	*Q2*	-0.058	1,198.12	1.025	1.23
Covid_crash W1		-0.048	1,052.86	1.032	1.20
Short_Selling_Ban W2		-0.105	597.96	1.079	1.21
De_escalation W3		-0.025	889.31	1.024	1.19
Pre_covid W0	*Q1*	-0.057	685.33	1.028	1.35
Covid_crash W1		-0.057	622.41	1.053	1.34
Short_Selling_Ban W2		-0.117	352.44	1.107	1.42
De_escalation W3		-0.039	514.22	1.026	1.39

Table 2.5. Panel A of the table presents the median values for the price efficiency measures considered in the four periods under study, for all the IBEX 35 constituents and each of the size (capitalization) quartiles, where Q4 refers to the quartile with the highest capitalization.

Table 2.5 Price efficiency measures (Cont.).

Panel B. Change in median: Price efficiency measures.

%		Median change	Median change	Median change	Median change
W1-W0	*IB*	-12.77 ***	-12.63 ***	0.82	-1.61 ***
W2-W0		68.28 ***	-54.50 ***	3.90 ***	3.42 ***
W3-W0		-42.17 ***	-28.54 ***	0.06 **	-0.10 **
W2-W1		92.92 ***	-47.92 ***	3.05 ***	5.11 ***
W3-W1		-33.70 ***	-18.21 ***	-0.76 ***	1.53 **
W3-W2		-65.64 ***	57.04 ***	-3.69 ***	-3.40 ***
W1-W0	*Q4*	-21.71 ***	-12.11 ***	0.46 ***	-2.88 **
W2-W0		8.71 ***	-39.13 ***	2.73 ***	-1.84 *
W3-W0		-48.09 ***	-23.58 ***	0.05	-3.45 **
W2-W1		38.86 ***	-30.74 ***	2.27 ***	1.08
W3-W1		-33.70 ***	-13.05 ***	-0.41 **	-0.58
W3-W2		-52.25 ***	25.54 ***	-2.61 ***	-1.64
W1-W0	*Q3*	-5.63	-10.06 ***	0.90 ***	-0.60 **
W2-W0		101.76 ***	-50.24 ***	1.94 ***	4.33
W3-W0		-100 ***	-29.82 ***	0.25 ***	-0.18 *
W2-W1		113.80 ***	-44.67 ***	1.03 ***	4.96 ***
W3-W1		-100 ***	-21.96 ***	-0.65 ***	0.43
W3-W2		-100 ***	41.05 ***	-1.66 ***	-4.32 **
W1-W0	*Q2*	-17.58 *	-12.12 ***	0.69 ***	-2.72 *
W2-W0		81.21 ***	-50.09 ***	5.29 ***	-1.68
W3-W0		-57.35 ***	25.77 ***	-0.05	-3.29 **
W2-W1		119.87 ***	-43.21 ***	4.58 ***	1.08
W3-W1		-48.25 ***	-15.53 ***	-0.73 ***	-0.58
W3-W2		-76.46 ***	48.72 ***	-5.08 ***	-1.64
W1-W0	*Q1*	0.05	9.18 ***	2.45 ***	-0.62
W2-W0		106.29 ***	-48.57 ***	7.74 ***	5.35 ***
W3-W0		-31.72 **	-21.97 ***	-0.18	2.81 ***
W2-W1		106.18 ***	-43.38 ***	5.17 ***	6.01 ***
W3-W1		-31.75	-17.38 ***	-2.56 ***	3.44 ***
W3-W2		-66.90 ***	45.91 ***	-7.35 ***	-2.42

Table 2.5. Panel B of the table shows the changes in the median from one subperiod to the others in the price efficiency measures, for all the IBEX 35 constituents and each of the size quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest capitalization stocks. *, **, and *** represent statistical significance of the Wilcoxon test at the 10%, 5%, and 1% levels, respectively.

The next parameters related to market quality that have been analyzed are the volatility coefficient ($COEF\_VOL$) that compares 30-min realized volatility to scaled up 1-minute realized volatility, and 1-min return autocorrelation ($AUTOCORR$). We find price efficiency deteriorates during the ban restriction much more than during the COVID-19 crisis period before the ban was in force, returning back to the Pre_COVID W0 levels or better when the ban was lifted, regarding 1-min autocorrelation and volatility coefficient.

We find the following results when comparing 1-min return volatility with 30-min return volatility. During the period under study, $COEF\_VOL$ ($AUTOCORR$) medians decrease by -1.61% (-12.77%) from pre-COVID W0 to COVID crisis W1, and by -0.10% (-42.17%) when comparing pre-COVID W0 to de-escalation W3. On the other hand, $COEF\_VOL$

($AUTOCORR$) raises by 3.42% (68.28%) from pre-COVID W0 to selling ban period W2. The increase holds when comparing periods W1 and W2, where $COEF\_VOL$ ($AUTOCORR$), increases 5.11% (77.09%), decreasing by – 3.40% (-65.64%) when the SSR was lifted in de-escalation W3. Changes at the quartile level by market capitalization are concentrated in Q4 and Q3, (see Table 2.5 and Figure 2.3). These results are consistent with Hypothesis 2 and, we cannot ignore that although there is a reduction in volatility due to the SSR, the distortion of price efficiency captured by the greater increase in volatility at high frequencies (1-min) related to lower frequencies (30-min) as well as the negative autocorrelation of returns, requires a global consideration of the impact of the measure taken, assessing the joint impact it generates in the results of fund managers and investors' decision making.

In Table 2.6 we present results of panel least squares regression (fixed effects) for each variable. We find that during the COVID crisis, spread, relative spread and depth, deteriorated at significant levels. These results indicate the variation generated in each subperiod for the complete set of quality variables. Regarding the implicit costs generated by a widened relative spread during the non-ban subperiods, W0, W1 and W3, the extra cost in euro for spread and basis points for relative spread increase in a similar manner, 0.017 (13.6 – 15.5 bps) during crisis and de-escalation, but worsen by an 82.35% (73.20%) during the SSR. These implicit costs have to be added to losses in liquidity due to the depth deterioration, while during non-ban periods a decrease of (8.374 – 8.723) increases more than 4.5 times to 39.038, deteriorating liquidity drastically.

Regarding price efficiency measures, results show how during the crisis period W1, the slope of the LOB decreases due to divergences in price and value beliefs. This is common under uncertainty situations, but it reaches its maximum loss during the period of restriction of short selling, eliminating the liquidity and information efficiency that short sellers provide to the market (Boehmer and Wu 2010). We would like to highlight that after the prohibition was released, the slope of the LOB showed a situation worse than the ones in W0 and W1, but it was nonetheless a 32.36% better than in the previous SSR period W2.

Finally, one of the challenges of this study is to analyze the behavior of high frequency activity under an environment of turmoil. We can assert that high frequency activity decreases drastically during the SSR period according to the HFT characterization of MiFID II, where Midprice changes, messages per second and messages per trade were drastically reduced during the ban. We find that it is not the case of messages per 100 euro traded, where we can conclude that euro-average trade did not change significantly during this period.

Table 2.6 Fixed effect panel regression coefficients (standard error).

Coefficients	Spread	Relative Spread %	Depth	Amihud 10^{-6}	Elob	Slope
Intercept	0.005 (0.002) **	-0.028 (0.009) ***	79.849 (1.534) ***	13.181 (9.909)	0.867 (0.066) ***	1480.501 (35.364) ***
Pre-covid W0	0.014 (0.002) ***	0.121 (0.010) ***	-8.374 (1.566) ***	-3.535 (10.121)	0.158 (0.067) **	-99.918 (36.119) ***
Covid crisis W1	0.017 (0.002) ***	0.136 (0.009) ***	-9.346 (1.498) ***	-6.150 (9.682)	0.193 (0.064) ***	-241.908 (34.550) ***
Ban period W2	0.031 (0.002) ***	0.252 (0.009) ***	-39.038 (1.500) ***	0.040 (9.693)	0.165 (0.064) **	-763.373 (36.119) ***
De-escalation W3	0.017 (0.002) ***	0.155 (0.010) ***	-8.723 (1.566) ***	2.110 (10.121)	0.167 (0.067) **	-516.373 (36.119) ***
Adjusted R	0.810	0.765	0.707	0.057	0.024	0.812

Coefficients	Realized_Vol %	Vol Coef	Autocorr	Midprice Changes	Mssg Sec	Mssg Tr	Mssg Eur
Intercept	-0.124 (0.009) ***	1.389 (0.045) ***	-0.031 (0.008) ***	986.828 (1.277.187)	0.793 (0.094) ***	9.443 (0.544) ***	0.174 (0.016) ***
Pre-covid W0	0.185 (0.009) ***	-0.040 (0.046)	-0.036 (0.008) ***	3.136.770 (1.304.473) **	-0.046 (0.096)	-0.905 (0555)	-0.038 (0.016) **
Covid crisis W1	0.230 (0.008) ***	-0.0797 (0.044)	-0.026 (0.008) ***	9.687.549 (1.247.859) ***	0.736 (0.09) ***	-0.356 (0.531)	-0.003 (0.015)
Ban period W2	0.305 (0.008) ***	-0.0103 (0.044)	-0.076 (0.008) ***	8.461.500 (1.249.336) ***	0.234 (0.09) **	-1.050 (0.532) **	-0.001 (0.015)
De-escalation W3	0.252 (0.009) ***	-0.048 (0.046)	-0.015 (0.008) **	12.046.030 (1.304.473) ***	0.923 (0.10) ***	1.477 (0.555) ***	0.074 (0.016) ***
Adjusted R	0.263	0.053	0.436	0.589	0.652	0.786	0.231

Table 2.6 Shows fixed effect panel regression coefficients (standard error) for all the IBEX 35 constituents and each of the size (capitalization) quartiles, where Q4 refers to the quartile with the highest capitalization stocks and Q1 refers to the quartile with the lowest capitalization stocks. *, **, and *** represent statistical significance of the Wilcoxon test at the 10%, 5%, and 1% significance levels, respectively.

Causality

Another important contribution is to find the causality in variables at intraday level. We run VECM and DH test, as well as analyze the impulse responses on the short run of those variables. One of the most discussed causality issues in HFT financial literature, is whether HFT causes changes on volatility or is the opposite, changes on volatility attract high frequency activity. Results have been found in both directions (Virgilio 2019), and it is still a topic to what degree.

In our study we investigate this by applying Granger causality between realized volatility and the HFT proxy. We complete the causality analysis of the volatility by analyzing the relationship between realized volatility and the slope of the LOB, two fundamental price efficiency metrics.

We start by testing for unit-roots in heterogeneous panel data following Hadri (2000); the first pair of variables to be analyzed are 1-min realized volatility and messages per trade (HFT) and find that both are co-integrated I (1) variables, non-stationary at level but stationary in first order difference. We include the optimal lag length (10) which minimizes Schwartz information criterion (SIC) to test Johansen cointegration for long run relationship, and (optimal – 1 lag) range in the VECM. We test Johansen cointegration (1) to optimal (10), both trace and maximum eigenvalues, where one cointegrated equation exists at 0,05 level (Mackinnon, Haug and Michelis 1999). We use Panel VECM because our purpose is purely to examine the relationship between the variables, reducing lags to (9), and finally we use the Wald test to determine Granger causality. We include 1-min realized volatility (REALIZED_VOL) and messages per trade (HFT) as relevant variables. We find that VEC Granger causality and Block exogeneity Wald test indicate that (HFT) unidirectionally Granger causes (REALIZED_VOL) at 0.05 level of significance, something consistent with Hypothesis 5 (see Table 2.7, Panel A). VEC Lag exclusion Wald test is rejected for the nine lags. The analysis has been repeated with panel DH test for robustness reasons, obtaining results similar to the ones shown in the tables which are available from the authors upon request.

The VECM equation is:

$$\Delta REALIZED_{VOL_t} = \partial + \sum_{i=1}^{lags-1} \gamma_i \cdot \mathrm{REALIZED}_{\mathrm{VOL}_{t-i}} + \sum_{m=1}^{lags-1} \eta_m \cdot \mathrm{HFT}_{t-m} + \lambda \cdot ECT_{t-1} \quad (21)$$

Where ∂ is the intercept of VECM equation, and γ_i and γ_m are the coefficients of the regressors. VECM has no restrictions.

Later, we apply the unit-root test (Hadri 2000) to the natural logarithm of the slope of the LOB (LNSLOPE) and 1-min realized volatility (REALIZED_VOL) and find that both are co-integrated variables I (1), not stationary at level but stationary in first-order difference. We include the optimal lag (9) which minimizes Schwartz information criterion (SIC) to test Johansen cointegration for long run relationship, and (optimal – 1 lag) range in the VECM. We test Johansen cointegration (1) to optimal lag (9), both the trace eigenvalues and the maximums, where there is a cointegrated equation at level 0.05. Again, we use VECM Panel because our purpose is purely to examine the relationship between these endogenous variables, and we find that Granger VEC causality and Wald's block exogeneity test indicate that (LNSLOPE) causes bidirectional Granger (REALIZED_VOL) (see Table 2.7, Panel B).

Table 2.7. Panel Granger Causality / Block exogeneity Wald tests.

VECM and Panel Granger Causality								
Panel A. Realized Volatility and HFT	$\boldsymbol{\xi}$	$\boldsymbol{\mu}$	$\boldsymbol{\lambda}$	$\boldsymbol{\partial}$	$\boldsymbol{\gamma_i}$	$\boldsymbol{\eta_m}$	**Chi-sq**	p-value
Long run cointegrating equation ECT_{t-1} *	$-1.08\cdot10^{-5}$	-0.001158						
VECM Equation			-0.1016	$3.27\cdot10^{-6}$				
Lag (1)					-0.33295	$-6.76\cdot10^{-6}$		
Lag (2)					-0.15369	$-2.93\cdot10^{-6}$		
Lag (3)					-0.06585	$6.91\cdot10^{-7}$		
Lag (4)					-0.00661	$-7.23\cdot10^{-7}$		
Lag (5)					0.02862	$-8.91\cdot10^{-8}$		
Lag (6)					0.01534	$2.72\cdot10^{-6}$		
Lag (7)					-0.01898	$1.18\cdot10^{-6}$		
Lag (8)					-0.02616	$2.98\cdot10^{-6}$		
Lag (9)					0.02010	$6.00\cdot10^{-7}$		
HFT Granger causes 1-min Realized Volatility							20.0095	0.0179
1-min Realized Volatility does not Granger cause HFT							14.5797	0.1031
Panel B. Realized Volatility and LNSLOPE	$\boldsymbol{\xi}$	$\boldsymbol{\mu}$	$\boldsymbol{\lambda}$	$\boldsymbol{\partial}$	$\boldsymbol{\gamma_i}$	$\boldsymbol{\eta_m}$	**Chi-sq**	p-value
Long run cointegrating equation ECT_{t-1} *	0.000346	-0.003593						
VECM Equation			-0.1095	$2.64\cdot10^{-6}$				
Lag (1)					-0.36147	-0.00025		
Lag (2)					-0.18476	-0.00031		
Lag (3)					-0.12068	-0.00032		
Lag (4)					-0.03289	$-1.68\cdot10^{-5}$		
Lag (5)					0.03733	0.00018		
Lag (6)					0.02358	0.00012		
Lag (7)					-0.00789	0.00015		
Lag (8)					-0.02764	$5.72\cdot10^{-6}$		
Ln SLOPE Granger causes 1-min Realized Volatility							74.0635	0.0000
1-min Realized Volatility Granger causes Ln SLOPE							236.823	0.0000

Table 2.7. Panel A. The table shows the estimates for the Granger causality tests for the optimal lag-length (ten lags) for HFT. The VECM model with 1 cointegrating equation is specified by the error correction term (ECT) obtained from the long-run cointegrating equation, that explains previous period's deviation from long run equilibrium influences short-run movement in the variable of interest. (λ) Lambda coefficient of the ECT is the speed of adjustment at wich dependent variable returns to equilibrium. The cointegrating equation and long run model is $ECT_{t-1} = \left[\mathrm{REALIZED}_{\mathrm{VOL}_{t-1}} - \xi \cdot HFT_{t-1} + \mu\right]$

Panel B presents the estimates for the Granger causality tests for the optimal lag-length (nine lags) for LNSLOPE. The VECM model with 1 cointegrating equation is specified by the error correction term (ECT) obtained from the long-run cointegrating equation, that explains previous period's deviation from long run equilibrium influences short-run movement in the variable of interest. (λ) Lambda coefficient of the ECT is the speed of adjustment at wich dependent variable returns to equilibrium. The cointegrating equation and long run model is $ECT_{t-1} = \left[\mathrm{REALIZED}_{\mathrm{VOL}_{t-1}} - \xi \cdot \mathrm{LNSLOPE}_{t-1} + \mu\right]$

The VECM equation is:

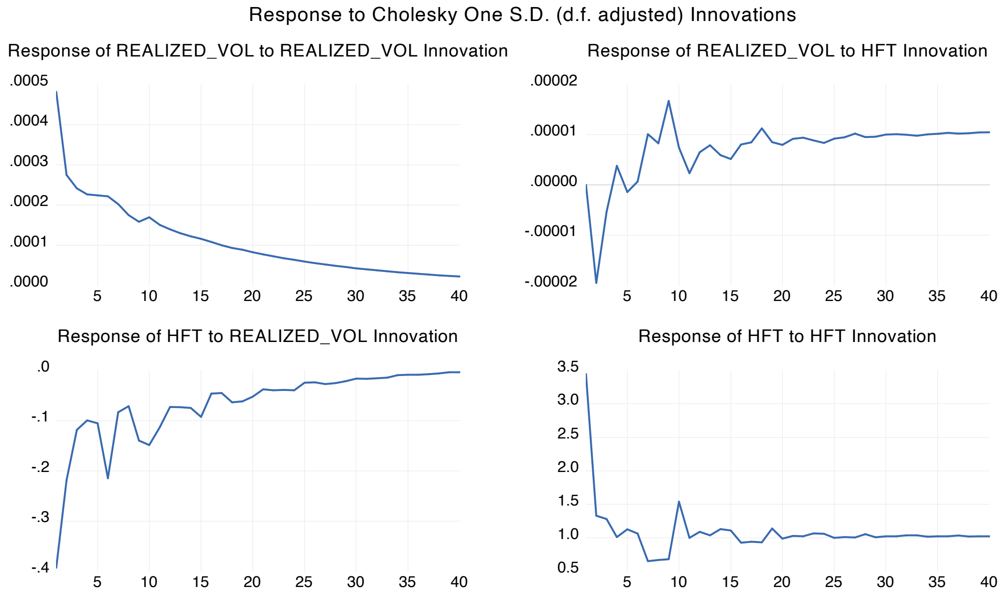
$$\Delta REALIZED\_VOL_t = \partial + \sum_{i=1}^{lags-1} \gamma_i \cdot \mathrm{REALIZED\_VOL}_{t-i} + \sum_{m=1}^{lags-1} \eta_m \cdot \mathrm{LNSLOPE}_{t-m} + \boldsymbol{\lambda} \cdot ECT_{t-1} \tag{22}$$

Where ∂ is the intercept of VECM equation, and γ_i and γ_m are the coefficients of the regressors. VECM has no restrictions.

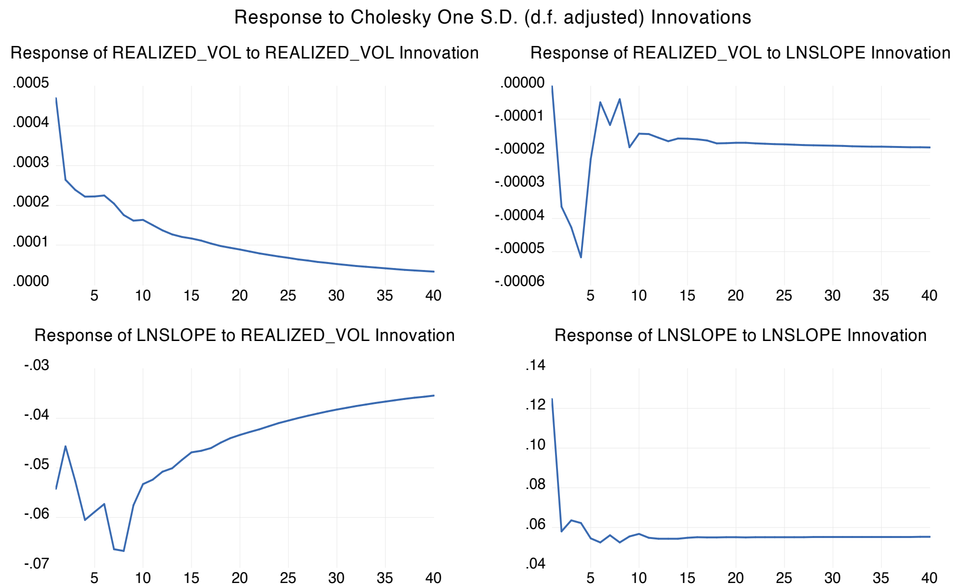
The impulse response interpretation is how 1-min realized volatility responds to a standard deviation shock of high frequency trading activity through the proxy HFT. We use a forty-period window to analyze this response. We find that 1-min realized volatility decreases in the very short run to a standard deviation shock of HFT (periods 0 and 1) exacerbating later (2 to 8) and continues stable on the long run (10 to 40 periods). This indicates that realized volatility is very sensitive to changes in standard deviation shocks of HFT. The previous period deviation from the long run equilibrium is corrected in the current period at a speed of 10.16%, and a percentage change in HFT is associated with a -6.76 10^{-6}% decrease on average (ceteris paribus) in the short run.

In the case of the slope of the LOB measured through the natural logarithm of SLOPE, Granger causality is bidirectional, what is partially consistent with Hypothesis 5, and we find that 1-min realized volatility decreases drastically in the short run (periods 0 to 4) due to an innovation of one standard deviation, returning back to close to previous levels, and going stable in the long run. The previous period deviation from the long run equilibrium is corrected at a speed of 10.95%, and a percentage change in HFT is associated with a -0.00025% decrease on average (ceteris paribus) in the short run. It is observable how the natural logarithm of SLOPE reacts decreasing during the short-medium periods (1-8) and returns slower in the long run (8-10) in a concave shape. This indicates that the LOB takes more time to be reconstructed after a shock generating less efficiency and liquidity issues.

Figure 2.4 Impulse response Volatility, HFT and Slope



(a) Response to Cholesky One S.D. (REALIZED_VOL / HFT)



(b) Response to Cholesky One S.D. (REALIZED_VOL / LNSLOPE)

Figure 2.4. Impulse responses of VECM (a) Response to Cholesky One S.D. Innovations of REALIZED_VOL to HFT innovations up-right panel; (b) Response to Cholesky One S.D. Innovations of REALIZED_VOL to the natural logarithm of SLOPE innovations and vice versa in up-right and down-left panels.

2.5 Conclusions

Market intervention through banning net short selling positions is a usual mechanism that the regulator is using to prevent extreme volatility during crisis and turmoil. We examine how short selling restriction in the Spanish equity market affects the quality of stock prices under a high frequency approach due to the context of increasingly automated equity markets.

We analyze a range of liquidity and price efficiency and realized volatility measures. Our evidence supports the idea that short selling restrictions worsens the main quality measures, generating high implicit costs for managers and investors in an intraday basis.

Although the SSR eliminates some intraday volatility, it is far from its objective of eliminating the extreme instability that results from falling returns during a shock as the one produced during the COVID-19 lockdown period (Hypothesis 1). High frequency activity, which increases realized volatility in the short run, crowds out on the SSR period; returning when the restriction is released (Hypothesis 3). We find fairly robust results by applying different econometric approaches to test for panel Granger causality and we show that during the period under study, the HFT proxy Granger causes unidirectionally realized volatility (Hypothesis 5).

This type of restrictions keeps prices out of line with fundamentals, worsening equilibrium among price and value, which itself generates volatility, reflected in a much lower slope of the LOB. This SSR period with non or residual short sellers, has deteriorated even more price efficiency, increasing return negative autocorrelation, as well as increasing volatility coefficient, what finally impacts intraday and automated trading (Hypothesis 2). We show that, when short sellers disappear, the impact in both sides of the LOB is not symmetrical, dispersing sell orders from the fundamental value much more than the buy intentions. This effect disappears when shorting constraints are lifted (Hypothesis 4).

Taken together, these deterioration in liquidity and price efficiency, all suggest that SSR contributes significantly to create high intraday implicit costs, that are not always visible on a low-frequency approach. (Hypothesis 2). Moreover, the lack of liquidity, the increase on intraday autocorrelation, and prices consistently (intraday) separated from value, opens the door to destabilizing or manipulative trading by at least giving advantage to speculation. These measures can bring consequences, far from protecting the investor, penalizing with very high implicit costs and deteriorating price quality in the sense that prices are not closer to efficient or fundamental values. Our results have important implications for recent regulatory actions that restrict short selling. Specifically, it is necessary to take into account that an SSR reduces high frequency activity, which subsequently reduces realized volatility in the short run. And, in crisis times, constrains liquidity providers, reducing depth, significally increasing transaction costs as well as being likely to alter the price-efficiency in markets.

In this sense, it would be interesting to deepen the analysis and understanding of these effects. A possible alternative would be to use a dynamic approach in the style of Tilfani, Ferreira and El Boukfaoui (2021) to study the relationship between the different variables, so that instead of obtaining isolated figures for each subperiod, we would be able to visualize the temporal evolution of the aforementioned relationships thereby capturing information that might otherwise be hidden by data aggregation. Another example in this direction would be to group the assets based on the prevalence of HFT/AT in each of them and analyze whether there are differences in the deterioration of market quality measures based on the amount of automatic trading recorded on each asset, as Chakrabarty and Pascual (2022) show. In this way relations between this type of negotiation and the impact of the policy measure (SSR) on the quality of the market could be established.

In line with the studies that have detected intraday seasonality, it could be of interest to divide the days into time slots so that it can be observed whether the effects are generalized or vary in moments of high volume vs. moments of low volume traded. Finally, related to the study of the market microstructure in this interesting period, future steps in the research could include analyzing phenomena such as the intraday momentum effect, already observed in the FX market.

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3. The role of informed trading and belief consensus in market volatility

Abstract

This study investigates the interactive dynamics between informed trading, beliefs distribution on the Limit Order Book, liquidity and volatility, and examines the changes in these dynamics observed during the COVID-19 event, along with the short selling ban imposed on some components of the IBEX-35. The primary findings include: (1) The level of non-contemporaneous informed trading shows a positive relationship with investor consensus regarding the fundamental value; (2) Our findings indicate Granger causal relationships between informed trading, order book consensus, and volatility, occurring with significant differences across different asset capitalization levels; and (3) The beliefs distribution on the Limit Order Book shows greater predictive power for volatility compared to informed trading. These results provide meaningful insights into market microstructure and the complex interplay between the probability of informed trading, the distribution of beliefs on the Limit Order Book, and market volatility, highlighting how both informed trading and consensus on the Limit Order Book directly condition and impact market volatility.

Keywords: Informed trading, dispersion of beliefs, Limit Order Book, VPIN, volatility, liquidity, COVID-19, Short-selling ban, Granger causality.

3.1 Introduction

Informed trading is a relevant topic due to its significant impact on various aspects of financial markets, such as market dynamics, price movements, information integration, and market quality. It involves using material non-public information by traders to directly or indirectly influence security prices (Chao et al., 2018). The implications of informed trading are far-reaching, affecting security price movements and information integration at the market level (Easley et al., 1998; Hu, 2018). Informed trading has been found to increase the speed of firm-specific information integration while negatively impacting the speed of market-level information integration due to trading costs associated with information asymmetry (Hu, 2018).

Additionally, the role of informed trading in the informational environment and its implications for market quality and information asymmetry have been highlighted, underscoring its importance for market microstructure and regulatory policies (Pan & Misra, 2020).

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, often referred to as market toxicity, can increase liquidity-induced volatility (Easley et al., 2012; Tiniç et al., 2023). However, other research indicates that informed trading tends to reduce volatility by accelerating the integration of firm-specific information into prices (Avramov et al., 2006; Easley et al., 1998; Hu, 2018) in heavily traded and highly capitalized stocks (Blasco & Corredor, 2017). Others, such as Huang and Chang (2014), have found that the effect of informed trading on volatility is asymmetric, as for securities with less private information, an increase in informed trading activity may lead to higher volatility of returns. The relationship between informed trading and volatility is not consistent, which may be due to the existence of interrelationships and feedback between the two variables and other factors, such as the impact of information asymmetry or the role of liquidity. Unravelling these interrelationships is particularly important, given that volatility in financial markets (whether it is liquidity-driven or information-driven) is known to have significant adverse effects on various aspects of market stability and investor behavior, as well as necessary to comprehensively grasp market dynamics.

One of the most commonly used measures in the literature for quantifying informed trading activity and information asymmetry is the Volume-Synchronized Probability of Informed Trading (known as VPIN) (Easley et al., 2011), which is a dynamic measure of order flow imbalance, introduced as a tool to predict extreme events, such as "flash crashes" in high-frequency trading (Easley et al., 2012). However, it has been extensively discussed in the literature as a measure of high-frequency adverse selection and informed trading activity, being considered a barometer of information asymmetry, as it quantifies the likelihood that trading volumes are driven by informed participants. Abad et al. (2018) measure the presence of extreme market toxicity using a threshold in the cumulative distribution function (CDF) of VPIN (greater than 0.99 for stocks), and observe that if the threshold is exceeded, exacerbated volatility can be observed. The mechanism by which this happens could be twofold: On the one hand, market toxicity is associated with the presence of adverse selection risk in high-frequency trading, which can lead to liquidity problems and then increased volatility (Rzayev & Ibikunle, 2019) due to the sudden disappearance of market liquidity (Brunnermeier & Pedersen, 2012); on the other hand, research has demonstrated that a high VPIN is positively correlated with investor sentiment which also has an impact on volatility (Gao et al., 2022). Therefore, when there is an extreme increase in toxicity, as measured by overcoming a specified threshold of the CDF of VPIN, it can contribute to higher volatility due to the impact of investor sentiment and market liquidity. This understanding is particularly relevant in high-frequency trading environments where market toxicity is associated with adverse selection risk. Hence, we aim to delve into the dual influence of informed trading: its potential to reduce liquidity, particularly for liquidity providers, and its ability to enhance consensus in investor beliefs due to more informed limit orders within the order book.

In the context of asymmetric information, where one party has more or better information than the other, the use of market or limit orders becomes highly significant. Traditional financial theories often posit that traders with access to time-sensitive information (known as informed traders) choose market orders to execute transactions based on their superior knowledge quickly. This preference is attributed to their urgency to capitalize on the ephemeral nature of their informational advantage. However, this conventional narrative has been nuanced by a series of theoretical and empirical studies. Theoretical expositions by Seppi (1997), Harris (1998), Kaniel and Liu (2006), and Goettler et al. (2009) suggest that limit orders are not exclusively the domain of uninformed or liquidity-motivated traders. On the contrary, informed traders can also strategically employ limit orders, particularly in market conditions with higher informational volatility (Pascual & Veredas, 2006). Empirical corroboration of this theoretical framework is provided by studies from Bloomfield et al. (2015) and Anand et al. (2005), all of which present evidence supporting the use of limit orders by informed traders.

This revelation suggests that the impact of information asymmetry on market prices would extend beyond executed transactions to include order submissions. Indeed, previous literature indicates that the Limit Order Book (LOB henceforth) is informative and even orders other than the best bid and ask to contribute to price discovery (Liu & Ouyang, 2014). According to this evidence, the slope of the LOB (Næs & Skjeltorp, 2006; Tripathi et al., 2020), a measure that examines the relationship between the depth of the LOB and its distance from the prevailing market price, provides a more comprehensive view of market dynamics and information asymmetry, as it encompasses the entire LOB, reflecting trading intentions and not just executed transactions (Aidov & Lobanova, 2021a; Cont et al., 2013a; Roşu, 2009). Traditionally, the slope of the LOB has been considered a measure of liquidity, though it also incorporates information about the degree of market consensus regarding fundamental value. Kang and Zhang (2013) note that a lower dispersion of beliefs (higher consensus) could be associated with a higher proportion of informed limit orders, implying that informed traders are active, integrating their private information into the order book. Conversely, greater dispersion of orders in the LOB (indicating low consensus) could indicate that the orders are more likely to be uninformed, leading to a less efficient market, as informed orders tend to cluster around prices that reflect the underlying private information. Uninformed market makers can perceive this dispersion in the LOB as an expectation of high volatility by informed market makers, leading to a reluctance to post limit orders. This finding supports the notion that the slope of the LOB can be seen as a reflection of the dispersion of beliefs among market participants, influencing market dynamics. In this sense, this measure, which allows the level of consensus to be quantified, will enable us to investigate further the relationship between informed trading, consensus and volatility. This is particularly interesting given that the interaction between informed trading and belief consensus can create feedback loops that further exacerbate volatility.

Market liquidity also plays a crucial role in determining the level of volatility, as a sudden disappearance of the former can lead to increased levels of the latter (Brunnermeier & Pedersen, 2012). Notably, informed trading is often perceived to consume liquidity (Heflin & Shaw, 2000). That is, informed trading could potentially decrease the depth of the LOB and widen the bid-ask spread while contributing to a more informed and efficient price formation process and greater consensus between value and price, possibly due to informed orders in the upper part of the book. This dual effect could have far-reaching implications for market participants and would presumably be more pronounced in the large-cap sector due to higher analyst coverage and a smaller pool of uninformed liquidity, leading to a more unified investor consensus on their fundamental values.

The objective of this paper is threefold: First, it aims to analyze the impact of informed trading on consensus within the LOB and its effects on external market liquidity (measured by the relative spread) and internal liquidity (measured by depth). Second, the paper seeks to shed light on the dynamics of market volatility by examining the relationship between informed trading, belief consensus in the LOB, and market volatility itself. This investigation will explore whether these relationships are bidirectional or unidirectional, utilizing Granger causality tests to identify any potential causal links. Finally, aligning with this framework, the third objective is to assess whether the slope of the LOB can complement or even surpass the VPIN in certain aspects. This involves weighing the predictive power of belief consensus against informed trading, considering both short-term variations (as represented by VPIN) and periods of high activity by informed traders (reflected in the Cumulative Distribution Function of VPIN). The insights gained from this analysis are essential for developing strategies aimed at enhancing market efficiency and stability by fostering the involvement and activities of informed traders.

Specifically, the hypotheses under study are as follows:

(H1a) Informed trading improves the consensus of beliefs of investors in LOB.

(H1b) Informed trading consumes external and internal liquidity.

(H2a) Informed trading positively Granger causes consensus in the LOB in familiar stocks.

(H2b) There is a bidirectional negative relationship between consensus and volatility.

(H2c) When informed trading is present, volatility tends to decrease. However, when informed trading reaches extreme levels, volatility increases due to the resulting lack of liquidity.

(H3) The dispersion of beliefs in the LOB is a better predictor of market volatility than informed trading.

Finally, it is worth recalling that during the recent COVID-19 pandemic, financial markets experienced unprecedented levels of volatility and the IBEX 35 index was no exception (Ali et al., 2020; Broadstock et al., 2021; Goodell, 2020; Ramelli & Wagner, 2020). The COVID-19 pandemic also introduced notable levels of uncertainty, information asymmetry, and regulatory interventions in financial markets (Albulescu, 2021; Ashraf, 2020; Baig et al., 2021; Ramelli & Wagner, 2020; Zaremba et al., 2021), posing significant challenges for both market participants and regulators. This makes this period an opportune time to study the complex dynamics related to market volatility.

This study contributes to the market microstructure literature by investigating the interaction between informed trading, LOB liquidity, consensus of beliefs, and volatility. It explores how informed trading, traditionally associated with market orders, impacts liquidity and volatility metrics, focusing on price consensus in the LOB, which also contains informed orders. In addition, possible differences between assets with different capitalization levels are considered.

To our knowledge, this is the first study to incorporate LOB information to study informed trading and its impact on other market variables.

Additionally, the study employs a volume-clock perspective to work with intraday data. It applies high-frequency, tick-by-tick data analysis using containers defined by each stock's volume clock, considering all LOB levels. This approach allows for a detailed representation of market dynamics, especially during the COVID-19 pandemic period, observing potential relationships between these variables and how they have been affected by this black swan event.

The remainder of the paper 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.

3.2 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. Informational volatility, often triggered by new data or events, in turn influences internal liquidity, represented by the depth of the LOB, and external liquidity, captured through measures such as the relative spread. Drechsler et al. (2021) 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 (Cahill et al., 2020). The distinction between informational and liquidity-driven volatility becomes particularly significant in market stress, where their respective roles can compound or offset one another.

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 (Jena et al., 2021; Salisu et al., 2018) 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 & Bhaduri, 2019).

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 & 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.

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 & Jiang, 2014).

From a microstructural perspective, 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. This liquidity-driven stability is particularly important in market stress, where fragmented liquidity can lead to abrupt and exaggerated price movements. Wang et al. (2020) further explain that informed traders enhance market liquidity by reducing information asymmetry, as they cluster their limit orders around prices that reflect their superior knowledge. This concentration of orders supports price stability, reducing return volatility.

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.

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. This dual role is especially pronounced in large-cap stocks, where the presence of more analysts and less information asymmetry leads to greater consensus on asset values (Brunnermeier & Pedersen, 2012). 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. This interaction between liquidity consumption and price discovery highlights informed traders' nuanced role in stabilizing and destabilizing markets depending on the context.

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, especially in high-frequency trading environments, where liquidity can rapidly disappear, leading to extreme volatility events.

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 informed traders cluster their limit orders around prices that reflect their private information, thereby aligning market prices more closely with fundamental values. This clustering enhances market liquidity, leading to lower volatility. 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; Frey & Sandås, 2017; Kang & Zhang, 2013).

This comprehensive literature review highlights the intricate relationships between informed trading, liquidity, and volatility, underscoring the importance of both VPIN and the slope of the LOB as tools for understanding market dynamics. 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.

3.3 Data

Our sample consists of 18 Spanish stocks belonging to the IBEX 35 index, categorized as in Abad & Yagüe (2012), divided into three 6-stock portfolios representing different levels of capitalization and activity (large, medium, and small). Six stocks were chosen for each category based on their proximity to the median in terms of both capitalization and trading volume, as seen in Table 3.1. The identified companies for the large-CAP category are Amadeus IT Group, S. A. (AMS), Repsol YPF (REP), Telefónica (TEF), Banco Bilbao Vizcaya Argentaria (BBVA), Caixabank, S. A. (CABK), and Iberdrola (IBE). For the mid-CAP category, the selected companies are Gamesa Corporación Tecnológica (SGRE), ACS, Actividades de Construcción y Servicios (ACS), Red Eléctrica de España (REE), Banco de Sabadell (SAB), Mapfre, S. A. (MAP), and International Consolidated Airlines Group, S. A. (IAG). The small-cap category includes Acerinox (ACX), Gestevisión Telecinco (TL5), CIE Automotive (CIE), Viscofan (VIS), Indra Sistemas (IDR), and Bankia, S. A. (BKIA).

Table 3.1 Market capitalization and volume negotiated in 2019 (€M)

	Market Cap	Volume	Distance to Market Cap Median	Distance to Volume Median
Panel A: Large-Cap				
AMS	31396.3	24731.1	532.6	3785.1
REP	21276.6	28540.5	10652.3	24.3
TEF	32331.4	39769.5	402.5	11253.3
BBVA	33226.1	39001.9	1297.2	10485.7
CABK	16736.1	12285.9	15192.8	16230.3
IBR	58403.8	36493.2	26474.9	7977.0
Panel B: Mid-Cap				
SGRE	10649.7	6329.6	475.4	485.5
ACS	11217.8	7955.2	1043.5	1140.1
REE	9698.9	9804.2	475.4	2989.1
SAB	5852.0	7300.6	4322.3	485.5
IAG	3784.9	5452.4	3610.6	1362.7
MAP	7267.7	3061.0	2906.6	3754.1
Panel C: Small-Cap				
ACX	2717.6	2411.0	263.7	854.7
TL5	1853.3	1777.7	600.6	221.4
CIE	2719.3	1327.9	265.4	228.4
VIS	2190.2	1230.8	263.7	325.5
IDR	1798.3	1334.9	655.6	221.4
BKIA	5839.8	4091.0	3385.9	2534.7

Table 3.1. This table presents the median values of 2019 for market capitalization and volume, along with their distances to the category median, across three panels: large-cap (Panel A), mid-cap (Panel B), and small-cap (Panel C).

The time frame spans from 20th November of 2019 to 13th July of 2020, encompassing the COVID-19 crisis, over a period that covers pre-pandemic (W0) from November 20th, 2019, to January 20th, 2020; pandemic crash (W1) from January 21st, 2020, to March 17th, 2020; short selling ban (W2) from March 18th, 2020, to May 18th, 2020; de-escalation (W3) 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. to 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. to 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.

3.4 Methodology and results

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 data2. 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. 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

[2] 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).

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 ($\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}$), 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 ($\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}$). 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 Equation (3), where the bucket size n encompasses the aggregate number of volume buckets. VPIN is estimated utilizing a moving window of l-length volume buckets. For example, the initial VPIN calculation employs volume buckets within the interval [1, 50]. Successive VPIN estimations are derived by incrementally shifting the moving window, for instance, from the range [2, 51] in the 50-length case, and proceeding accordingly.

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

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.

The variation of VPIN will be used to measure the incorporation of informed trading in the very short run. A positive value of VPIN variation indicates an increase in the activity of informed traders, while a negative value suggests a decrease. A high CDF value may indicate a period of high activity by informed traders, whereas a low value may suggest the opposite.

Liquidity and dispersion of beliefs measures.

Relative quoted spread (RS) and depth of the LOB are used as indicators of liquidity. These measures provide insights into different aspects of liquidity: We use RS (as shown in Equation 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 Equation 5).

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

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

$DEPTH_{i,\tau}$ 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 across the limit order book. A steeper slope indicates a higher concentration of informed orders, as informed traders tend to place orders closer to the fundamental prices they know or anticipate. Conversely, a flatter slope suggests the predominance of uninformed orders, indicating greater dispersion of beliefs and less accuracy in the underlying information driving prices. It is a key metric that can also be used as a proxy for liquidity provision in the market, as it is not limited to the best prices (bid-ask), but rather encompasses both the spread and the depth of orders on the buy and sell sides (Kempf & Mayston, 2008). Its ability to capture both spread and depth makes it a more comprehensive indicator of market liquidity, offering a holistic view that goes beyond top-of-book quotes by examining the entire structure of the order book.

Thus, the slope not only acts as a measure of consensus but also captures liquidity dynamics. By integrating both spread and depth, the slope provides a more detailed representation of liquidity provision in the market and can distinguish between situations where orders are predominantly informed or uninformed. In contexts of higher informational asymmetry, a steeper slope reflects the activity of informed traders who actively shape the order book structure, contributing to the price discovery process (Ghysels & Nguyen, 2019). This link between the slope and the informational content of orders is further supported by studies such as Cenesizoglu et al. (2014), which demonstrated that the state of the LOB effectively predicts short-term price changes, underscoring the importance of the slope as an indicator of future price dynamics based on order distribution.

Additionally, the concept of order flow imbalance (Maglaras et al., 2015) reinforces this idea by noting that a greater imbalance in order flow, whether on the buy or sell side, tends to result in a steeper slope, indicating a higher concentration of informed trading activity. By acting on their advantage, informed traders shape the LOB, which affects market liquidity and volatility.

The slope of the demand side and the supply side in the visible order book is obtained following Næs and Skjeltorp (2006) as in equations (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 sell (buy) 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 levels 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.

Volatility measures

The volatility of intraday returns is proxied through the absolute value of bucket returns. Additionally, for robustness tests, we use the absolute value of the return residual from the return regression as Jones et al. (1994) (Equations 9 and 10) and conditional volatility EGARCH (Equation 11). Specifically, the absolute value of bucket returns serves as our primary volatility proxy, while the absolute return residual and conditional volatility offer a robust alternative measure.

$$R_{i\tau} = \sum_{r=1}^{S} b_{i,r} R_{i,\tau-r} + u_{i,\tau} \tag{9}$$

$$|u_{i\tau}| = \phi_i + \sum_{k=1}^{q} \rho_{ik}\left|u_{i,\tau-r}\right| + c_i bucket + \sum_{j=1}^{2} \psi_i\ h_i + \zeta_{i\tau} \tag{10}$$

Where $R_{i\tau}$ is the return of stock i on bucket τ , $u_{i,\tau}$ is the residual in equation (9), $R_{i,\tau-r}$ and $\left|u_{i,\tau-k}\right|$ are the relevant lags of $R_{i\tau}$ and $u_{i\tau}$ to deal with autocorrelation3. Due to the use of event clock, the bucket number is used as a proxy of volume to orthogonalize volatility; h_i are the dummies for hours 9 and 17 included to deal with U-shape in intraday volatility, q is the optimal lag and $\zeta_{i\tau}$ is the residual in equation (10).

An additional analysis using conditional volatility through an EGARCH model has been conducted to strengthen the robustness of our findings. This approach is well-suited for capturing volatility's persistence and complex dynamics, offering a more nuanced view of return variability. Unlike traditional GARCH models, the EGARCH model directly models the logarithm of conditional variance, allowing volatility to respond asymmetrically to past shocks, effectively capturing volatility clustering. The EGARCH model's flexibility enhances volatility modelling by incorporating both its own lags and error term lags while accounting for leverage effects—where negative news increases volatility more than positive news of the same magnitude. This provides deeper insights into how past innovations and historical volatility influence current volatility, complementing our initial estimates. The model's autoregressive and volatility components orders were selected based on information criteria such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC), with parameter significance assessed to confirm the model's ability to capture temporal volatility dynamics. The robustness of the EGARCH model was verified by analyzing standardized residuals, ensuring the absence of autocorrelation, and confirming that the model specification captures the temporal dependence structure.

[3] The number of lags included varies for stock depending on the significance of the correlation with SC criteria.

Table 3.2 Descriptive statistics

	VPIN	CDFVPIN	SLOPE	RS	DEPTH	ABSRET	ABSRES	EGARCH	BUCKET
Panel A: Large-Cap									
Mean	0.0543	0.4702	2159.815	0.0006	80.5003	0.0026	0.0017	0.0035	40.8953
Median	0.0528	0.4591	1928.982	0.0004	78.0000	0.0019	0.0013	0.0032	30.0000
Maximum	0.1286	1.0000	10786.02	0.0259	535.0000	0.0720	0.0615	0.0156	330.0000
Minimum	0.0213	0.0001	40.59731	0.0001	21.5000	0.0000	0.0000	0.0010	1.0000
Std. Dev.	0.0112	0.2842	1310.728	0.0007	36.1923	0.0028	0.0019	0.0015	38.5439
Skewness	0.6390	0.1081	1.369359	8.1911	2.0630	3.7681	6.2143	1.5246	2.2646
Kurtosis	3.8349	1.8505	6.116113	171.5169	14.9058	39.8992	101.8684	7.2904	10.9297
Obs.	52849	52849	52849	52849	52849	52849	52849	52849	52849
Panel B: Mid-Cap									
Mean	0.0932	0.4750	1323.431	0.0011	67.9232	0.0023	0.0015	0.0030	139.7934
Median	0.0930	0.4608	1108.818	0.0007	66.0000	0.0016	0.0011	0.0027	78.0000
Maximum	0.1686	1.0000	6013.598	0.07749	337.5000	0.07190	0.0633	0.01854	1237.0000
Minimum	0.0100	0.0000	22.0008	0.0002	22.0000	0.0000	0.0000	0.0006	1.0000
Std. Dev.	0.0186	0.2759	840.8662	0.0012	25.9599	0.0026	0.0018	0.0012	175.9626
Skewness	-0.0212	0.1297	1.04255	8.2196	1.7418	4.1347	6.4483	2.1746	2.5184
Kurtosis	3.1712	1.9095	3.9830	265.3542	12.2922	46.3080	99.8824	12.1416	10.4641
Obs.	91629	91629	91629	91629	91629	91629	91629	91629	91629
Panel C: Small-Cap									
Mean	0.1240	0.5617	1013.483	0.0014	58.4497	0.0024	0.0016	0.0031	75.3785
Median	0.1255	0.5887	762.5435	0.0010	60.0000	0.0016	0.0011	0.0025	46.0000
Maximum	0.2296	1.0000	5631.287	0.0450	147.5000	0.1118	0.0987	0.0212	671.0000
Minimum	0.0439	0.0001	16.38013	0.0002	21.50000	0.0000	0.0000	0.0008	1.0000
Std. Dev.	0.0268	0.2881	803.5303	0.0015	18.11895	0.0029	0.0021	0.0016	84.8009
Skewness	-0.0672	-0.2412	1.887295	6.8470	0.099288	6.1478	10.0628	2.2868	2.2056
Kurtosis	2.9358	1.8638	6.707771	101.0826	2.405170	116.0595	277.5993	10.3241	9.30213
Obs.	61226	61226	61226	61226	61226	61226	61226	61226	61226

Table 3.2 presents the descriptive statistics of the selected variables, distinguishing between large-, mid- and small-cap portfolios. All statistics refer to the 20th of November 2019 to 13th of July 2020 period.

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

$$log(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i g(Z_{t-i}) + \sum_{j=1}^{q} \beta_j \, log(\sigma_{t-j}^2); \quad \varsigma_t = exp\left(\frac{log(\sigma_t^2)}{2}\right) \tag{11}$$

Where, $\log(\sigma_t^2)$ 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 3.1 shows the descriptive statistics for the variables under examination.

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

We first address hypothesis (H1a) and hypothesis (H1b), investigating the impact of informed trading over consensus and liquidity measures in a non-contemporaneous relationship. As in Hendershott et al. (2011) and Yildiz et al. (2020), we control for trading activity using order count in each bucket as a proxy for the number of transactions per day. 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 the 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):

$$\begin{aligned} \boldsymbol{Y_{i,\tau} = \beta_{i,\tau} + \beta_{i,1} \cdot CDFVPIN_{i,\tau-1} + \beta_{i,2} \cdot CRASH_{i,\tau-1} + \beta_{i,3} \cdot SSB_{i,\tau-1}} &+ \\ \boldsymbol{+ \beta_{i,4} \cdot DECAL_{i,\tau-1} + \beta_{i,5} \cdot Bucket_{i,\tau-1} + \beta_{i,6} \cdot Volatility_{i,\tau-1} + \varepsilon_{i,\tau}} & \end{aligned} \tag{12}$$

The slope of the LOB, market or external liquidity (RS) and internal liquidity of the LOB (DEPTH) are taken as dependent variables $(\mathrm{Y}_{\mathrm{i},\tau})$. $\mathrm{CDFVPIN}_{\mathrm{i},\tau-1}$ proxies for the level of informed trading as measured by the cumulative distribution of VPIN. The dummy variables $\mathrm{CRASH}_{\mathrm{i},\tau-1}$, $\mathrm{SSB}_{\mathrm{i},\tau-1}$, and $\mathrm{DECAL}_{\mathrm{i},\tau-1}$ reflect the COVID-19 crash window (W1), the regulatory imposition of a short-selling ban (W2) and de-escalation (W3). These dummies take a value of 1 when the respective events occur (W1, W2, or W3), and zero otherwise. We establish the PRE-CRASH period (W0) as dummy reference. $\text{Bucket}_{i,\tau-1}$ elucidates market fragmentation through the lens of order count in each bucket, while $\text{Volatility}_{i,\tau-1}$, is the absolute value of return, and quantifies market volatility. 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.

Table 3.3 shows the estimates of Eq. (12) for the stocks in each category. The analysis of large-cap, mid-cap, and small-cap companies reveals important patterns in how the level of informed trading differentially affects consensus in the LOB (SLOPE), external liquidity (RS), and internal liquidity (DEPTH).

The presence of informed trading in large-cap companies significantly influences the consensus of beliefs in the order book, although the nature of this relationship is unclear. For companies like TEF and CABK, there is a direct relationship between informed trading and consensus, indicating that informed trading helps to align market participants' beliefs about the stock's value. In contrast, for AMS and BBVA, the relationship is inverse, with a negative impact of VPIN on the slope. Moreover, the relationship between informed trading and both internal and external liquidity is interconnected with the relationship between VPIN and SLOPE. External liquidity is measured by the cost of immediate transactions (RS), while internal liquidity is represented by the total volume available in the order book. In cases where informed trading positive impact on consensus, liquidity improves as informed trading increases, leading to lower transaction costs and/or greater depth (TEF and CABK). However, in situations where VPIN negatively impacts consensus or where the relationship is not significant, an increase in informed trading tends to worsen liquidity, resulting in higher spread and/or lower depth (AMS, REP, BBVA and IBE). This suggests that informed trading consumes internal liquidity, likely because liquidity providers withdraw from the market to avoid adverse selection risks.

Table 3.3 Non-contemporaneous relationship between consensus, liquidity, and informed trading

SLOPE 10⁻³ *RS 10³* *DEPTH 10⁻²*		C	$CDFVPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$BUCKET_{\tau-1}$	$ABSRET_{\tau-1}$	$ADJ\ R^2$
Panel A: Large-Cap	TEF	4.2003***	0.1708***	-0.6887***	-1.9266***	-1.3716***	-0.0028***	-70.9454***	0.1882
		0.1505***	-0.0363	0.0964***	0.4009***	0.0777***	0.0011***	63.8149***	0.1631
		0.9247***	0.0274**	-0.1379***	-0.3316***	-0.0312***	-0.0008***	-20.1954***	0.2881
	AMS	2.0000***	-0.0913***	-0.3658***	-0.3482***	-0.3139***	-0.0006	-39.2153***	0.0631
		0.2312***	0.0731***	0.1280***	0.2678***	0.0682***	0.0000	53.3817***	0.1018
		0.8563***	-0.0192***	-0.0225***	-0.2870***	-0.0249***	-0.0014***	-12.7516***	0.4286
	REP	2.2849***	-0.0116	-0.3997***	-0.4934***	0.056**	0.0011***	-61.9656***	0.1089
		0.3004***	0.0601**	0.1669***	0.3886***	0.0063***	-0.0005***	58.22.38***	0.1252
		1.4920***	-0.2366***	0.0619***	-0.5618***	-0.3512***	-0.0021***	-31.9931***	0.4435
	CABK	0.9377***	0.2408***	0.9253***	0.7306***	0.9430***	-0.0004*	-54.6283***	0.0473
		0.7539***	-0.2449***	-0.1239***	0.1249***	-0.1829***	0.0002	66.0697***	0.0969
		0.5023***	-0.0137	0.5240***	0.2362***	0.3832***	-0.0006***	-22.8156***	0.1919
	BBVA	4.4683***	-0.1986***	-0.6977***	-2.5016***	-2.1474***	-0.0043***	-66.0435***	0.3132
		0.1537***	0.0226	0.1800***	0.6077***	0.2496***	0.0004	43.2456***	0.1962
		0.8116***	-0.0335**	-0.1295***	-0.0057	0.1763***	-0.0005***	-19.3686***	0.1354
	IBE	3.6842***	0.0469	-1.2255***	-1.0700***	-1.1505***	-0.0030***	-76.6571***	0.2448
		0.1973***	0.03329**	0.1853***	0.1706***	0.1348***	0.0009***	31.3659***	0.1251
		1.0748***	-0.1697***	0.1019***	-0.3381***	0.0863***	-0.0025***	-22.9651***	0.4461

Table 3.3 Non-contemporaneous relationship between consensus, liquidity, and informed trading (continued)

SLOPE 10^{-3} *RS* 10^{3} *DEPTH* 10^{-2}		C	$CDFVPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$BUCKET_{\tau-1}$	$ABSRET_{\tau-1}$	$ADJ\ R^2$
Panel B: Mid-Cap	SGRE	1.5951***	-0.0671	-0.0698*	-0.6833***	-0.1632***	-0.0004	-20.5890***	0.1113
		0.3297***	0.2976**	0.0977*	0.8379***	0.0580	0.0002	46.4703***	0.1026
		0.8444***	-0.0707***	-0.0922***	-0.4062***	-0.0279***	-0.0007***	-7.6884***	0.4279
	IAG	2.0251***	0.0411**	-0.5194***	-1.1401***	-0.9040***	0.0005***	-50.9572***	0.1567
		0.4876***	-0.5039***	0.3778***	1.2757***	0.8404***	-0.0009***	147.4212***	0.1809
		0.7032***	0.0049	-0.0871***	0.02472***	0.0514***	0.0002***	-251013***	0.1055
	ACS	2.0123***	-0.0134	-0.4608***	-0.9314***	-0.4290***	-0.0004***	-38.9866***	0.2807
		0.1906***	0.0849***	0.1761***	0.8027***	0.0809***	0.0017***	46.3355***	0.2294
		0.8599***	-0.0219***	0.0200***	-0.2533***	-0.0147***	-0.0015***	-11.6371***	0.4223
	REE	2.0681***	0.2916***	-0.3414***	-0.9349***	-0.5290***	0.0005***	-64.4004***	0.2113
		0.3943***	-0.1847***	0.1500***	0.5547***	0.6687***	-0.0011***	110.3763***	0.1294
		0.8037***	0.1017***	-0.0901***	-0.3985***	-0.4008***	0.0003***	-11.3929***	0.5729
	SAB	1.8632***	0.39014***	0.2708***	-0.6612***	-0.5740***	0.0003	-30.6121***	0.1139
		0.5757***	-0.4593***	0.1809***	1.0247***	0.2027***	0.0010***	104.4180***	0.1696
		0.9351***	0.0041	-0.3515***	-0.4453***	-0.1069***	-0.0007***	-14.14405***	0.3527
	MAP	1.7382***	-0.0148	-0.3182***	-0.8023***	-0.4290***	-0.0004***	-38.9866***	0.1936
		0.4840***	-0.0075	0.2132***	1.0405***	0.0809***	0.0017***	46.3355***	0.1645
		0.9372***	-0.0564***	-0.1393***	-0.3813***	-0.0147***	-0.0015***	-11.6371***	0.4049

Table 3.3 Non-contemporaneous relationship between consensus, liquidity, and informed trading (continued)

SLOPE 10⁻³ ***RS 10³*** ***DEPTH 10⁻²***		C	$CDFVPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$BUCKET_{\tau-1}$	$ABSRET_{\tau-1}$	$ADJ\ R^2$
Panel C: Small-Cap	ACX	1.9419***	-0.1993***	-0.3872***	-0.9652***	-0.5870***	-0.0018**	-18.401***	0.1540
		0.3215***	0.2635***	0.2764***	1.2173***	0.2574***	0.0029**	46.4388***	0.1893
		0.6804***	-0.0634***	-0.0588***	-0.2811***	0.0049	-0.0008***	-3.7454***	0.4892
	TL5	1.1576***	-0.1262***	0.02592	-0.5270***	-0.3107***	0.0016***	-16.0421***	0.1445
		0.6824***	0.2041**	0.5038***	1.7655***	0.4111***	-0.0039***	127.8844***	0.1469
		0.5993***	0.0188***	-0.1092***	-0.2270***	-0.0523***	-0.0007	-5.2840***	0.3110
	BKIA	2.0123***	0.0837***	-0.6034***	-1.0505***	-0.7270***	0.0004***	-51.0776***	0.1243
		0.4241***	-0.2192***	0.3594***	1.4453***	0.5184***	-0.0003***	208.2111***	0.2337
		0.6982***	-0.0364***	-0.0281***	-0.2728***	-0.1131***	-0.0001***	-7.2798***	0.3703
	CIE	0.6738***	-0.0800***	0.0262*	-0.1250***	0.0740***	0.0010	-6.6369***	0.0784
		0.8974***	0.3683***	0.0853	1.1068***	-0.1276**	0.0101**	50.5859***	0.1407
		0.8724***	-0.1024***	-0.1390***	-0.3918***	-0.1030***	-0.0021***	-2.0591***	0.5728
	IDR	0.8725***	0.0138	-0.1860***	-0.3024***	-0.1247***	0.0007***	-20.1431***	0.1246
		0.8497***	0.0943***	0.3364***	0.9694***	0.1633***	-0.0011***	125.8856***	0.1628
		0.8368***	-0.1245***	-0.0704***	-0.2778***	0.0410***	-0.0001	-15.7082***	0.4867
	VIS	0.8120***	0.0430***	-0.0961***	-0.3056***	-0.2488***	-0.0001	-18.5335***	0.1463
		0.8426***	-0.0689	0.2333***	0.9566***	0.2688***	-0.0002	121.1974***	0.1549
		0.7324***	-0.0767***	-0.0257***	-0.2433***	0.02260***	-0.0006***	-10.1955***	0.5414

Table 3.3 presents the estimates of the non-contemporaneous relationship for the period from November 20th, 2019, to July 13th, 2020, represented by $Y_{i,\tau} = \beta_{i,\tau} + \beta_{i,1} \cdot CDFVPIN_{i,\tau-1} + \beta_{i,2} \cdot CRASH_{i,\tau-1} + \beta_{i,3} \cdot SSB_{i,\tau-1} + \beta_{i,4} \cdot DECAL_{i,\tau-1} + \beta_{i,5} \cdot Bucket_{i,\tau-1} + \beta_{i,6} \cdot Volatility_{i,\tau-1} + \varepsilon_{i,\tau}$ The coefficients are expressed in transformed units (Slope x 10^{-3}, RS x 10^{3}, depth of the LOB x 10^{-2}). *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

The analysis of mid-cap companies shows results similar to those of large-cap companies. In three instances—specifically, IAG, REE, and SAB—increased informed trading is associated with a higher consensus within the LOB. In these cases, the relationship between informed trading and liquidity is positive; specifically, there are decreases in the relative spreads (RS) and/or increases in depth as the CDF of VPIN rises. Conversely, for SGRE, ACS, and MAP, liquidity deteriorates as the level of informed trading increases. In these companies, the coefficient of the CDF of VPIN is not significant when considering SLOPE as the dependent variable.

Small-cap companies exhibit some distinct patterns compared to previous cases, although there is also notable variability in the relationship between informed trading and consensus. Specifically, BKIA and VIS show a positive and significant relationship, while in the case of ACX, TL5, and CIE the relationship is negative. Regarding the impact on liquidity, both ACX, CIE, and IDR align with the trends seen in large and mid-cap companies. In these cases, a negative or non-significant relationship between informed trading and consensus correlates with a decline in both external and internal liquidity as the CDF of VPIN increases. Conversely, for BKIA and VIS, despite the positive relationship between informed trading and consensus, a higher CDF of VPIN results in decreased internal liquidity (depth). For TL5, a negative relationship between consensus and VPIN is found, which is associated with an improvement in depth. The findings for these three small-cap companies highlight the varying interrelationships among the variables based on company size. Unlike large and mid-cap firms, where despite not being able to draw clear conclusions about H1a and H1b, a certain patterns were observable—meaning that if H1b was accepted, H1a was rejected, and vice versa—, this does not hold true for small-cap companies.

In addition to individual regressions, the study has been completed by applying panel data techniques for each asset class. For each category, the Panel EGLS (Cross-section weights) technique was employed to handle heteroscedasticity and the unbalanced nature of the data. Cross-section weights addressed heteroscedasticity and period clustering was applied to correct for serial correlation. Individual regressions captured the specificities of each stock, while the panel data model aggregated these results, providing a more robust and generalized view by category. Before estimating the panel data model, the Hausman test confirmed the suitability of the fixed effects model. The model controls for significant periods, including the COVID-19 crash, the short-selling restriction, and the initial de-escalation, and incorporates volatility measures as control variables. These adjustments account for unique market conditions and regulatory changes during the analysis period. Using a panel data model captures effects not observable in individual regressions, providing greater precision in estimating the impact of explanatory variables on liquidity measures. This approach offers a more comprehensive view by stock category, surpassing the limitations of isolated stock analyses.

The test was conducted using different proxies for volatility to improve the robustness of the results: absolute returns (Table 3.4), residual absolute returns as in Jones et al. (1994) (Table 3.5), and conditional volatility from an EGARCH model (Table 3.6). The analysis for consensus demonstrates that informed trading significantly enhances order book consensus across various volatility proxies, particularly for large- and small-cap stocks. For mid-caps, the effect is significant only when using the EGARCH proxy, which suggests that in mid-cap stocks, the impact of informed trading on consensus is more pronounced under conditions of persistent volatility captured by the EGARCH model. These findings support Hypothesis H1a, which proposes that informed trading increases the consensus of beliefs within the Limit Order Book. This aligns with Chang et al. (2021), who highlight that in algorithmic trading environments, insider trading can counteract the adverse effects of diminished information acquisition, thereby increasing the informativeness of trades and supporting efficient price discovery.

Regarding external liquidity, the analysis shows that informed trading generally reduces the bid-ask spread, improving external liquidity when significant. This result does not support Hypothesis H1b, which suggests that informed trading consumes external liquidity. The observed negative coefficients, particularly when using the EGARCH proxy, indicate that informed traders may execute trades when market liquidity is high and illiquidity is minimal, reducing the bid-ask spread. This is consistent with the strategic behavior proposed by Collin-Dufresne and Fos (2016), where informed traders delay acting on their information until favorable market conditions arise.

Concerning internal liquidity, the analysis reveals that informed trading consistently reduces the depth of the LOB across all volatility proxies and stock categories, supporting H1b. This reduction in the depth suggests that informed trading adversely impacts the willingness of liquidity providers to place limit orders throughout the order book. These results align with theoretical models like those of Kyle (1985), which propose that the presence of informed traders can deter uninformed liquidity providers from participating, reducing overall book depth. The effect is especially significant in mid and small caps, indicating higher sensitivity to informed trading activity.

Overall, the analysis confirms that informed trading has a significant impact on both consensus and liquidity in the market, with effects varying based on the volatility proxy used and the stock category. These findings highlight the dual role of informed trading in improving price discovery while adversely affecting internal liquidity, especially in small-cap stocks. The analysis suggests that while informed trading enhances consensus and price efficiency, it also leads to reduced depth in the order book, potentially increasing liquidity costs for certain market participants. We hypothesize that informed trading typically causes an increase in consensus within the LOB due to the incorporation of informed orders. While we expect that a higher consensus will result in reduced volatility, a significant decrease in liquidity—triggered by an increase in the CDF of VPIN to levels considered “market toxicity”—could lead to a temporary rise in volatility.

Moreover, these findings are consistent with Jones et al. (1994), indicating that volatility dynamics significantly shape the relationship between informed trading and consensus formation. Notably, the EGARCH model’s ability to capture the persistent nature of volatility helps explain the enhanced impact of informed trading on consensus in mid-caps, underscoring the importance of modelling approaches in understanding market behavior. Additionally, employing EGARCH, which captures conditional volatility, provides a nuanced understanding of volatility effects, making the observed relationships more robust.

The varying impact of informed trading across different stock capitalizations suggests that company size influences how informed trading affects consensus and liquidity. Small-cap stocks show higher sensitivity to informed trading, possibly due to lower liquidity and less information coverage. This underscores the importance for liquidity providers and market participants to consider market capitalization when assessing the risks associated with informed trading. Moreover, the significant effects of control variables (i.e. the COVID-19 crash or short-selling restriction periods) confirm that market events and regulatory interventions substantially impact liquidity and consensus. This emphasizes the need to carefully evaluate regulatory policies, as interventions may have unintended consequences on market dynamics.

Future research could explore mechanisms to mitigate the adverse liquidity effects of informed trading while maintaining its benefits for price efficiency. Potential areas include examining whether there are thresholds where the impact of informed trading changes significantly and investigating strategies for liquidity providers to manage risks in the presence of informed trading. Additionally, incorporating other variables such as trading volume or market sentiment indicators could enrich the understanding of these dynamics.

Table 3.4 Non-Contemporaneous EGLS Panel relationship between consensus, liquidity and informed trading controlled by absolute value of return

	C	$CDFVPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$BUCKET_{\tau-1}$	$ABSRET_{\tau-1}$	$ADJ\ R2$
Panel A. Large-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	2.8261***	0.05167***	-0.5713***	-0.7760***	-0.5344***	-0.0002	-56.2778***	0.2105
RS	0.2746***	-0.0151	0.1600***	0.3352***	0.0972***	0.0004	51.1313***	0.1392
DEPTH	1.0304***	-0.0690***	-0.0105***	-0.3044***	-0.0347***	-0.0013***	-18.2688***	0.3214
Panel B. Mid-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	1.9591***	-0.0026	-0.3609***	-0.9046***	-0.6477***	-0.0003***	-44.1581***	0.1986
RS	0.5328***	-0.0685***	0.2218***	-0.8915***	-0.3399***	-0.0006***	104.8256***	0.1901
DEPTH	0.8886***	-0.0591***	-0.1431***	-0.3041***	-0.1146***	-0.0000***	-16.7415***	0.2575
Panel C. Small-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	1.2216***	0.0274***	-0.1736***	-0.3895***	-0.2174***	-0.0003***	-18.7799***	0.2535
RS	0.6814***	-0.0223	0.3176***	1.1847***	0.2915***	-0.0004***	-126.6509***	0.1806
DEPTH	0.7493***	-0.0967***	-0.0544***	-0.2682***	-0.0286***	-0.0002***	-7.0833***	0.4608

Table 3.4 presents the estimates of the non-contemporaneous relationship of the independent variables CDFVPIN, SSB, BUCKET, DECAL and ABSRET with respect to consensus measured by the slope of the LOB, RS and depth of the LOB for the period from November 20th, 2019, to July 13th, 2020. The analysis applies a fixed effects panel data model, which was chosen after conducting the Hausman test to determine its appropriateness. The model estimated is as follows: $Y_{i,\tau} = \beta_i + \beta_1 \cdot CDFVPIN_{i,\tau-1} + \beta_2 \cdot CRASH_{i,\tau-1} + \beta_3 \cdot SSB_{i,\tau-1} + \beta_4 \cdot DECAL_{i,\tau-1} + \beta_5 \cdot BUCKET_{i,\tau-1} + \beta_6 \cdot ABSRET_{i,\tau-1} + \varepsilon_{i,\tau}$. The estimation is carried out using Panel EGLS with cross-section weights, along with White cross-section period clustering to address heteroscedasticity and serial correlation in unbalanced panel data. The model controls for the COVID-19 crash period, the short-selling restriction period, and the initial de-escalation period, ensuring the robustness of the findings across significant market conditions. The resulting coefficients are presented in transformed units, with statistical significance denoted by * and ** for the 95% and 99% confidence levels, corresponding to significance thresholds of 5% and 1%, respectively. Adjusted statistics and t-statistic probabilities were corrected for period clustering to ensure robustness against serial correlation and heteroscedasticity, given the discontinuous temporal observations across stocks.

Table 3.5 Non-Contemporaneous EGLS Panel relationship between consensus, liquidity and informed trading controlled by absolute value of residual of returns

	C	$CDFVPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$BUCKET_{\tau-1}$	$ABSRESID_{\tau-1}$	$ADJ\ R2$
Panel A. Large-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	2.8254***	0.0495***	-0.5845***	-0.7951***	-0.5512***	-0.0002	-76.6195***	0.2081
RS	0.2699***	-0.0118	0.1666***	0.3438***	0.1075***	0.0004***	75.4925***	0.1399
DEPTH	1.0301***	-0.0700***	-0.0150***	-0.3106***	-0.0401***	-0.0013***	-24.6607***	0.3177
Panel B. Mid-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	1.9488***	-0.0042	-0.3727***	-0.9226***	-0.6587***	0.0003***	-53.4417***	0.1925
RS	0.5336***	-0.0649***	0.2374***	0.9092***	0.3556***	-0.0006***	149.3438***	0.1884
DEPTH	0.8870***	-0.0595***	-0.1470***	-0.3091***	-0.1181***	0.0001***	-22.2364***	0.2530
Panel C. Small-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	1.2184***	0.0244***	-0.1767***	-0.3936***	-0.2205***	-0.0003***	-23.4534***	0.2517
RS	0.6728***	-0.0086	0.3300***	1.1903***	0.3073***	-0.0004***	182.6828***	0.1848
DEPTH	0.7496***	-0.0973***	-0.0554***	-0.2688***	-0.0298***	-0.0002***	-9.9812***	0.4611

Table 3.5 presents the estimates of the non-contemporaneous relationship of the independent variables CDFVPIN, SSB, BUCKET, DECAL and ABSRESID with respect to consensus measured by the slope of the LOB, RS and depth of the LOB for the period from November 20th, 2019, to July 13th, 2020. The analysis applies a fixed effects panel data model, which was chosen after conducting the Hausman test to determine its appropriateness. The model estimated is as follows: $Y_{i,\tau} = \beta_i + \beta_1 \cdot CDFVPIN_{i,\tau-1} + \beta_2 \cdot CRASH_{i,\tau-1} + \beta_3 \cdot SSB_{i,\tau-1} + \beta_4 \cdot DECAL_{i,\tau-1} + \beta_5 \cdot BUCKET_{i,\tau-1} + \beta_6 \cdot ABSRESID_{i,\tau-1} + \varepsilon_{i,\tau}$. The estimation is carried out using Panel EGLS with cross-section weights, along with White cross-section period clustering to address heteroscedasticity and serial correlation in unbalanced panel data. The model controls for the COVID-19 crash period, the short-selling restriction period, and the initial de-escalation period, ensuring the robustness of the findings across significant market conditions. The resulting coefficients are presented in transformed units, with statistical significance denoted by * and ** for the 95% and 99% confidence levels, corresponding to significance thresholds of 5% and 1%, respectively. Adjusted statistics and t-statistic probabilities were corrected for period clustering to ensure robustness against serial correlation and heteroscedasticity, given the discontinuous temporal observations across stocks.

Table 3.6 Non-Contemporaneous EGLS Panel relationship between consensus, liquidity and informed trading controlled by EGARCH

$SLOPE$	C	$CDFVPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$BUCKET_{\tau-1}$	$EGARCH_{\tau-1}$	*ADJ R2*
Panel A. Large-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	3.1701***	0.1014***	-0.3853***	-0.3091***	-0.3041***	0.0010***	-234.1346***	0.2454
RS	0.03685***	-0.0575***	0.01752***	-0.0340***	-0.0800***	-0.0008***	183.3645***	0.1954
DEPTH	1.1492***	-0.0565***	0.0619***	-0.1337***	0.0503***	-0.0008***	-81.9150***	0.3835
Panel B. Mid-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	2.2176***	0.02378**	-0.2480***	-0.6944***	-0.5540***	0.0002***	-159.6743***	0.2233
RS	0.0651***	-0.1057***	0.0537***	0.5586***	0.2063***	-0.0005***	296.9709***	0.2071
DEPTH	1.0213***	-0.04256***	-0.0767***	-0.1730***	-0.0545***	-0.0000*	-82.0410***	0.3445
Panel C. Small-Cap Panel EGLS (Cross-section weights) and White cross-section period clustering								
SLOPE	1.3729***	0.0697***	-0.1305***	-0.2869***	-0.1802***	0.0003***	-85.7516***	0.2661
RS	-0.024330	-0.1666***	0.1028***	0.6926***	0.0856***	-0.0001	423.7381***	0.2024
DEPTH	0.8147***	-0.0865***	-0.03300***	-0.2188***	-0.0042**	-0.0003***	-35.8207***	0.4916

Table 3.6 presents the estimates of the non-contemporaneous relationship of the independent variables CDFVPIN, SSB, BUCKET, DECAL and EGARCH with respect to consensus measured by the slope of the LOB, RS and depth of the LOB for the period from November 20th, 2019, to July 13th, 2020. The analysis applies a fixed effects panel data model, which was chosen after conducting the Hausman test to determine its appropriateness. The model estimated is as follows: $Y_{i,\tau} = \beta_i + \beta_1 \cdot CDFVPIN_{i,\tau-1} + \beta_2 \cdot CRASH_{i,\tau-1} + \beta_3 \cdot SSB_{i,\tau-1} + \beta_4 \cdot DECAL_{i,\tau-1} + \beta_5 \cdot BUCKET_{i,\tau-1} + \beta_6 \cdot EGARCH_{i,\tau-1} + \varepsilon_{i,\tau}$. The estimation is carried out using Panel EGLS with cross-section weights, along with White cross-section period clustering to address heteroscedasticity and serial correlation in unbalanced panel data. The model controls for the COVID-19 crash period, the short-selling restriction period, and the initial de-escalation period, ensuring the robustness of the findings across significant market conditions. The resulting coefficients are presented in transformed units, with statistical significance denoted by * and ** for the 95% and 99% confidence levels, corresponding to significance thresholds of 5% and 1%, respectively. Adjusted statistics and t-statistic probabilities were corrected for period clustering to ensure robustness against serial correlation and heteroscedasticity, given the discontinuous temporal observations across stocks.

Informed trading, consensus and volatility causality

Informed trading manifests primarily through market orders (as measured by VPIN), and specific limit orders that achieve greater consensus in certain price zones within the LOB. There is a considerable amount of literature examining the relationship between volatility and informativeness, both in the broader market and within the limit order book (Abergel et al., 2016; Beltran-Lopez et al., 2016; Easley et al., 2011). However, these studies often overlook causal relationships, particularly when considering unexecuted orders (intentions) within the LOB. We use a Vector Autoregressive model[4] (VAR) to explore the dynamics between volatility, consensus in the LOB and informed trading to address this gap in the literature. Specifically, Granger-Causality tests are used to investigate the causal relationships between volatility, consensus in the Limit Order Book, and informed trading. We investigate whether a Granger causal relation exists between volatility and informed trading. We extend this causality analyzing if informed trading influences consensus in the LOB through the presence of informed limit orders, which in turn reduces volatility. This will imply that informed trading Granger-causes consensus when informed limit orders exist in the LOB but does not do so in their absence. We also use impulse-response functions to analyze how current and future values of each variable respond to a one-unit increase in the current value of one of the VAR errors.

The selected variables include market volatility measured by the absolute value of bucket returns (ABSRET), informed trading (VPIN), and consensus in the LOB (slope of the LOB), which measures the extent to which limit orders achieve consensus in specific price zones. The VAR model is implemented in its reduced form, expressing each variable as a function of its own lagged values, the lagged values of all other variables, and a serially uncorrelated error term. We focus on the event-clock data, using same-period observations. Each equation is estimated using ordinary least squares (OLS) regression, and the number of lagged values to include is determined using criteria such as the Schwarz Criterion (SC). Dummies for the COVID crash period (W1) and the short-selling restriction imposed (W2) are incorporated as exogenous variables.

The VAR model comprises three equations: the current volatility of portfolio returns as a function of past values of portfolio return volatility, consensus in the LOB, and informed trading; consensus in the LOB as a function of past values of consensus, volatility, and

[4] VAR is a widely used tool in multivariate time series analysis (Zhang et al., 2024; Ding et al., 2017).

informed trading; and similarly for the informed trading equation. The optimal number of lags, p, is selected based on the Schwarz Criterion (SC). The error terms in these regressions represent the unexpected movements in the variables after accounting for their past values. Thus, the reduced VAR model can be expressed with the following three equations:

$$ABSRET_{i,t} = \alpha_{1i} + \sum_{j=1}^{p} \beta_{11,j} ABSRET_{i,t-j} + \sum_{j=1}^{p} \beta_{12,j} SLOPE_{i,t-j} + \sum_{j=1}^{p} \beta_{13,j} CDFVPIN_{i,t-j} + \gamma_1 CRASH_{i,t} + \gamma_2 SSB_{i,t} + \epsilon_{1,i,t} \tag{13}$$

$$SLOPE_{i,t} = \alpha_{2i} + \sum_{j=1}^{p} \beta_{21,j} ABSRET_{i,t-j} + \sum_{j=1}^{p} \beta_{22,j} SLOPE_{i,t-j} + \sum_{j=1}^{p} \beta_{23,j} CDFVPIN_{i,t-j} + \gamma_3 CRASH_{i,t} + \gamma_4 SSB_{i,t} + \epsilon_{2,i,t} \tag{14}$$

$$CDFVPIN_{i,t} = \alpha_{3i} + \sum_{j=1}^{p} \beta_{31,j} ABSRET_{i,t-j} + \sum_{j=1}^{p} \beta_{32,j} SLOPE_{i,t-j} + \sum_{j=1}^{p} \beta_{33,j} CDFVPIN_{i,t-j} + \gamma_5 CRASH_{i,t} + \gamma_6 SSB_{i,t} + \epsilon_{3,i,t} \tag{15}$$

$ABSRET_{\mathrm{i,t}}$ is the current absolute value of bucket returns for panel (category) stock i in bucket t. $SLOPE_{\ i,t}$ is current consensus of LOB for panel (category) stock i in bucket t. $CDFVPIN_{\ i,t}$ is cumulative informed trading for panel (category) stock i in bucket t. $ABSRET_{i,t-j}$, $SLOPE_{\ i,t-j}$, $CDFVPIN_{\ i,t-j}$ are lagged values of the respective variables for panel (category) stock i (j ranges from 1 to p). $CRASH_{i,t}$ and $SSB_{i,t}$ are dummy variables for the COVID-19 crash and short selling ban. α_{ki} is the individual fixed effect for category stock i in equation k ($k = 1, 2, 3$). $\epsilon_{\mathrm{k,i,t}}$ are the error terms for each equation, assumed to be serially uncorrelated.

We conduct stability tests for the VAR model, including unit root tests for the characteristic polynomial and autocorrelation of the optimal lag. The results indicate that the VAR model satisfies the stability condition and that the variables are stationary. Given that different variables are typically correlated in intraday market microstructure applications, the error terms in the reduced form model are also likely to be correlated across equations.

The results of the VAR model are presented in Table 3.7. They reveal significant interactions between market volatility, consensus within the LOB, and informed trading across different firm sizes—large-cap, mid-cap, and small-cap. These findings provide valuable insights into the dynamic and complex relationships that shape market behavior, emphasizing the differentiated mechanisms across various market capitalization levels. Given the high-frequency nature of the data, we will conduct an analysis of the cumulative impact of these lags through impulse-response function graphs and perform a Granger causality test to further investigate these dynamics.

The volatility equation demonstrates persistence for large-cap stocks, with past volatility significantly influencing current levels. This persistence is consistent with established findings, which indicate that volatility persistence is common in financial time series (Næs & Skjeltorp, 2006; Tripathi et al., 2020). Moreover, a higher level of consensus in the limit order book, reflecting a well-balanced order book, is associated with reduced volatility, supporting the notion that a stable order book lowers market uncertainty and enhances stability (Kang & Zhang, 2013; Næs & Skjeltorp, 2006). Higher levels of informed trading are also linked to lower volatility, as informed traders facilitate the efficient incorporation of firm-specific information into asset prices, thereby contributing to market stability (Easley et al., 1998; Hu, 2018). This stabilizing effect of informed trading is more evident in heavily traded stocks, as suggested by Blasco and Corredor (2017). Additionally, systemic shocks, such as the COVID-19 crash period (CRASH) and the short-selling ban (SSB), significantly increase volatility, underscoring the heightened uncertainty during crises and regulatory interventions.

The consensus equation for large cap indicates that past volatility negatively impacts the current level of consensus, suggesting that increased volatility disrupts order book balance, leading to trading frictions (Kang & Zhang, 2013). The relationship between market consensus and informed trading reveals a complex and, according to the results in Table 3.7, asymmetric dynamic. We observe that the coefficients where consensus impacts informed trading are statistically significant only at the third lag, indicating a very mild effect. Specifically, a slightly lower consensus may attract informed trading, as suggested by the negative coefficient. In contrast, the reverse relationship—where informed trading positively influences consensus—is statistically significant, but only at specific lags, such as the fifth and the 36th lag. These distributed lags indicate that informed traders in large-cap stocks strategically place orders over multiple periods rather than reacting instantaneously.

For mid-caps, the interaction between volatility, informed trading, and LOB consensus is more dynamic. Similar to large-caps, volatility exhibits significant persistence, and LOB consensus reduces volatility. As shown in Table 3.7, the coefficients related to LOB consensus are consistently negative and significant, indicating that a balanced order book plays an essential role in stabilizing mid-cap stocks, possibly due to their reduced analyst coverage compared to large-caps (Hu, 2018). Informed trading also plays a role in mitigating volatility for mid-caps, as evidenced by the negative and significant coefficient in the volatility equation. Additionally, informed trading positively influences LOB consensus, as seen in the significant positive coefficients in Table 3.7, suggesting that limit informed orders contribute to a more balanced order book, ultimately enhancing market stability (Seppi, 1997; Bloomfield, O'Hara, & Saar, 2015). The dynamic interplay between informed trading and consensus highlights the responsiveness of mid-cap markets to informed activity. However, consensus negatively impacts informed trading in mid-caps, as the negative coefficient indicates. Interestingly, past volatility significantly influences informed trading levels in mid-caps, with positive and significant coefficients. This suggests that heightened volatility and dispersed beliefs on LOB present opportunities for traders to exploit information asymmetries, which are more prevalent in these less liquid stocks (Chao et al., 2018). Informed trading decreased significantly for mid-caps during the SSB, highlighting that traders tend to become more cautious in less liquid environments during periods of heightened uncertainty (Goodell, 2020; Broadstock et al., 2021). The exogenous impacts of systemic shocks, such as the COVID-19 crash and the short-selling ban (SSB), have been observed to consistently increase volatility across large-cap and mid-cap stocks. This underscores the significant influence of systemic shocks and regulatory interventions on market behavior.

With regard to small-caps, heightened sensitivity to market conditions is evident. Volatility remains persistent, with past volatility having a significant impact on current levels, consistent with findings for larger capitalization stocks. The VAR results indicate that volatility significantly influences informed trading in small caps, suggesting that increased market uncertainty leads to greater informed trading activity rather than the other way around. The effect of LOB consensus on volatility is also significant, though less pronounced than for mid-cap stocks. Informed trading also reduces volatility in small-caps, as shown by the negative coefficients in the volatility equation, reinforcing its stabilizing role (Huang & Chang, 2014). However, the relationship between informed trading and LOB consensus is not significant in small-caps. This indicates that informed trading does not have a meaningful impact on achieving a balanced order book in less liquid stocks. The lack of significance in the coefficients suggests that the stabilizing effect of informed trading on market consensus is weaker in small-caps, possibly due to their reduced depth and heightened volatility, which limit the effectiveness of informed orders in stabilizing the order book. As for mid-caps, past volatility significantly influences informed trading levels in small-caps, with positive and significant coefficients. The relatively low liquidity in small caps exacerbates these effects.

The exogenous impacts of the COVID-19 crash increased volatility and led to a decrease in informed trading, while the short-selling ban (SSB) significantly impacted both volatility and trading behavior, with varying effects on consensus depending on market capitalization.

The differences observed in the interactions between volatility, informed trading, and LOB consensus across large-caps, mid-caps, and small-caps can be attributed to market structure, liquidity, and information asymmetries. Large-caps benefit from higher liquidity, greater order book depth, and extensive analyst coverage, which contribute to a stable environment where informed trading effectively stabilizes volatility. The presence of numerous market participants also helps absorb shocks, reducing their impact on informed trading behavior.

Mid-caps exhibit a different dynamic, where maintaining a well-balanced LOB plays a more role in ensuring stability. Due to their lower liquidity and less extensive coverage compared to large-caps, the role of LOB consensus is more prominent in mid-cap stocks. The responsiveness of mid-caps to informed trading is evident, as informed traders contribute directly to price stabilization and order book balance.

For small-caps, heightened sensitivity to volatility is linked to lower liquidity and reduced market depth, exacerbating information asymmetries. In these markets, increased volatility appears to drive more informed trading, possibly due to greater opportunities for exploiting informational advantages. This highlights the dual role of informed trading: while it serves as a stabilizing force in more liquid markets, it exacerbates when volatility increases in less liquid markets (Easley et al., 1998; Avramov et al., 2006; Huang & Chang, 2014).

In summary, the VAR model analysis highlights distinct dynamics across different market capitalizations. Informed trading enhances LOB consensus in mid-cap stocks, contributing to market stability. However, the stabilizing role of informed trading diminishes in small-cap stocks, where increased volatility leads to heightened trading activity driven by information asymmetries, and the impact on consensus is not significant. These findings align with the existing literature, emphasizing the dual role of informed trading in both improving market stability through efficient information integration and potentially increasing volatility in less liquid markets (Easley et al., 1998; Avramov et al., 2006; Huang & Chang, 2014).

Table 3.7 Coefficients of the reduced VAR model for each category of stocks

	Large-Cap			Mid-Cap			Small-Cap		
	ABSRET	SLOPE$\cdot 10^{-3}$	CDFVPIN	ABSRET	SLOPE$\cdot 10^{-3}$	CDFVPIN	ABSRET	SLOPE$\cdot 10^{-3}$	CDFVPIN
ABSRET (-1)	0.1121***	-18.1424***	0.1487	0.1459***	-15.0874***	0.1613*	0.1556***	-9.8900***	0.3315***
ABSRET (-2)	0.0922***	-4.8582**	0.0421	0.0854***	-7.6673***	0.0990	0.1127***	-4.4161***	0.0060
ABSRET (-3)	0.0559***	-4.4124**	0.1165	0.0605***	-5.0110***	-0.0607	0.0438***	-1.5587	-0.0249
...	...	...	...	...	...	...	...	...	...
ABSRET (-49) / (-19)	0.0111*	-0.8897	0.0314	0.0047	0.0140	-0.0318	0.0275***	0.9063	0.0336
ABSRET (-50) / (-20)	0.0121**	-1.1914	-0.0901	0.0045	1.1239	-0.0423	0.0278***	1.1458	0.0546
ABSRET (-51) / (-21)	0.0141***	1.0382	-0.1051	0.0077	2.2580*	-0.0805	0.0228***	0.7000	0.0236
SLOPE$\cdot 10^{-3}$ (-1)	-0.0002***	0.1314***	0.0003	-0.0003***	0.1319***	-0.0012***	-0.0002***	0.1252***	-0.0008***
SLOPE$\cdot 10^{-3}$ (-2)	-0.0001***	0.0877***	0.0004	-0.0001***	0.0891***	0.0001	-0.0001***	0.0881***	-0.0003
SLOPE$\cdot 10^{-3}$ (-3)	-0.0000	0.0682***	-0.0004**	-0.0000***	0.0538***	-0.0001	-0.0000	0.0662***	-0.0003
...	...	...	...	...	...	...	...	...	...
SLOPE$\cdot 10^{-3}$ (-49) / (-19)	0.0000	0.0117**	-0.0002	0.0000	0.0117**	-0.0002	0.0000	0.0265***	0.0000
SLOPE$\cdot 10^{-3}$ (-50) / (-20)	0.0000	0.0193***	0.0002	0.0000	0.0193***	0.0002	0.0000	0.0229***	0.0005
SLOPE$\cdot 10^{-3}$ (-51) / (-21)	0.0000	0.0151***	-0.0002	0.0000	0.0151***	-0.0002	-0.0000	0.0325***	0.0001
CDFVPIN (-1)	-0.0008***	0.1409	0.9875***	-0.0010***	0.1315**	1.0011***	-0.0006***	0.0792	1.0259***
CDFVPIN (-2)	0.0004	0.0533	0.0065	0.0007***	-0.0623	-0.0169***	0.0007***	-0.0539	-0.0290***
CDFVPIN (-3)	0.0004	-0.1216	0.0003	-0.0002	0.1303	0.0047	-0.0004	0.0155	-0.0009
...	...	...	...	...	...	...	...	...	...
CDFVPIN (-5)	...	245.6696***	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
CDFVPIN (-36)	...	297.4849***	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
CDFVPIN (-49) / (-19)	-0.0004	0.1950	-0.0030	-0.0004	0.1950	-0.0030	0.0002	-0.1433	0.0135***
CDFVPIN (-50) / (-20)	0.0003	-0.1789	0.0053	0.0003	-0.1789	0.0053	-0.0002	0.0694	-0.0001
CDFVPIN (-51) / (-21)	0.0002	-0.0690	-0.0103	0.0002	-0.0690	-0.0103	0.0003	0.0058	-0.0182***
CRASH	0.0001**	-0.0186*	0.0002	0.0001***	0.0195***	-0.0005	0.0001***	-0.0103	-0.0025***
SSB	0.0002***	-0.0233*	0.0003	0.0001***	-0.0470***	-0.0010*	0.0002***	-0.0483***	-0.0001
R-SQUARED	0.1891	0.4075	0.9710	0.1859	0.2912	0.9724	0.1856	0.3200	0.9692
ADJ. R-SQUARED	0.1867	0.4058	0.9709	0.1845	0.2900	0.9724	0.1847	0.3193	0.9691

Table 3.7: This table presents the estimates of the Vector Autoregressive (VAR) model applied to volatility, consensus and informed trading for large-, mid-, and small-cap stocks. Although the full model contains more lags, this table only includes the coefficients for the first and last lags from the optimal lag selection process. The VAR model is structured according to the following equations:

$$ABSRET_{i,t} = \alpha_{1i} + \sum_{j=1}^{p} \beta_{11,j} ABSRET_{i,t-j} + \sum_{j=1}^{p} \beta_{12,j} SLOPE_{i,t-j} + \sum_{j=1}^{p} \beta_{13,j} CDFVPIN_{i,t-j} + \gamma_1 CRASH_{i,t} + \gamma_2 \mathrm{SSB}_{i,t} + \epsilon_{1,i,t};$$

$$SLOPE_{i,t} = \alpha_{2i} + \sum_{j=1}^{p} \beta_{21,j} ABSRET_{i,t-j} + \sum_{j=1}^{p} \beta_{22,j} SLOPE_{i,t-j} + \sum_{j=1}^{p} \beta_{23,j} CDFVPIN_{i,t-j} + \gamma_3 CRASH_{i,t} + \gamma_4 SSB_{i,t} + \epsilon_{2,i,t};$$

$$CDFVPIN_{i,t} = \alpha_{3i} + \sum_{j=1}^{p} \beta_{31,j} ABSRET_{i,t-j} + \sum_{j=1}^{p} \beta_{32,j} SLOPE_{i,t-j} + \sum_{j=1}^{p} \beta_{33,j} CDFVPIN_{i,t-j} + \gamma_5 CRASH_{i,t} + \gamma_6 SSB_{i,t} + \epsilon_{3,i,t}$$

Granger causality and impulse response analysis.

A Granger causality analysis is conducted to determine if the flow of information from informed trading precedes and influences market consensus rather than vice versa, as suggested by the preliminary results. This observed asymmetry underscores the importance of informed limit orders as key determinants of market consensus behavior. The analysis will examine all pairwise relationships among the three variables—volatility, consensus, and informed trading—within the VAR framework, providing further insights into their dynamic interactions.

The analysis of accumulated responses to innovations in informed trading and consensus for the three categories of stocks – large-caps, mid-caps, and small-caps – reveals significant differences in how volatility and consensus respond in each of these groups. These differences can be explained by factors such as liquidity, market depth, and the ability of informed investors to influence market equilibrium. Furthermore, the Granger Causality test results support and complement these observations, providing evidence of specific causal relationships among the variables across different capitalization segments.

Table 3.8 Granger Causality/Block Exogeneity Wald Tests

DEPENDENT VARIABLE	REGRESSORS		
Large-Cap	**Informed Trading**	**Consensus in LOB**	**Volatility**
Informed Trading	-	0.1665	0.1018
Consensus in LOB	**0.0307**	-	**0.0000**
Volatility	**0.0624**	**0.0000**	-
Mid-Cap	**Informed Trading**	**Consensus in LOB**	**Volatility**
Informed Trading	-	**0.0000**	**0.0178**
Consensus in LOB	**0.0307**	-	**0.0000**
Volatility	**0.0000**	**0.0000**	-
Small-Cap	**Informed Trading**	**Consensus in LOB**	**Volatility**
Informed Trading	-	0.1963	**0.0000**
Consensus in LOB	0.1055	-	**0.0000**
Volatility	**0.0123**	**0.0000**	-

Table 3.8 presents the estimates (p-values) for the Granger causality tests.

According to the Granger causality tests (see results in Table 3.8), informed trading drives changes in consensus in large-cap stocks. This finding reinforces the role of informed orders in shaping market consensus by improving the balance and stability of the Limit Order Book, particularly in volume-based settings. Figure 3.1(a) bottom demonstrates that an initial innovation in informed trading leads to a statistically significant increase in consensus, with the response stabilizing over time at an elevated level relative to its initial state. This lasting impact highlights the capacity of informed trading to promote a well-structured and stable order book. In contrast, Figure 3.1(b) shows that while a shock in consensus in large-caps can reduce participation from informed investors, this effect is relatively weak. Greater consensus creates a more reliable market environment, but it does not directly influence informed trading activity in highly liquid markets. Instead, factors such as volume and market depth play a more critical role in attracting informed investors. The accumulated response of informed trading to innovations in consensus reveals an initial reaction that diminishes over time, with confidence intervals confirming that these changes are not statistically significant.

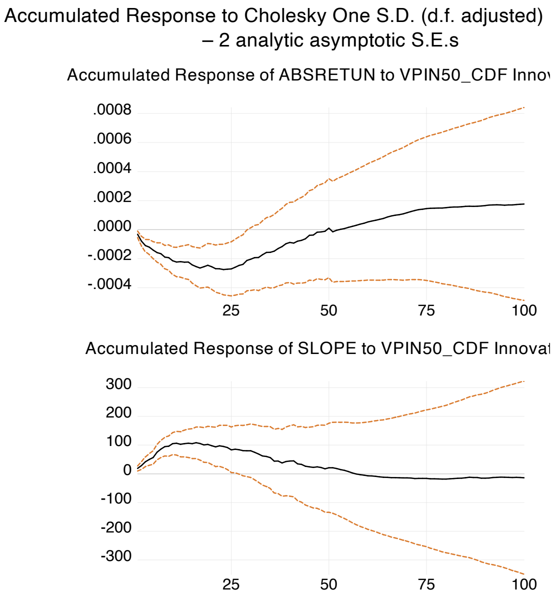
Informed trading unidirectionally causes volatility in large-cap stocks, while a bidirectional relationship exists between consensus and volatility. As shown in Figure 3.1, panel (a) top, the accumulated impulse response analysis indicates that volatility decreases immediately after an innovation in informed trading for large-caps. This short-term stabilization aligns with previous literature (Hu, 2018), which associates informed trading with the efficient incorporation of information. However, this effect diminishes in the long term, likely due to noise factors and heightened activity in highly liquid markets (Avramov et al., 2006; Blasco and Corredor, 2017; Easley et al., 1998).

Overall, informed trading plays a pivotal role not only in reducing market volatility but also in enhancing market consensus by fostering an orderly accumulation of orders within the LOB. These findings support the notion that informed traders improve market quality by stabilizing the order book (Hu, 2018). However, while informed trading significantly enhances consensus, its long-term impact on reducing volatility is limited, likely due to the complexities of highly liquid market dynamics.

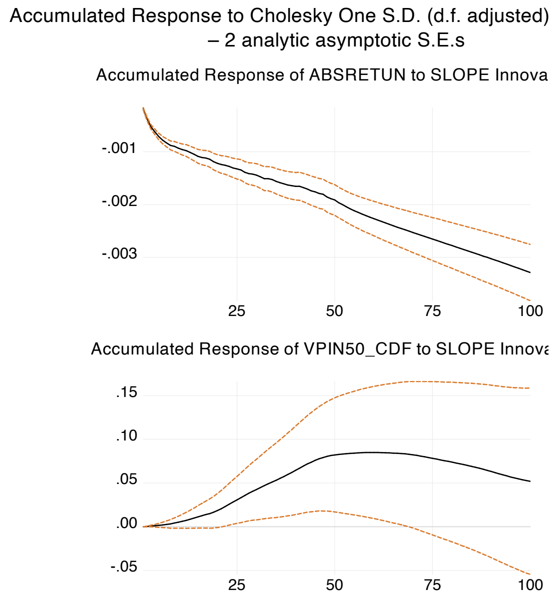
In mid-cap stocks, consensus and informed trading exhibit a bidirectional relationship, as do consensus and volatility. Furthermore, informed trading and volatility also show a two-way relationship. The bidirectional relationship between consensus and informed trading suggests that, in less liquid markets, market participants adjust their expectations and behaviors based on both new information and prevailing consensus, reinforcing market stability. The decline in volatility in response to innovations in consensus and informed trading shows that both factors play complementary roles in stabilizing the market, as reported in previous studies (Hu, 2018; Blasco and Corredor, 2017; Easley et al., 1998).

Figure 3.1 Impulse-response

Panel A. Large-Cap

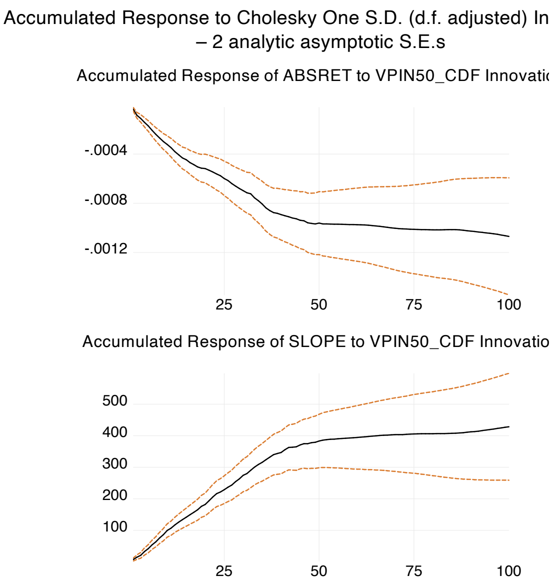


(a) Large-Cap accumulated response of volatility and consensus of LOB to an informed trading innovation

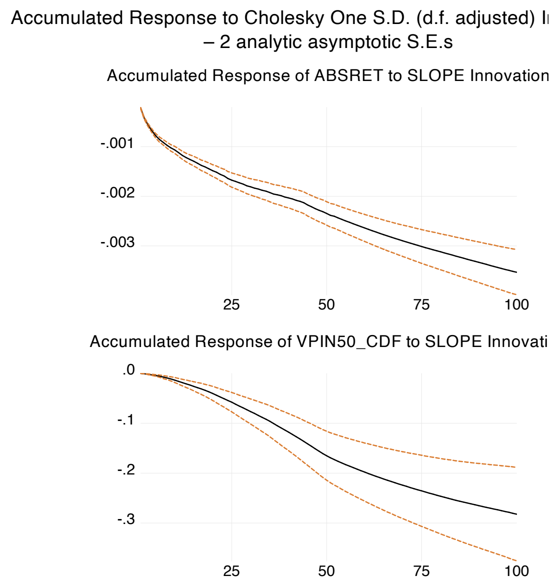


(b) Large-Cap accumulated response of volatility and informed trading to a consensus of LOB innovation.

Panel B. Mid-Cap



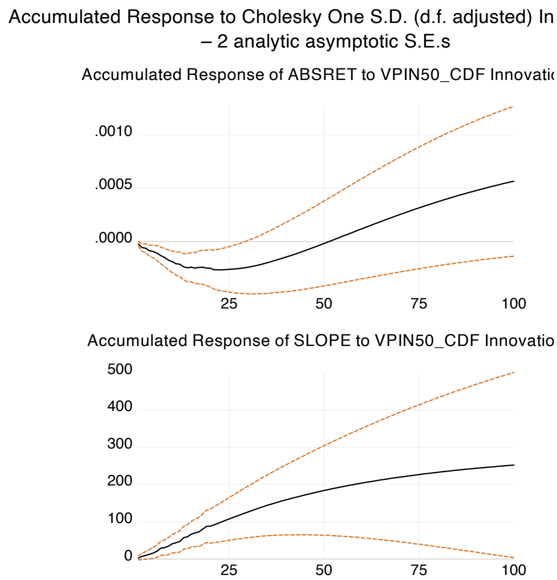
(c) Mid-Cap accumulated response of volatility and consensus of LOB to an informed trading innovation



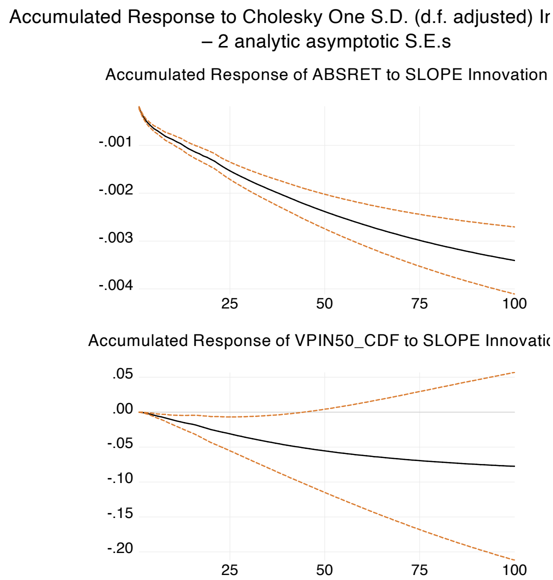
(d) Mid-Cap accumulated response of volatility and informed trading to a consensus of LOB innovation.

Figure 3.1. Impulse-response (continued)

Panel C. Small-Cap



(e) Small-Cap accumulated response of volatility and consensus of LOB to an informed trading innovation



(f) Small-Cap accumulated response of volatility and informed trading to a consensus of LOB innovation.

Figure 3.1. Impulse-response of VAR: Response to Cholesky One S.D. Innovations of Volatility and consensus of LOB to Informed trading innovations up-left panel; Response to Cholesky One S.D. Innovations of Volatility and informed trading to Informed consensus of the LOB up-left panel. (a, b) in large cap category, (c, d) in mid cap category and (e, f) in small cap category.

The accumulated response analysis indicates that consensus has a clear effect in reducing volatility in mid-caps, where a stabilization trend is observed (Figure 3.1 (d)). Similarly, the accumulated response of volatility to innovations in informed trading in mid-caps (Figure 3.1 (c) top) reveals a significant decrease in volatility. This decline suggests that informed trading has a stabilizing effect, similar to the observed behavior in large-caps. However, this decrease is more pronounced in mid-caps, likely due to the comparatively lower liquidity and market depth, making these markets more responsive to changes in informed trading. Over time, the stabilizing effect remains significant, indicating a lasting impact of informed trading on market volatility compared to large-caps.

In terms of the response of volatility to innovations in consensus (Figure 3.1 (d) top), the accumulated response analysis shows that volatility also decreases significantly following an innovation in consensus. This supports the role of consensus in reducing uncertainty and stabilizing prices, which is particularly important in mid-caps due to their lower analyst coverage compared to large-caps. The persistent negative response over time indicates that consensus contributes to maintaining a stable market environment, reducing volatility in the medium term.

The accumulated response of consensus to innovations in informed trading (Figure 3.1 (c) bottom) suggests an initial increase in consensus following an innovation in informed trading. This positive response indicates that informed trading enhances consensus in the Limit Order Book, helping to stabilize market dynamics. Over time, this response gradually stabilizes, with confidence intervals suggesting statistical significance that diminishes over time. In contrast, the response of informed trading to innovations in consensus (Figure 3.1 (d) bottom) shows an initial negative effect, consistent with the estimated coefficient of the first lag of consensus explaining informed trading in the VAR model. However, subsequent lags are not statistically significant, indicating that the effect is not reinforced over time. Despite the lack of significance in later periods, the accumulated response remains negative and does not revert to zero, suggesting that the initial impact has a lasting influence on informed trading dynamics. This implies that while consensus fluctuations may momentarily influence informed trading, the effect persists in an accumulated manner rather than being strongly driven by ongoing innovations in consensus. Confidence intervals indicate that statistical significance fades over time, reinforcing the idea that consensus alone does not substantially drive informed trading activity in mid-caps.

Overall, the bidirectional relationships between consensus, informed trading, and volatility in mid-caps contribute to a stabilizing cycle. Innovations in informed trading initially influence consensus, albeit with a diminishing effect over time, while consensus plays a stronger and more persistent role in reducing volatility. This dynamic interaction suggests that while informed trading can enhance market stability by fostering consensus, its impact is not sustained over time. Conversely, consensus appears to have a more direct and lasting effect on stabilizing volatility, reinforcing the importance of order book dynamics in maintaining market stability for mid-cap stocks.

In small-cap stocks, there is no evidence of causality between informed trading and consensus. However, a bidirectional relationship exists between consensus and volatility, and informed trading bidirectionally causes volatility. This dynamic suggests that in less liquid markets, consensus formation has a limited impact on informed trading activity, likely due to lower market depth and fewer opportunities for informed investors to significantly influence consensus. Volatility significantly decreases following innovations in both consensus and informed trading, underscoring the vulnerability of these markets to fluctuations and the importance of maintaining strong consensus to minimize volatility's impact.

The accumulated response analysis for volatility to innovations in informed trading in small-caps (Figure 3.1 (e) top) shows that volatility initially decreases after an innovation in informed trading. However, unlike large-caps and mid-caps, this reduction in volatility is less pronounced and tends to stabilize at a higher level over time. This behavior reflects the challenges of maintaining stability in less liquid markets. Confidence intervals suggest that the effect, while present, may not be as robust or sustained as in more liquid segments. Similarly, the response of volatility to innovations in consensus (Figure 3.1 (f) top) reveals that volatility decreases after a consensus innovation, indicating that consensus plays a stabilizing role in small-caps. However, this effect is limited, reflecting the difficulties in achieving long-term stability in smaller markets.

For small-caps, the bidirectional relationship between consensus and informed trading appears weak and short-lived. The response of consensus to innovations in informed trading (Figure 3.1 (e) bottom) shows a minimal initial positive effect that quickly fades, suggesting that informed trading has limited influence in enhancing consensus in less liquid markets. Similarly, the response of informed trading to innovations in consensus (Figure 3.1 (f) bottom) remains weak, with the accumulated response indicating that increases in consensus do not significantly alter informed trading behavior. This lack of sustained interaction reflects the constraints of smaller markets, where limited market depth and low liquidity hinder the long-term impact of these dynamics. Confidence intervals confirm that neither effect remains statistically significant beyond the initial response period.

In summary, for small-caps, the accumulated response analyses indicate that both consensus and informed trading contribute to reducing volatility, but their effects are weaker and less sustained compared to larger market segments. The limited liquidity and depth of small-caps make achieving long-term stability more challenging, and the interactions between consensus and informed trading are less pronounced. This highlights the unique dynamics of small-cap markets, where the stability of market conditions is more constrained, and trading behavior has a less predictable influence on consensus and volatility.

Joint conditional probability results

In the final part of this study, we aim to test Hypothesis H3 by examining whether the dispersion of beliefs in the LOB serves as a better predictor of market volatility than informed trading. This is based on the observation that the dispersion of beliefs provides insights not only into the actual transactions that have occurred but also reflects the intentions of traders as shown in the LOB. In our analysis we employed Conditional Probability Tables (CPTs), as shown in Table 3.9, due to their effectiveness in representing complex, non-linear associations and offering clear probabilistic predictions. This approach allows for a detailed exploration of the dynamics between informed trading, the level of consensus in the LOB and volatility, focusing on the capitalization-based portfolios. We analyzed lagged VPIN variations between buckets to evaluate short-term changes in informed trading, the CDF of VPIN to measure accumulated informed trading and the slope of the LOB to assess market consensus.

The VPIN variation between adjacent buckets reflects how the moving average of order imbalance changes over time. This variation serves as a proxy for assessing whether informed trading is being incorporated into market dynamics and its subsequent effect on volatility. VPIN variation is particularly valuable for analyzing short-term changes in trading activity, as it captures incremental shifts in imbalance that may indicate increased or decreased informed trading over consecutive periods. On its part, the CDF of VPIN represents the cumulative probability that VPIN will take a value less than or equal to a given threshold. The CDF of VPIN is used to assess the accumulation of informed trading activity over time, providing a longer-term perspective on market conditions. High CDF values suggest that informed trading has accumulated to a level that may compromise market stability, leading to increased volatility induced by a lack of liquidity, particularly under stressed market conditions. When the CDF approaches 0.99 for stocks, it may indicate market toxicity—a phenomenon discussed by Easley et al. (2012).

The analysis of large-cap stocks (Panel a) indicates that when the slope of the LOB falls within the lower range (40.6 - 705.17) at bucket $\tau-1$, 50.72% of returns are in the low-volatility range (between 0.0 to 0.01) at bucket τ. In contrast, within the highest slope range (4901.66 - 10926.13), 90.72% of returns are clustered in the low-volatility category, with only 0.11% in higher volatility categories. This trend is even more pronounced for small-cap stocks, where, in the highest slope ranges (2763.78 - 5631.29), 97.51% of returns are found within the lowest volatility range. Mid-cap stocks exhibit a similar stabilizing effect: in lower slope ranges (22.0 - 405.32) 52.93% of returns fall within the 0.0 to 0.01 range, increasing to 87.58% in the highest slope range (3157.23 - 6013.6). In small, mid, and large-caps, a consistent pattern emerges: a low slope of the LOB corresponds to a lower concentration of returns in the low-volatility range, while a high slope is associated with an increased concentration of low-volatility returns.

The magnitude of this effect varies across stock categories, being more pronounced in small-caps due to their lower liquidity and analytical coverage.

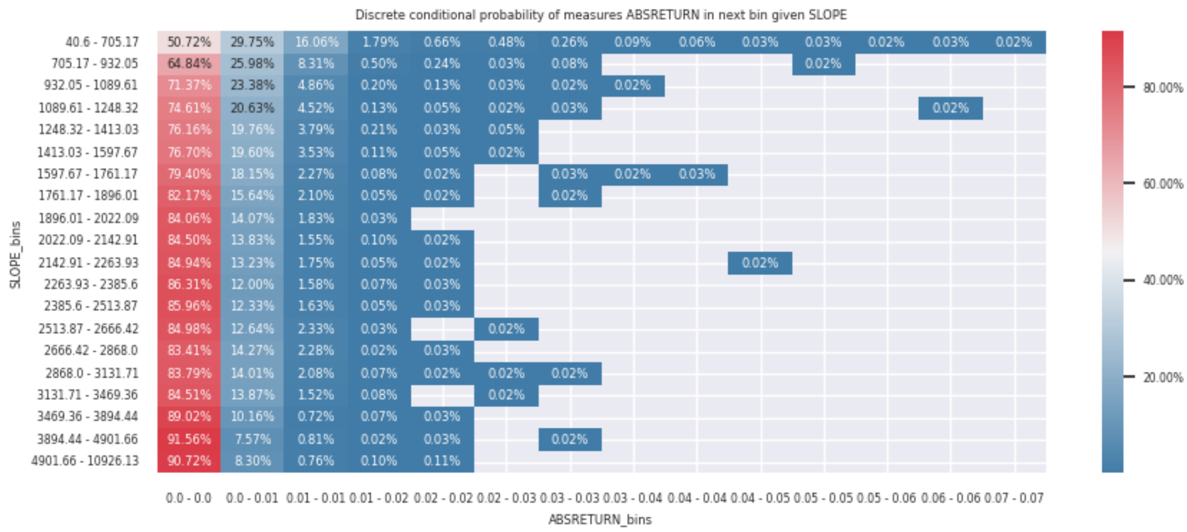
When analyzing the impact of VPIN variation, no significant effect is observed in terms of the concentration of low-volatility returns. However, there are notable differences between portfolios based on market capitalization. For large-cap stocks, a positive variation of VPIN (0.0 - 0.04) results in 80.57% of the returns being concentrated in the low-volatility range, while a negative change of a similar magnitude leads to a nearly identical value of 80.50%. For mid-cap stocks the percentage of returns in the low-volatility range increases, ranging from 82.99% to 84.47%, with no significant relationship observed between the VPIN variation and greater or lower percentages. In the case of small-cap stocks, a positive VPIN variation (0.0 - 0.04) results in a high concentration of low returns, reaching 93.86%, whereas a similar negative variation throws a percentage of 92.79% of returns in the low-volatility range. According to these results, we could say that volatility is generally lower in lower capitalization stocks but the variation in VPIN has no influence on volatility.

The examination of the CDF of VPIN reveals that small-caps consistently show a high concentration of low returns across all CDF ranges, with a slight decrease in the higher ranges (93.46% in low ranges vs. 91.03% in high ranges). For mid-caps, the concentration of low returns increases from 79.26% in the lower CDF ranges to 83.89% in higher ranges. In large-caps, the concentration slightly decreases from 80.87% in lower CDF levels to 78.98% in higher levels. These observations suggest that the CDF of VPIN is a less effective predictor across categories, though extreme CDF values (close to 1) may still predict increased volatility under high market stress conditions.

Our findings demonstrate that the slope of the LOB is a more effective predictor of market volatility than informed trading metrics, such as VPIN. This conclusion contrasts with previous studies that highlighted the predictive power of informed trading in identifying volatility and adverse market events. The results indicate that market consensus, reflected by the slope of the LOB, more directly signals market stability. This could be because the slope effectively captures the aggregate willingness of market participants to trade at different prices. A steep slope indicates a concentration of orders around the current price, suggesting a strong consensus on the asset's value and, consequently, lower volatility. Additionally, a steep slope implies greater market depth, which enhances liquidity and minimizes the impact of large orders on price fluctuations. In conclusion, our results highlight the slope as the best predictor of volatility across small, mid, and large-caps, with a pronounced effect in small-caps. These results are in line with research emphasizing the importance of the LOB in price formation and volatility (Parlour & Seppi, 2008).

Table 3.9 Conditional probability distributions of volatility based on the consensus of the LOB and informed trading.

(a). Large-cap. Slope of the LOB.



(b). Large-cap. VPIN variation.

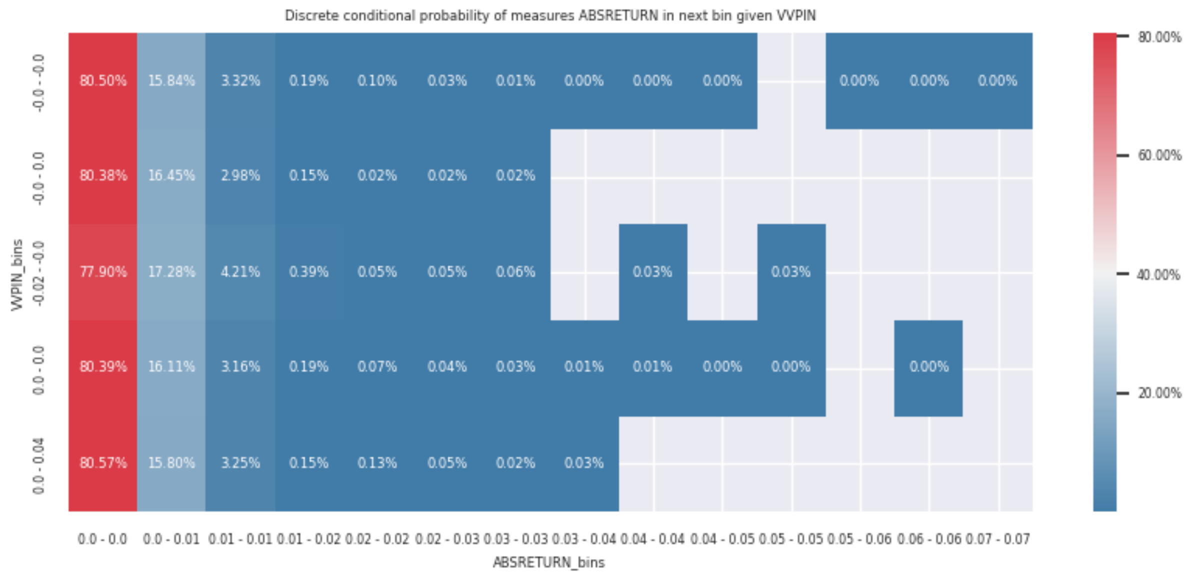
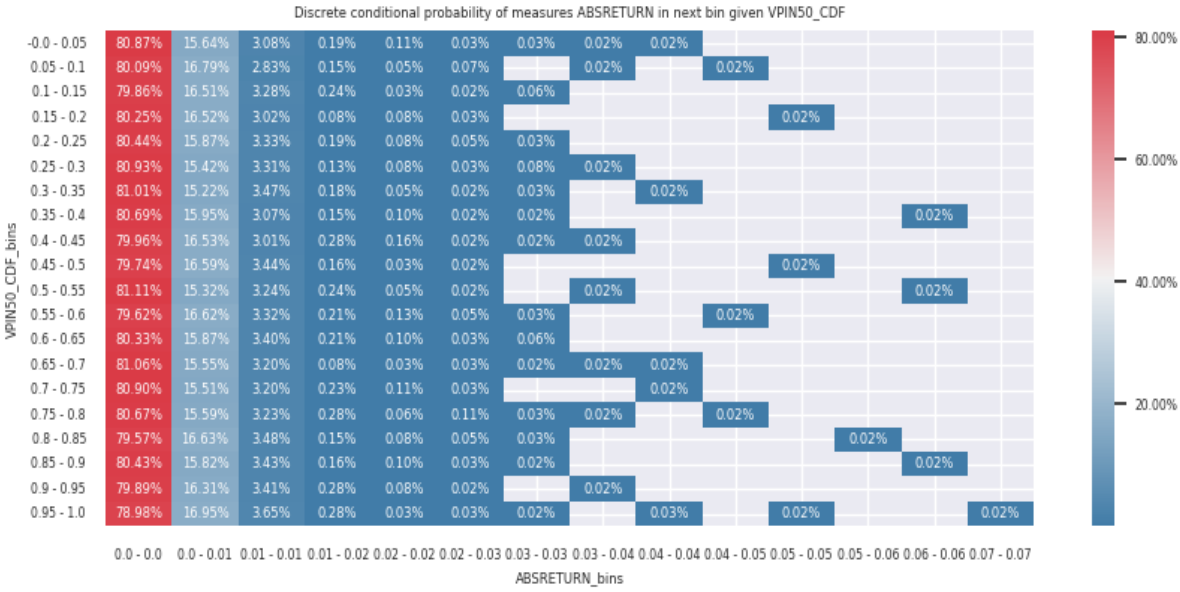


Table 3.9 Conditional probability distributions of volatility based on the consensus of the LOB and informed trading. (Cont.)

(c) Large-cap. CDF of VPIN.



(d) Mid-cap. Slope of the LOB.

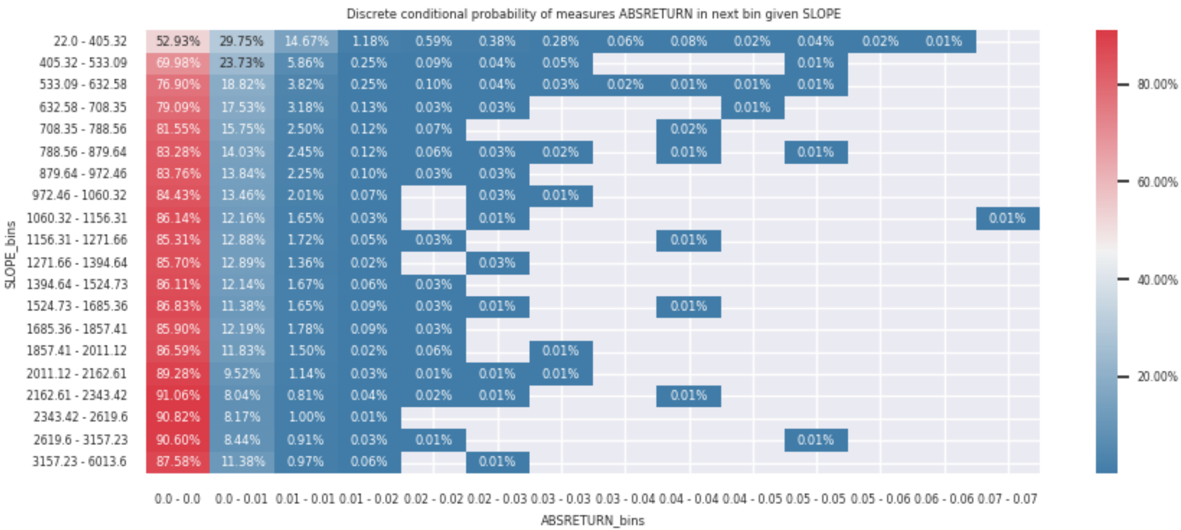
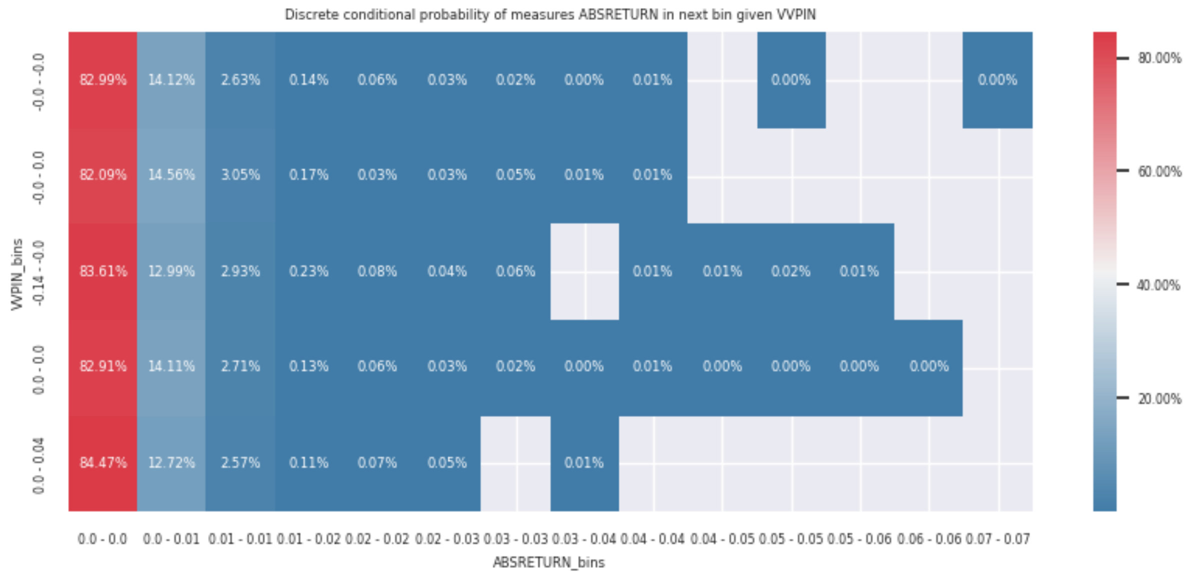


Table 3.9 Conditional probability distributions of volatility based on the consensus of the LOB and informed trading. (Cont.)

(e) Mid-cap. VPIN variation.



(f) Mid-cap. CDF of VPIN.

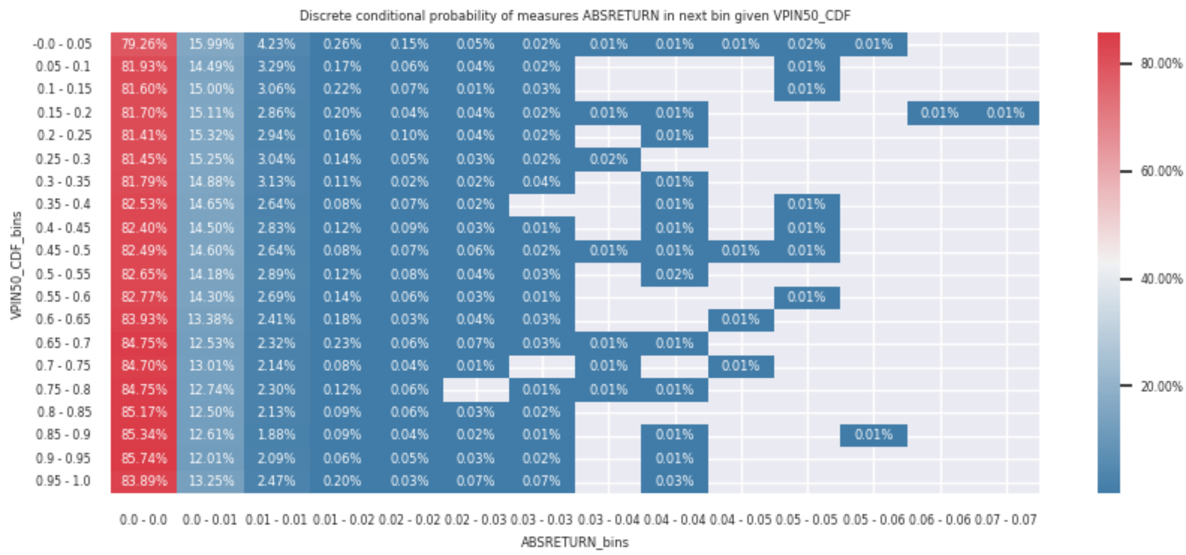
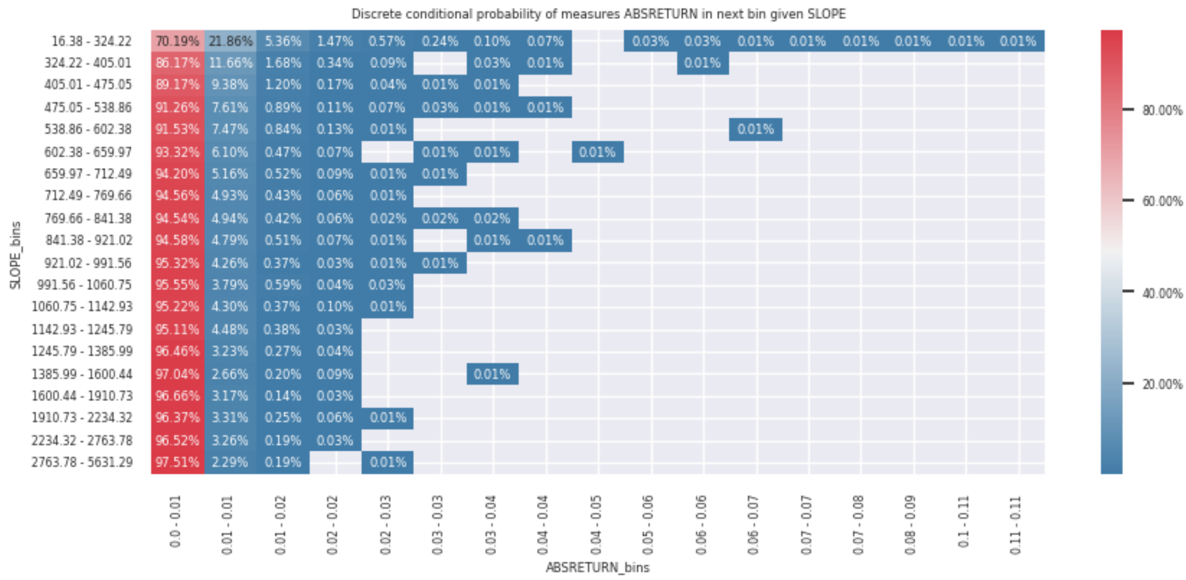


Table 3.9 Conditional probability distributions of volatility based on the consensus of the LOB and informed trading. (Cont.)

(g) Small-cap. Slope of the LOB.



(h) Small-cap. VPIN variation.

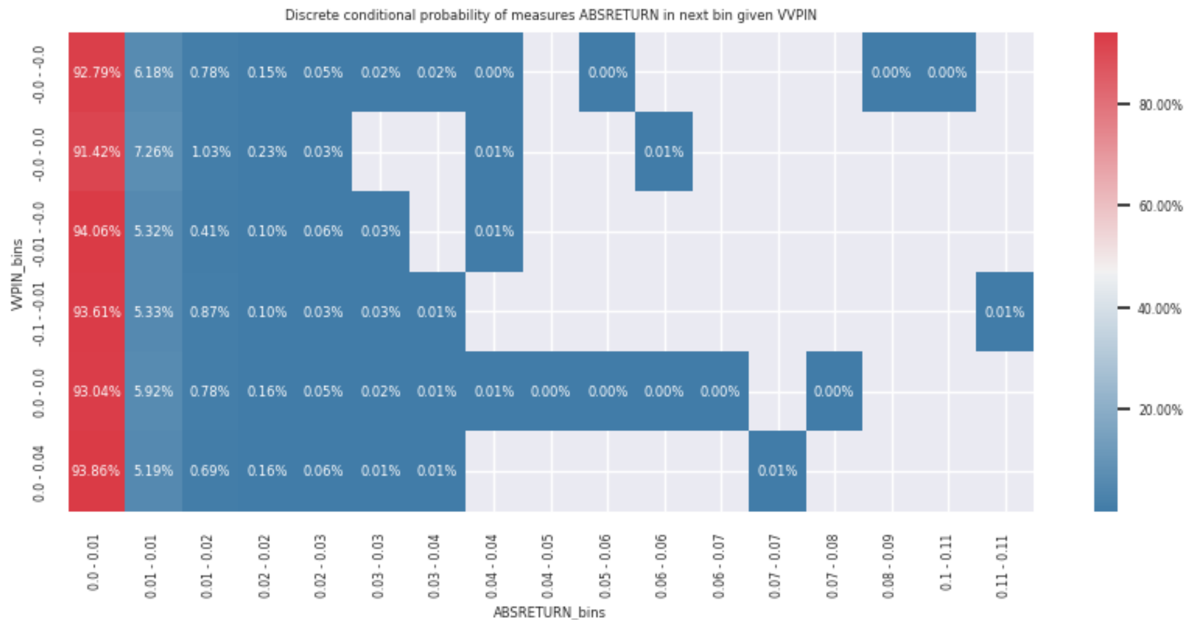


Table 3.9 Conditional probability distributions of volatility based on the consensus of the LOB and informed trading. (Cont.)

(i) Small-cap. CDF of VPIN.

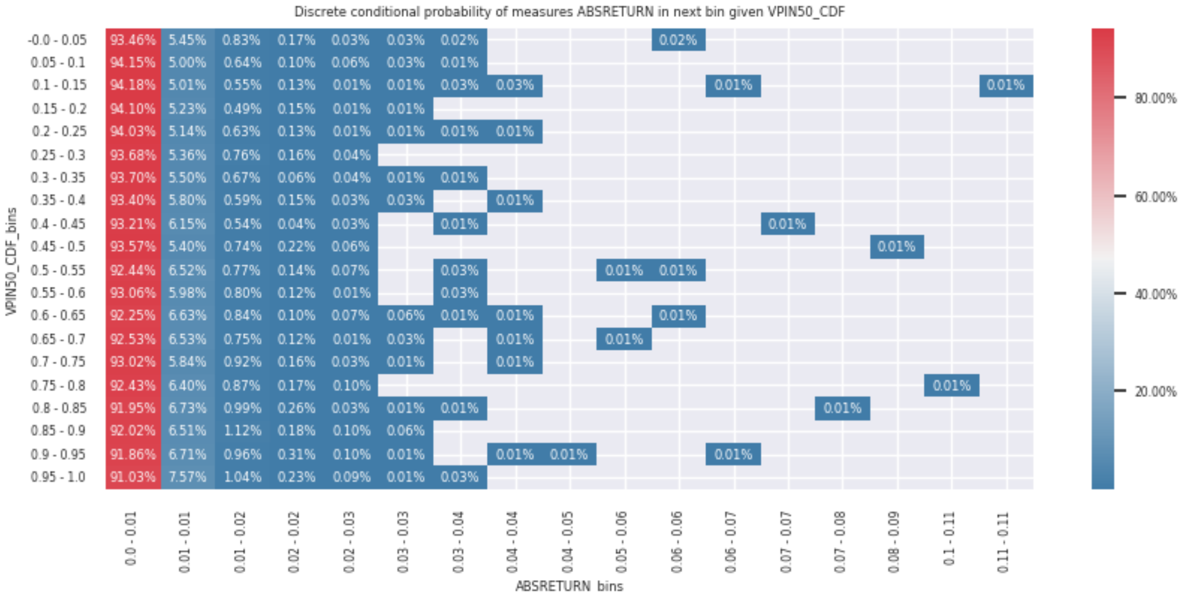


Table 3.9. Conditional probability distributions of volatility based on the consensus of the LOB and informed trading. Panels (a), (d), and (g) show volatility distributions at bucket τ given consensus of LOB at bucket τ−1 for large-, mid- and small-caps. Panels (b), (e), and (h) display volatility distributions at τ based on the variation in informed trading at bucket τ−1. Finally, panels (c), (f), and (i) present volatility distributions at τ given informed trading probability at bucket τ−1.

Our study also questions the previously assumed superiority of informed trading metrics in predicting volatility. VPIN was not designed to predict volatility directly but rather to measure market toxicity. Extreme values of the CDF of VPIN can anticipate volatility that arises from by liquidity issues, related to the exit of uninformed traders from the order book. On the other hand, while VPIN reflects information asymmetry and the potential for informed trading to increase volatility, it can also rise in illiquid markets, where it may fail to distinguish between volatility caused by informed trading and that caused by limited market depth. This limitation undermines VPIN's ability to fully explain the drivers of volatility compared to the LOB slope, which better captures the stabilizing influences of market consensus and liquidity.

Our results demonstrate a strong and consistent correlation between the slope of the LOB and volatility compared to VPIN, underscoring its potential as a reliable predictor across different stock categories. By demonstrating the superiority of the LOB slope, we shift the focus toward market structure and collective behavior metrics, rather than focusing solely on information asymmetry.

3.5 Conclusions

This comprehensive study set out to investigate the intricate relationships between informed trading, consensus, market liquidity and volatility among selected constituents of the IBEX 35 index. To this end, 18 companies were analyzed, with these companies being categorized into large-cap, mid-cap, and small-cap portfolios. The aim was to understand how these dynamics vary across different market capitalizations under normal and extraordinary market conditions, including the exceptional period of the COVID-19 pandemic, and the short-selling ban on Spanish stocks. The findings of the study provide nuanced insights into the role of informed trading and its impact on market quality, consensus within the Limit Order Book, liquidity and volatility. Specifically, the study set out to test several hypotheses in order to unravel these complex interactions.

The results obtained lend support to Hypothesis H1a, which suggests that the presence of informed traders leads to an increase in the alignment of beliefs within the LOB across all market capitalizations. This finding suggests that informed traders contribute to a more cohesive market consensus by incorporating their superior information into limit orders, thereby enhancing the informativeness of the order book. This finding is consistent with the observations reported by Chang et al. (2021), who noted that insider trading can enhance trade informativeness and support efficient price discovery. However, it is important to note that while informed trading enhances consensus, the degree of this effect varies among large-cap, mid-cap, and small-cap firms, potentially due to differences in liquidity and information asymmetry.

Contrary to Hypothesis H1b, the present study found that informed trading generally reduces the bid-ask spread, thereby improving external liquidity. This unexpected result suggests that informed traders may provide liquidity by placing limit orders that narrow the spread, possibly aiming to capitalize on their informational advantage in a more cost-effective manner. This observation is consistent with the findings of Collin-Dufresne and Fos (2015), who proposed that informed traders might delay trades until favorable conditions arise, thus reducing the illiquidity component of the spread. However, with regard to internal liquidity, our findings indicate that informed trading reduces order book depth, thereby supporting the notion that it consumes internal liquidity. Informed traders appear to deter uninformed liquidity providers from submitting limit orders at multiple price levels, leading to a thinner order book. This effect is more pronounced in mid-cap and small-cap firms, which may be more sensitive to shifts in internal liquidity due to lower overall market depth. This behavior aligns with Kyle's

(1985) theoretical model, which suggests that informed trading can discourage uninformed participants, reducing liquidity at various price levels.

In large-cap companies, a unidirectional relationship was observed, wherein informed trading positively influenced consensus within the limit order book (LOB), thereby supporting Hypothesis H2a. The enhancement of consensus through the practice of informed trading appears to temporarily reduce market volatility by improving price discovery mechanisms. This finding corroborates previous research indicating that informed trading can mitigate market uncertainty by accelerating the incorporation of information into prices (Easley et al., 1998; Hu, 2018). However, this effect is not significant in small-cap companies, where informed trading does not influence (Granger) consensus, nor does consensus influence informed trading, confirming the absence of a causal relationship.

In the context of mid-cap companies, the relationship becomes more intricate. The present study reveals that informed trading and consensus exert a reciprocal influence on each other, suggesting a dynamic interplay wherein market participants adjust their beliefs based on both new information and prevailing consensus. A lack of consensus attracts informed trading, which in turn increases consensus, leading to a reinforcing cycle. This mutual reinforcement contributes to market stability by reducing volatility over time. The findings underscore the significance of both informed trading and consensus in enhancing market quality in mid-cap stocks.

Furthermore, the findings of this study demonstrate a bidirectional negative relationship between consensus and volatility across all size categories, thereby providing support for Hypothesis H2b. It is evident that higher consensus within the LOB is associated with reduced volatility, while increased volatility can disrupt consensus among investors. This interplay suggests that, in large-cap firms where liquidity is ample, consensus functions as a stabilizing force in the market. However, in smaller-cap firms, this relationship is less pronounced due to limited liquidity, making it more challenging to maintain consistent consensus.

The findings of this study provide partial support for Hypothesis H2c in the context of small-cap companies. The results indicate that market volatility attracts informed trading. This finding suggests that, in less liquid markets, high levels of volatility may exacerbate informed trading, increasing trading activity as market participants react to uncertainty. The limited depth and liquidity inherent in small-cap stocks render them more susceptible to price impacts derived from informed trading.

Additionally, the role that consensus within the LOB plays in mitigating volatility in small-cap firms is limited. The reduced market depth and lower participation of uninformed traders may hinder the formation of a strong consensus, diminishing its stabilizing effect. This underscores the challenges of achieving market stability in less liquid environments and highlights the need for mechanisms to enhance liquidity and information dissemination in small-cap markets.

The present study provides substantial evidence in support of Hypothesis H3, which posits that the dispersion of beliefs in the LOB, as measured by the slope, serves as a more effective predictor of volatility than informed trading metrics such as VPIN. High slope values, indicative of strong market consensus, are associated with a significant concentration of returns in low-volatility ranges across all market capitalizations. This effect is most pronounced in small-cap stocks, where liquidity constraints amplify the impact of consensus on stabilizing prices. In contrast, while VPIN and its cumulative distribution function (CDF) can signal potential volatility spikes under extreme market stress, their overall predictive power is limited under normal trading conditions. This finding indicates that metrics which capture collective market behavior and consensus, such as the LOB slope, provide more reliable indicators of market stability than those focusing solely on information asymmetry. These findings are consistent with studies emphasizing the importance of the LOB in price formation and volatility (Parlour & Seppi, 2008). By demonstrating the efficacy of the LOB slope as a predictive tool, we contribute to the extant literature by highlighting the value of market structure metrics over traditional informed trading measures, especially in markets with varying liquidity levels.

The findings of this study offer valuable insights for traders, investors, and regulators. It is asserted that the LOB slope can function as a reliable predictor of volatility, thereby assisting market participants in adjusting their strategies to manage risk more effectively. For instance, monitoring changes in the LOB slope could enable traders to anticipate periods of heightened volatility and adjust their positions accordingly. These findings may also be of relevance to regulators. Enhancing transparency around LOB data and encouraging practices that promote market consensus could help stabilize markets, particularly in less liquid segments like small-cap stocks. Furthermore, a comprehensive understanding of the multifaceted effects of informed trading on liquidity and volatility can inform regulatory policies aimed at achieving a balance between market efficiency and stability.

Whilst the present study provides significant insights, it is essential to acknowledge its limitations. The analysis is confined to a subset of IBEX 35 constituents during an extraordinary period characterized by the emergence of the COVID-19 pandemic and the imposition of a short-selling ban in the Spanish market. It is therefore acknowledged that the findings may not be easily generalized to more typical market environments. To enhance the robustness of the conclusions drawn, it would be advisable for future research to extend the analysis to different time frames, markets, or to include a broader range of securities. Furthermore, the study's utilization of high-frequency data and the employment of specific metrics such as VPIN and the LOB slope indicates that alternative metrics or methodologies could offer supplementary insights. The investigation of alternative indicators of informed trading and consensus, or the employment of different modelling techniques, has the potential to enhance our understanding of these complex dynamics.

To summarize, the present study highlights the multifaceted role of informed trading in financial markets. While it can enhance market quality through improved consensus and efficient price discovery, it also poses challenges by affecting liquidity and volatility, especially in less liquid markets. The LOB slope emerges as a valuable tool for predicting volatility, offering practical benefits for market participants and informing regulatory considerations. By emphasizing the interplay between informed trading, market consensus, and volatility across different market capitalizations, we contribute to a more profound understanding of market microstructure and lay the foundation for future exploration in this critical area of financial research.

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4. Analysis of the components of the Slope of the Limit Order Book through a state-space model: Impact on the market.

Abstract

This study applies a state-space model to the analysis of the information contained on the slope of the limit order book (LOB), distinguishing between two unobservable components: the permanent component, which corresponds to efficient information, and the transitory component, influenced by uninformed trading variations, typically algorithms for liquidity provision or feedback trading. Using an event-time clock approach, this research examines how these components relate to volatility, adverse selection costs, and liquidity. The results indicate that the permanent component helps mitigate volatility, reduces adverse selection costs, and enhances liquidity. In contrast, the transitory component increases these measures. Additionally, it is observed that the transitory component of the LOB slope provides modest predictive power regarding subsequent intraday trading profitability.

Keywords: Informed trading, dispersion of beliefs, Limit Order Book, VPIN, volatility, liquidity, COVID-19, Short-selling ban, State-space model.

4.1 Introduction

The specialized literature has extensively addressed the topic of informed trading within the microstructure of financial markets, particularly focusing on explicit transactions. Traditionally, it is understood that by incorporating new relevant information that is exploitable over a short period, market orders absorb the existing liquidity in the limit order book. It has been generally considered that this book is primarily populated by orders that do not aim to introduce new information to the market but rather to provide liquidity. However, recent research, including that conducted by Cao et al. (2009), Collin-Dufresne & Fos (2015), Pascual et al. (2004), and Pascual & Veredas (2006), has challenged this traditional view. They have identified the existence of informed limit orders, which underlying information can have more enduring relevance and exploitation. This discovery suggests that traders with efficient long-term information might prefer to submit limit orders instead of market orders, a behavior that alters the conventional understanding of how information is distributed in the market.

In intraday trading, it is essential to distinguish between informed trading based on efficient information and uninformed trading, which typically includes trend-following or technical analysis-based operations. Research indicates that informed trades can be differentiated from uninformed trades by analyzing return autocorrelation, where informed trades result in no autocorrelation. In contrast, uninformed trades lead to negative autocorrelation (Kittiakarasakun et al., 2012). Additionally, informed traders consume liquidity, whereas uninformed traders typically provide liquidity (Chun Wei et al., 2013). This distinction underscores how different trading behaviors influence market dynamics.

In this study, we analyze the Limit Order Book (LOB) from the perspective of its slope (SLOPE), investigating how the different components of this slope influence market quality, including aspects such as volatility, adverse selection costs, and liquidity. The slope of the LOB has been identified as a crucial indicator that reflects not only market dynamics and the price discovery process but also the consensus on asset value and market participants' expectations. Previous studies suggest that a steeper slope (higher in value) is associated with a broader consensus on an asset's fundamental value, which in turn tends to stabilize the market by reducing trading activity and price volatility (Næs & Skjeltorp, 2006; Tripathi et al., 2020). This consensus is essentially a reflection of the collective beliefs of traders, who use limit orders to express their expectations about future price movements.

The consensus on value reflected in the LOB slope is also associated with market liquidity and trade informativeness, suggesting that the LOB structure fosters competition among liquidity providers, thereby contributing to a more efficient market. Moreover, imbalances between demand and supply within the book have been significantly correlated with short-term returns, reinforcing the informative nature of the LOB (Cao et al., 2009). By decomposing the LOB slope into two unobservable components—one permanent and the other transitory—we can discern how the component based on long-term efficient information and liquidity or algorithmic trading operations influence volatility, adverse selection costs, and liquidity.

The permanent component, associated with the non-stationary local level, reflects long-term efficient information. This element of the slope indicates a widespread agreement among informed investors about the asset's underlying value and indicates a market that efficiently reflects fundamental information in asset prices (Eisler et al., 2009; Valenzuela et al., 2015).

In contrast, the transitory component, a stationary autoregressive series, captures short-term fluctuations influenced by trading operations not based on fundamental valuation but rather on liquidity trading, reactions to events, or algorithmic trading (Tripathi et al., 2020). These fluctuations are critical for understanding how the latter affect volatility and other market quality measures in the short-term market dynamics, as they provide insights into how factors external to fundamental value can affect prices. The fact that this study can contribute to a better understanding of the functioning of prices justifies our decision to decompose the limit order book slope in our state-space model into differentiated components, reflecting the influences of long-term (permanent) informed and uninformed[5] (transitory) market influences.

Prior literature has revealed that informed trading, guided by analysis and data, typically enhances price rationality and stability, contributing to price discovery and market efficiency (Ozocak, 2015) and counteracting the erratic movements caused by uninformed traders (Barclay et al., 2003). While informed trading can stabilize prices by providing accurate information about underlying values (Blasco & Corredor, 2017), uninformed trading, often driven by herd behavior or emotional reactions to market events, tends to increase volatility (Avramov et al., 2006; Blasco et al., 2012). In our study, the SLOPE component related to efficient price reflects the market valuation based on available information and rational expectations. In contrast, the transitory uninformed trading component represents transactions occurring without the benefit of relevant information, often driven by speculative reactions to news or market events. This separation allows us to directly observe how each type of trading contributes to overall market volatility.

In addition, it has been found that when trades are conducted based on speculation, adverse selection costs tend to increase due to information asymmetry and market uncertainty (Huang & Stoll, 1997; Tiniç et al., 2023). This link could be explained by the fact that non-fundamental trading decisions alter market expectations and affect the efficiency of price formation, exacerbating the challenges associated with adverse selection and potentially increasing transaction costs.

The objective of this paper is to analyze whether the unobservable components of the slope of the LOB — those related to efficient pricing and those related to trading not based on

[5] In this study, we will refer to uninformed trades as those that are not based on fundamentals and do not influence the long term. This component includes reactions to specific events, certain short-term news, herd trading, liquidity changes, emotional reactions from investors, feedback trading, or algorithmic trading.

fundamental information — affect market quality measures (i.e. volatility, adverse selection costs, and liquidity) and how. Additionally, we will explore the existence of a non-contemporaneous relationship between these components and returns, as well as the possible predictability of returns through the permanent and transitory components of the SLOPE. By exclusively analyzing LOB orders and not market orders, we propose that the predictability of returns might be more closely linked to the uninformed trading component than to informed trades. Moreover, we will control for variables such as crash periods and short-selling restrictions during the COVID-19 crisis to discern their relative impact on our study.

Using a state-space model, combined with the Kalman filter, provides a robust framework for decomposing the slope series of the limit order book into two unobservable variables. This approach allows us to effectively separate the components related to efficient pricing based on fundamental information from those influenced by trading which is not based on fundamental information. According to Mann & O'Hara (1996), state-space models are fundamental in market microstructure theory for assessing price volatility and understanding market states. These models allow for a more accurate interpretation of factors such as order flow and liquidity, essential for understanding market behavior and its responses to stimuli (Peng et al., 2005). Moreover, in the context of our research, we propose as a novelty for the entire analysis the implementation of event clocks (based on executed transactions) instead of calendar clocks. According to studies like those of Carmona & Webster (2013), event clocks offer a more accurate representation of market dynamics because they are based on significant occurrences that affect the market rather than arbitrary time intervals. This approach leads to a normal distribution of intraday stock returns, indicating its effectiveness in better capturing market activity in intraday market microstructure (Ling, 2017). Therefore, the combination of an event clock and the use of a state-space model with the Kalman filter in our study not only aligns with practices in market microstructure research but also enhances our ability to analyze the implications of market dynamics more precisely and in greater detail. This positions us to gain deeper insights into the relationship between the components of the limit order book slope and market quality measures such as volatility and adverse selection costs, enabling a more comprehensive assessment of market efficiency and the quality of price formation.

This document is structured as follows: Section 2 provides a literature review and hypotheses, contextualizing our study within the field of market microstructure. Section 3 presents the data used from the IBEX35 and quality measures. Section 4 covers the methodology, detailing the construction of the state-space model, the analytical approach adopted to differentiate between the SLOPE components and the multiple regressions of the measures. Section 5 is dedicated to analyzing the results, examining the impact of the permanent and transitory components of SLOPE on market volatility, adverse selection costs, liquidity, and return predictive power. Finally, in Section 6, we conclude.

4.2 Literature review and hypotheses

Understanding the structure and dynamics of the limit order book is essential for analyzing how information is reflected in market measures such as volatility, adverse selection costs, and liquidity. Historically, market orders have been considered the primary bearers of information due to the urgency in their execution to exploit the advantage of new information. However, this focus has begun to be questioned and expanded. Informed trading within the limit order book (LOB) environment has been a topic of considerable research interest. For instance, studies have shown that informed traders tend to keep their orders small to avoid revealing their superior knowledge (Bouchaud, 2009). Previous research has also shown that the depth and information differential in order books goes beyond the primary level (Aidov & Lobanova, 2021) and how these LOB sections are influenced by overall market volatility (W. Kang & Zhang, 2013). Therefore, limit orders are not only crucial for managing liquidity and market depth but they also encapsulate significant informational content that influences price expectations and asset valuations (Cao et al., 2009; Collin-Dufresne & Fos, 2015; Liu & Ouyang, 2014). This rich informational content highlights the relevance of limit orders beyond their transactional function, serving as strategic tools in trading and price discovery.

Limit orders, containing approximately 78% of the information in the best bid-offer and 22% in the rest of the book, offer critical insights into future price expectations and asset valuations, providing an informational dimension that market orders cannot offer (Liu & Ouyang, 2014). Moreover, these orders can be strategically exploited over time, highlighting their enduring relevance in formulating trading strategies and price discovery (Liu & Ouyang, 2014). The literature suggests that informed traders, such as institutional investors and insiders, strategically use limit orders to manipulate or protect information related to future price movements. Studies like those of Lin et al. (2013) and Wei et al. (2014) have identified that informed traders often employ aggressive limit orders to influence the market, while research on informed trading indicates that these traders adjust their strategies to conceal or disseminate valuable information (Pyo, 2022). In addition, the growing role of algorithmic trading and insider trading highlights the evolution of market strategies, where limit orders play a crucial role in releasing and retaining information before significant announcements such as corporate earnings (Zhang et al., 2021). This complex environment underscores the need to analyze how limit orders not only reflect but can also manipulate market perception and liquidity.

Additional studies have highlighted the importance of the LOB slope as a reflection of market sentiment and a predictor of future price volatility, providing an additional layer of understanding of how investor disagreements can manifest in market dynamics (Næs & Skjeltorp, 2006). This dimension is key for understanding traders' expectations at an intraday level, how operators value fundamental information, and their trading motivations. Moreover, the slope on the buy side of the LOB has been found to be more informative than on the sell side, highlighting an asymmetry in the available information that may influence market perceptions regarding liquidity and future expectations (Duong et al., 2008).

In the context of market microstructure, adverse selection costs constitute a critical component that influences the efficiency of price discovery and overall market dynamics. Adverse selection costs, which include the impact of informed trading, constitute a significant portion of transaction costs in trading activities (Ahn et al., 2008). Previous research has shown that algorithmic trading, while accelerating price discovery and improving informational efficiency, also raises adverse selection costs, especially for slower traders (Chaboud et al., 2014). These costs are essential for understanding how informed traders exploit price discrepancies, distorting equilibrium prices and negatively impacting market efficiency (Caglio & Kavajecz, 2006; Layton, 2017). Adverse selection costs are intrinsically linked to price discovery, as price informativeness and the integration of information into prices are interconnected and fundamental concepts (Brogaard et al., 2019; Collin-Dufresne & Fos, 2015). Moreover, adverse selection components, order processing, and inventory components, influence bid-ask spreads in financial markets (Huang & Stoll, 1997). This phenomenon is observed across various markets and contexts, demonstrating how adverse selection costs can significantly distort prices in different sectors.

The relationship between order imbalances and adverse selection is essential for understanding market dynamics. Order imbalances have also been linked to informed trading, affecting the actual value of securities (Tiniç et al., 2023). Order flow volatility, closely related to order imbalances, can indicate information asymmetry costs (Chordia et al., 2019). Furthermore, retail marketable order imbalances have been used as indicators of liquidity provision, highlighting their relevance in assessing adverse selection (Boehmer et al., 2021). Hence, order imbalances cannot be ignored when analyzing liquidity and the effects of adverse selection. We will use the relative price spread and the Order Imbalance Ratio to assess adverse selection costs accurately. To measure the toxicity caused by excessive informed trading in order flow, we will employ metrics such as the Cumulative Distribution Function (CDF) of VPIN (Volume-Synchronized Probability of Informed Trading). VPIN has proven to be an effective tool for measuring order flow toxicity and is widely used to examine the effectiveness of quality metrics in varied market scenarios, including its ability to predict extreme events such as flash crashes (Kang et al., 2019). Previous studies have validated these indicators for their ability to reflect information asymmetry and its impact on adverse selection costs in critical market situations (Easley et al., 2012).

By integrating these instruments into our analysis, we aim to provide a detailed assessment of how the LOB slope components can serve as market dynamics indicators. The analysis of the LOB focuses on discerning whether there are efficient price components in its slope, which contain long-term information, and transitory components associated with operations seeking liquidity and not based on fundamental information, such as feedback trading, and how they influence several key aspects of the market, such as volatility, adverse selection costs, illiquidity, and intraday returns. This distinction will shed light on understanding the dynamics between informed and uninformed elements present in the order book and will contribute to a deeper and more nuanced understanding of market efficiency and price discovery. Through this analysis, we aim to determine whether the presence of informed and transitory traders significantly modifies these elements, which could offer important insights for understanding and managing risks in financial markets.

Next, we present the research hypotheses that emerge from the comprehensive review of the literature related to financial market behavior and the impact of information on these markets.

Hypothesis 1a (H1a): The efficient information component of SLOPE reduces volatility. Based on previous studies by Duong et al. (2008) and Kittiakarasakun et al. (2012), we postulate that the presence of informed traders, which can be detected through the slope of the order book, tends to decrease market volatility. This idea aligns with the theory that the informed component of SLOPE has a stabilizing effect, reducing uncertainty and providing relevant information about future market expectations.

Hypothesis 1b (H1b): The transitory component of SLOPE increases volatility. Uninformed trading, driven by short-term non-fundamental effects (liquidity, herding, feedback trading, emotional reactions to events) rather than long-term or efficient information, tends to increase volatility. This type of trading, often associated with uninformed behaviors, is a significant contributor to increased volatility due to its less predictive and more reactive nature.

Hypothesis 2a (H2a): The efficient information component of SLOPE reduces adverse selection costs. We propose that the presence of efficient information in the limit order book facilitates a more transparent and equitable trading environment, reducing adverse selection costs for all market participants. The high probability of informed trading is expected to be positively related to the permanent component of the order book slope, as it contains informed limit orders.

Hypothesis 2b (H2b): The transitory component of SLOPE increases adverse selection costs. The lack of information and the predominance of transitory orders can increase adverse selection costs, as market participants operate in a more uncertain and manipulation-prone environment. The high probability of informed trading is expected to be positively related to the transitory component of the order book slope, as it exacerbates the lack of liquidity for uninformed traders.

Hypothesis 3a (H3a): The efficient component of SLOPE reduces illiquidity. According to Cao et al. (2009), informed limit orders reflected in the slope of the order book provide significant value to the price formation process and improve liquidity by providing more options to execute transactions without significantly impacting prices.

Hypothesis 3b (H3b): The transitory component of SLOPE increases illiquidity. A higher number of transitory orders can lead to a decrease in the effective liquidity of the market, as these trades often do not provide stability or depth to the order book.

Hypothesis 4 (H4): The transitory component of SLOPE is a statistically significant predictor of intraday returns. Influenced by the findings of Aidov & Daigler (2015), we expect that uninformed trades captured by the transitory component of SLOPE significantly impact market volatility and prices, thus affecting intraday returns.

4.3 Data and measures

Data

For the analysis presented in this study, high-frequency data corresponding to 2019-2020 were utilized, encompassing the complete positions of the limit order book and daily quotes provided by the Spanish Stock Market Interconnection System (SIBE). This system plays a crucial role in stock market operations by facilitating transactions of the most traded stocks on the Spanish Stock Exchange. The trading hours, which extend from 9:00 a.m. to 5:30 p.m. GMT+1, include uninterrupted trading periods complemented by opening and closing auctions, which are key moments for the market.

The richness of the data collected allows us to examine the LOB dynamics in great detail, reaching up to 20 levels of depth in bid and ask information. This depth is constantly updated with each new order, modification, or cancellation. The LOB is indispensable for understanding the mechanics of price formation and liquidity in a market that operates without official market makers.

The detailed information gathered includes price, volume, and the most competitive quotes just before each transaction. To preserve the integrity of our analysis, special trades, such as those determining the allocation price in auctions, have been excluded from the study, focusing exclusively on standard transactions. Thanks to a common sequential identifier, it is possible to precisely synchronize transaction data with LOB data, accurately adjusting the order book snapshot at each transaction. This is key for the sequence of periods used in this study.

The analysis includes 33 stocks selected for their prolonged presence in the IBEX 35 during the study period. This approach prioritizes stability while also accounting for stocks with significant market contributions, ensuring a representative and comprehensive sample of Spanish stock market activity.

This high-frequency dataset provides a solid foundation for our analysis and allows for a detailed exploration of the influence of market microstructure on market quality measures. Using this dataset, the decomposition of the LOB slope into informed and liquidity components offers a unique opportunity to understand the underlying dynamics affecting return volatility, adverse selection costs, and liquidity on the Spanish Stock Exchange.

Measures of the SLOPE

The LOB, a manifest record of the set of transaction intentions and the dispersion of market participants' expectations, documents the buy and sell orders pending execution. These orders, not yet executed, are publicly visible and generally lack immediate temporal imperatives, motivated either by liquidity needs or value capture based on information that will affect the asset in the medium or long term. As graphically represented in Figure 4.1, the position of these orders is mapped on the horizontal axis, with buy orders (bids) aligned to the left and sell orders (asks) to the right, converging at the midpoint of the market price (P*), also known as the mid-price. On the vertical axis, the accumulation of buy orders is displayed on the left side, while sell orders are shown on the right.

Figure 4.1 Slope of the Limit Order Book

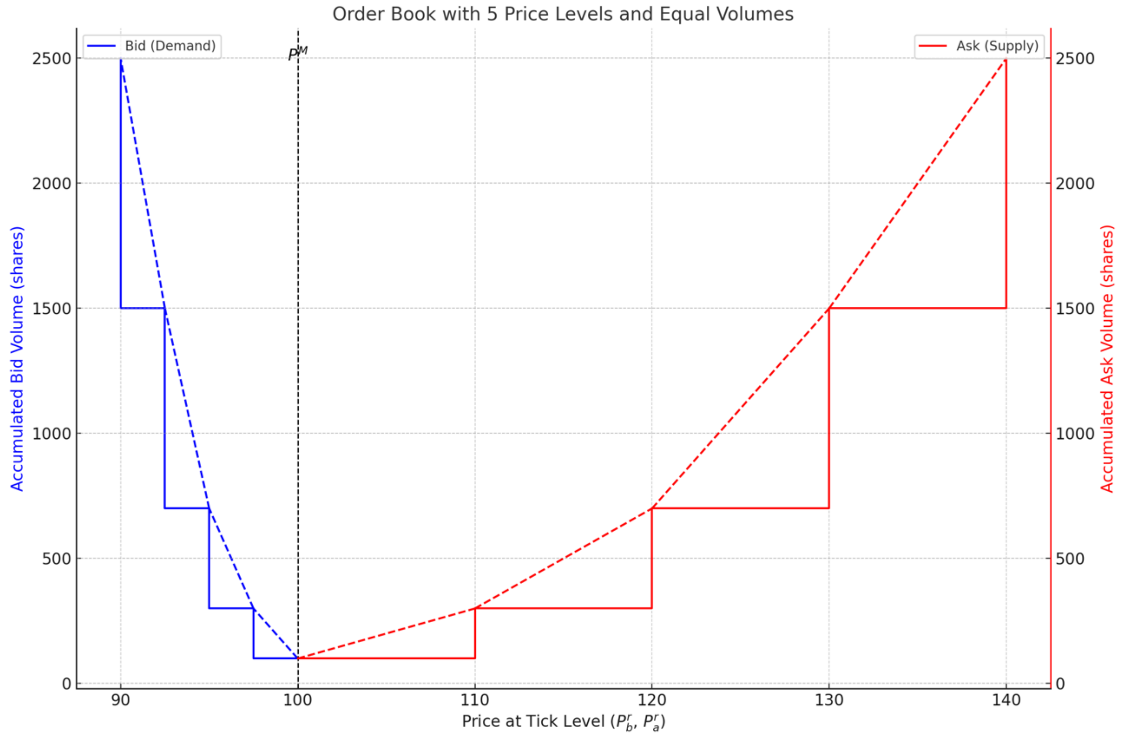

Figure 4.1 The illustration details the structure and dynamics of a corporate entity's order book at a specific moment. It reveals the arrangement of accumulated buy (BID) and sell (ASK) orders and highlights the behaviors of market participants at different prices. The graph displays two stepped curves representing the accumulated volume of buy and sell orders, respectively, with the market's mid-price (PM) located at their intersection.

This equilibrium point, where the highest bid matches the lowest ask, defines the market spread. The configuration of these orders indicates the market's depth and liquidity, which are essential for understanding the mechanics of price formation and order execution. Moreover, the slope of these curves not only reveals market liquidity but also indicates the consensus among investors' valuations regarding the asset’s current value: a steeper slope suggests a broader consensus among investors that the quoted price reflects the asset's intrinsic value. In turn, prices above P* suggest sell orders, while those below imply buy orders. The dotted lines interconnect the various price levels, illustrating how the cumulative volume of orders impacts the slope of the book.

To examine the dynamics of the order book instantaneously, we rely on the slope of the LOB on both the bid and ask sides as described by Næs and Skjeltorp (2006). We calculate the slope of the order book at each significant change rather than using daily averages. This method allows us to capture immediate variations in elasticity $\frac{\partial q}{\partial p}$, which shows how the quantity (q) supplied or demanded changes in response to adjustments in price (p). This approach is essential for understanding fluctuations along the supply and demand curves in real time. It is carried out through equations (1), (2) and (3).

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

$$DE_{i,\tau}^{S} = \frac{1}{N_B}\left\{\frac{v_1^B}{\left|p_1^B/p_0^B - 1\right|} + \sum_{l=1}^{N_B}\frac{v_{l+1}^B/v_l^B - 1}{\left|p_{l+1}^B/p_l^B - 1\right|}\right\} \tag{2}$$

$$SLOPE_{i,\tau} = \frac{1}{N_i}\sum_{s=1}^{N_i}\left\{\frac{SE_{i,\tau}^{S} + DE_{i,\tau}^{S}}{2}\right\} \tag{3}$$

Where $SE_{i,\tau}^{S}\left(DE_{i,\tau}^{S}\right)$ is the average slope estimate of the sell (buy) side, for security i during bucket τ[6], and measures the average rate at which available volume changes relative to price changes on the ask (bid) side. The parameters N_A and N_B represent the total number of ask and bid price levels (or tick levels) 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 and p_0^B are the best ask and bid prices, respectively. 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.

At the end of each bucket τ, we compute the last observed slope ($SLOPE_{i,\tau}$) for security i. This measure provides a summarized assessment of the LOB's liquidity and depth during each specific period. By maintaining these buckets τ for the periods, we can effectively analyze how the slope of the LOB evolves.

[6] τ indicates the buckets or bins. They represent a volume-defined interval, accumulated until a predefined volume V is reached. This approach is based on the volume clock, where intervals are determined by trading activity rather than calendar time. Buckets adjust dynamically to the market's intensity, allowing a more granular analysis during periods of high trading activity.

At the end of each bucket τ, the last observed slope ($SLOPE_{i,\tau}$) for security i is computed. This metric allows us to summarize the LOB's liquidity and depth for each volume-defined interval, maintaining consistency in the analysis regardless of variations in market activity.

Applying this analysis to the order book allows for a nuanced understanding of market liquidity and information, offering a detailed perspective on how market participants adjust their orders in response to price variations. The approach we will use is notable for its ability to distinguish between liquidity provision and information-based orders, thus facilitating a refined interpretation of market microdynamics and their implications for price formation.

The arrival of positive information, for example, tends to increase buy orders, causing the slope on the demand side to become steeper. This reflects an optimistic perception of the asset's future value, prompting investors to adjust their orders in anticipation of a price increase. Conversely, the dissemination of adverse news can lead to an increase in sell orders, resulting in a steeper slope on the supply side of the order book. This adjustment reflects a reevaluation of the asset's value by investors seeking to minimize losses in anticipation of a price decrease.

Beyond the immediate reaction to information, the order book slope also indicates market liquidity. A less steep slope suggests greater liquidity, facilitating the execution of orders at prices close to the mid-price without causing significant variations in the asset's price. Liquidity provision is crucial for market stability and price formation efficiency, allowing participants to execute transactions smoothly and at predictable prices.

Volatility measures

The methodology adopted for estimating return volatility is based on Jones et al. (1994), beginning with a linear regression model to discern the influence of lagged returns on current ones, selecting the appropriate number of lags using the Akaike Information Criterion. Volatility, determined by the absolute value of the model's residuals, provides a preliminary approximation of return fluctuations not explained by autocorrelation. In the present research, which exploits high-frequency data, we address the inherent challenges of return volatility, including the U-shaped pattern observed in intraday volatility and the average order size under an event-time clock. By normalizing intraday seasonal effects, we isolate and clarify the underlying dynamics that modulate volatility.

Therefore, we consider the widely known intraday pattern, characterized by high volatility at the beginning and end of trading sessions, controlling for the market’s opening (09:00 to

10:00) and closing hours (17:00 to 17:30). Additionally, we perform orthogonalization of the average transaction size to neutralize the impacts arising from discrepancies in transaction volume on volatility. This adjustment facilitates obtaining a refined volatility estimate, excluding effects linked to the time of day and transaction size. The final volatility measure, derived from the absolute value of the final residuals of the adjusted model, reflects unexpected deviations in returns, free from distortions attributable to temporal factors and transaction magnitude.

The following equations show the two measures used to proxy for intraday return volatility following Jones et al. (1994): absolute returns and absolute return residual from the return regression:

$$R_{i\tau} = \sum_{r=1}^{S} b_{i,r} R_{i,\tau-r} + u_{i,\tau} \tag{4}$$

$$|u_{i\tau}| = \phi_i + \sum_{k=1}^{q} \rho_{ik} \left|u_{i,\tau-r}\right| + c_i ATS + \sum_{j=1}^{2} \psi_i \; h_i + \zeta_{i\tau} \tag{5}$$

Where $R_{i\tau}$ is the return of stock i in bucket τ; $u_{i,\tau}$ is the regression residual; $R_{i,\tau-r}$ and $\left|u_{i,\tau-k}\right|$ are the relevant lags of $R_{i\tau}$ and $|u_{i\tau}|$ to address autocorrelation[7]; h_i are the dummy variables for hours 9 and 17, included to address the U-shape; $b_{i,r}$, c_i, ϕ_i, ρ_{ik} , ψ_i are the coefficients of the independent variables, q is the optimal lag, and $\zeta_{i\tau}$ is the residual in equation (5). Due to the use of a transaction volume clock instead of time, days of the week are not significant and are not included in equation (4). We use average trade size as the proxy for the number of orders in each bucket to orthogonalize volatility (5).

To consolidate the robustness of our findings, we have implemented a complementary analysis of conditional volatility using an EGARCH model to examine returns. This approach is particularly suitable for capturing volatility's complex dynamics and persistence over time, offering a more detailed and nuanced view of return variability. Unlike traditional GARCH models, the EGARCH model allows for the direct modelling of the logarithm of the conditional variance of returns, making it possible for volatility to respond asymmetrically to past shocks,

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[7] The number of lags included varies for the population based on the significance of the correlation according to the AIC criteria.

effectively capturing volatility clustering and the differentiated reaction of volatility to positive and negative innovations in returns.

Within this framework, the EGARCH model facilitates a more flexible and accurate modelling of volatility by allowing it to be a function not only of its lags and the lags of error terms but also by incorporating leverage effects, where volatility can increase more with bad news than with good news of the same magnitude. This method of assessing conditional volatility complements our initial estimation, providing a deeper understanding of how past innovations and historical volatility influence current volatility. The EGARCH model fitting is done by specifying orders for the autoregressive and conditional volatility components, selected based on information criteria such as the Akaike or Bayesian Information Criterion. After estimating the model, we evaluate the parameter's significance to confirm the model's ability to capture the temporal dynamics of volatility.

The robustness of the EGARCH model is verified by inspecting the standardized residuals, ensuring the absence of autocorrelation, and confirming that the model specification adequately captures the temporal dependence structure in the data. This verification acts as a robustness test. The EGARCH (1, 1) equation used is expressed as follows:

$$\log(\sigma_\tau^2) = \omega + \sum_{i=1}^{p} \alpha_i g(Z_{\tau-i}) + \sum_{j=1}^{q} \beta_j \log(\sigma_{\tau-j}^2); \quad \varsigma_t = \exp\left(\frac{\log(\sigma_\tau^2)}{2}\right) \tag{6}$$

Where $\log(\sigma_\tau^2)$ is the natural logarithm of the conditional variance in period τ. The function $g(Z_{\tau-i})$, defined as $g(Z_{\tau-i}) = \theta Z_{\tau-i} + \gamma(|Z_{\tau-i}| - E[|Z_{\tau-i}|])$, captures the effects of past shocks $(Z_{\tau-i})$ on volatility, where θ and γ allow the model to incorporate asymmetries and leverage effects. ω, α_i and β_j are parameters of the model that are estimated from the data. ς_τ is the conditional volatility.

Adverse selection cost measures

The VPIN measure is based on the premise that differences in buy and sell order volume can indicate asymmetric information in the market, which indicates adverse selection costs. This measure is calculated using the order imbalance in each time interval (bucket), defined as the 50-bucket moving average of the absolute difference between sell and buy order volumes, divided by the total transaction volume in that interval. This quantitative approach allows for a precise assessment of the impact of adverse selection on transaction costs, reflecting the likelihood that traded orders are informed and, thus, potentially imbalanced in terms of the information available to buyers and sellers.

The calculation of the VPIN toxicity measure follows the original method by Easley et al. (2012). This metric has been selected to encapsulate volume-specific data rather than price-specific information, with a focus on the imbalances between buying and selling pressures aligned with the event-time clock. Trades are classified based on one-minute periods, known as time bars, and the trade volume is recorded for each time bar. Consecutive time bars are accumulated until a volume bucket is filled. 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.

The bucket size, V, is defined as one-fiftieth of the average daily volume in 2019 (excluding auctions). Depending on trading activity, a volume bucket may span several time bars or only a portion of one. Ultimately, VPIN is characterized as the aggregate of the absolute variations between buy and sell volumes in each volume bucket. The trade direction is determined through the probabilistic volume categorization using the bulk volume classification approach. Specifically, the buy volume is obtained by multiplying the trading volume by the cumulative distribution function (CDF) of the standard normal distribution evaluated at the standardized price change, Z ($\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}$), where $\sigma_{\Delta P}$ represents the estimated weighted standard deviation of price changes between time bars. The selling volume is determined as the trading volume multiplied by 1 - Z ($\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}$). If there is no price change from the beginning to the end of a time bar, the volume within that time interval is divided equally between buy and sell volumes. If the price increases (decreases), the volume is weighted more towards buys (sells) than towards sells (buys).

$$V_\tau^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right) \tag{7}$$

$$V_\tau^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot \left[1 - Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)\right] = V - V_\tau^B \tag{8}$$

$$\text{VPIN} = \frac{(\sum_{\tau=1}^{n} |V_\tau^S - V_\tau^B|)}{n \cdot V} \tag{9}$$

In each volume bucket τ, $V_\tau^{B(S)}$ represents the accumulated buy (sell) volume. Then, VPIN is defined as in equation (9), where the volume bucket size, indicated as n, encompasses the aggregate number of volume buckets. As originally proposed, VPIN is estimated using a moving window of 50 volume buckets. For example, the initial calculation of VPIN is performed using volume buckets within the interval [1, 50]. Successive VPIN estimates are obtained by incrementally shifting the moving window, for instance, from the range [2, 51] in the case of 50-length windows, and proceeding accordingly.

Adverse selection refers to a situation where one party in a transaction possesses significantly better information than the other. In financial markets, this translates into a higher likelihood that informed traders will execute trades that take advantage of their knowledge, which is not available to the rest of the market, thereby imposing a cost on less informed traders. VPIN and order imbalance are measures that account for executed transactions. In this study, we analyze how the impact of the informed component of the limit order book—namely, the intentions and consensus along the LOB—affects realized adverse selection costs.

Methodologically, we also include the order imbalance ratio (OIR), as in equation (10). It is calculated as the order imbalance relative to the total volume in each bucket. First, the transaction data set is segmented into intervals of executed transaction volumes or buckets.

$$OIR = \frac{(|V_\tau^S - V_\tau^B|)}{V} \tag{10}$$

Then, for each interval, the order imbalance is calculated as the absolute difference between the sell and buy order volumes, normalized by the total transaction volume. This imbalance measure provides a quantitative indication of buying or selling pressure in the market, which is associated with the likelihood of adverse selection in each bucket.

Liquidity measures

In this study, we incorporate the LOB depth (DEPTH) as a standard metric of internal order book liquidity to analyze its structure and efficiency. The depth of the LOB, referred to as DEPTH, is defined as the average quantity of shares present at all bid and ask positions in the book. A higher DEPTH indicates that transactions have a reduced impact on market prices, thereby suggesting greater liquidity. Mathematically, the cumulative depth is calculated as equation (11). This calculation helps assess the market's ability to absorb large orders without significant price disruptions.

$$\mathrm{DEPTH}_{i,\tau} = \left(\frac{\sum_{1}^{20} number\ of\ bid\ orders_{i,\tau} + \sum_{1}^{20} number\ of\ ask\ orders_{i,\tau}}{2} \right) \tag{11}$$

As an external liquidity measure or adverse selection cost, we will use the Relative Spread (RS), which is the value of the Quoted Spread (QS) divided by the midpoint price.

The quoted spread (QS) and the dummy variables corresponding to the CRASH period and the prohibition of net short positions (SSB) will be used as control variables in the regressions. The definitions and descriptive statistics are presented in Table 4.1.

Table 4.1 Descriptive Statistics

Variable	Mean	Median	Std	Max	Min	Skew	Kurtosis	Obs
$VR_{i,\tau}$	0.0013	0.0010	0.0015	0.1464	0.0000	9.1617	341.9241	96237
$ER_{i,\tau}$	0.0027	0.0025	0.0012	0.0448	0.0002	2.3815	14.7170	96237
$QS_{i,\tau}$	0.0099	0.0050	0.0227	6.7500	0.0001	43.3174	9175.4838	96237
$RS_{i,\tau}$	0.0008	0.0006	0.0009	0.0775	0.0001	8.8670	236.2739	96237
$OIR_{i,\tau}$	0.0968	0.0721	0.0891	0.9721	0.0000	1.7170	4.3954	96237
$VPIN_{i,\tau}$	0.5004	0.5000	0.2879	1.0000	0.0000	0.0023	-1.1987	96237
$DEPTH_{i,\tau}$	69.6007	68.5000	25.6202	954.0000	20.0000	1.9859	22.6494	96237
ξ_{τ}	0.2576	0.2386	0.1497	5.6142	0.0226	3.8284	70.2268	96237
γ_{τ}	51.3309	51.9342	6.6154	85.3840	23.9678	-0.0394	0.4218	96237
$SLOPE_{i,\tau}$	1584.4117	1325.9309	1120.1265	12888.6925	16.3801	2.0749	6.8276	96237

Table 4.1. Variable Definitions and Descriptive Statistics. This table shows the variables calculated for each stock-interval i, τ, and reports the average descriptive statistics for the 33 stocks analyzed. All variables are calculated for each of the periods or buckets in the volume clock, with τ referring to each bucket. The sample contains the 33 constituent stocks of the IBEX 35 index from January 1, 2019, to December 31, 2020, on the Spanish stock market.

4.4 Methodology

In this study, we will analyze the slope of the LOB from the perspective of permanent and transitory components using a state-space model of unobserved components. This distinction between components offers a deeper insight into which we can discern long-term influences, encapsulating fundamental changes in asset price formation based on new and relevant information from short-term influences attributed to changes in noise-based algorithmic trading in the short term, typically uninformed.

We assign the permanent component to efficient information and the transitory component to uninformed trading. This is done because, although new information implies a permanent change in the LOB slope, this effect will only temporarily alter the price-volume relationship.

Once the slope reflects this information, informed traders will no longer maintain an informational advantage and will cease their trades based on the exploited information. Additionally, regarding returns, Kittiakarasakun et al. (2012) suggest that the distinction between informed and uninformed trades can be identified by examining return autocorrelation. Informed trades typically do not show autocorrelation in returns, while uninformed trades exhibit negative return autocorrelation. This indicates that informed traders react to new information, while uninformed traders do not influence prices based on private knowledge.

This formulation maintains the logic of market efficiency related to the absorption of new information and its permanent impact on market structure (LOB slope). At the same time, behavior based on informational advantage is only temporary. This approach underscores that the informed component of the SLOPE adjusts permanently, but the trading activity that exploits this information is transitory.

The permanent component of the SLOPE is interpreted as a reflection of long-term supply and demand, marking underlying trends influenced by structural adjustments in the market or changes in the perception of the intrinsic value of assets. A high value in this component indicates the presence of new information entering the market, generating a consensus among participants about the future value of an asset (Næs & Skjeltorp, 2006). This translates into a steeper slope of the order book, where limit orders cluster more closely around certain prices, reflecting this consensus. In contrast, a low value in the permanent component suggests that observed variations in the slope are primarily due to liquidity positions in the absence of significant new information, which manifests in a more even distribution of limit orders throughout the order book (Kalev & Duong, 2007).

As for the transitory component, it captures short-term dynamics in the order book slope, associated with temporary liquidity imbalances or trading operations driven by algorithms that are not based on the arrival of new information. In this context, uninformed trading algorithms play a crucial role by reacting to changes in market microstructure metrics, such as liquidity levels and volatility, without necessarily reflecting an informed assessment of fundamental changes in asset values. By following predetermined strategies, these algorithms can induce transitory variations in the SLOPE, reflecting changes in the disposition of limit orders motivated by adjustments in market conditions, rather than by new information.

The proposed methodology for analyzing the order book slope is inspired by and built upon traditional market microstructure models, which decompose quoted prices into a long-term or true efficient price and a transitory non-informative component. This approach follows the price decomposition logic of Hasbrouck (1991, 2018), who articulates how quoted prices can be understood as the sum of a long-term efficient price and transitory fluctuations that do not necessarily reflect changes in the fundamental information of assets.

In contrast to the non-stationary random walk model traditionally adopted for the fundamental price in the literature, our methodology is enriched by integrating a non-stationary local-level model for the permanent component. This choice is based on validation tests indicating that the permanent component of the LOB slope is more appropriately modelled as a local level process, capable of more effectively capturing abrupt changes or jumps in its level, as opposed to the gradual changes suggested by a random walk. This approach allows for a more accurate representation of how fundamental information and changes in market perception can more immediately and significantly influence the order book slope.

In the context of the LOB, where observable variables coexist with unobservable state variables, adopting a local-level model instead of a random walk model introduces an innovative approach to incorporating noise into the system. This local-level model implies observable variables influenced by unobservable state variables by adding noise vectors. Characterized by a structure where state variables evolve locally and efficiently, the local-level model overcomes the limitations of traditional random walk models, offering a more nuanced understanding of the dynamics within the LOB.

The validation of the local-level model over the random walk was conducted in two phases. First, state-space models with different configurations, such as random walk, random walk with drift, and seasonal patterns, were fitted, and their fit was evaluated using criteria such as AIC and BIC. Based on these criteria, the local-level model was the most appropriate because it obtained the lowest AIC and BIC values compared to the other models evaluated, which indicates that the local-level model achieves a better balance between fitting accuracy and penalization for model complexity. Finally, the residuals of the selected model were analyzed, patterns and autocorrelations were looked for, and their stationarity was confirmed with the augmented Dickey-Fuller test. This process evidenced that the local level model better captures the data dynamics, justifying its preference for its greater accuracy and suitability in reflecting the characteristics of the studied time series.

State Space model

This approach leverages high-frequency data from IBEX 35 stocks to distinguish between these components. State-space models, enriched by the Kalman filter to generate objective and optimized estimates, are analytical tools for decomposing high-frequency time series into latent factors, as evidenced by Brogaard et al. (2014) and Hendershott & Menkveld (2014). The LOB slope is modelled as the sum of a non-stationary permanent component (driven by the volume-price relationship in the order book linked to fundamental information or efficient price) and a stationary transitory component (driven by uninformed trading).

In the context of the elasticity of the limit order book slope, the permanent component captures the dynamics of informed positions that affect value perception and (efficient) price in the long term. Therefore, informed orders are expected to define the stable section, while changes in liquidity provision, feedback trading, or uninformed orders form the fluctuating section. This aligns with expectations based on the theoretical models of Glosten & Milgrom (1985) and Suominen (2001), which distinguish between the impacts of informed and uninformed trading on the market.

On the other hand, the transitory component, characterized by an autoregressive process (AR with optimal lags), reflects temporary market fluctuations, often linked to changes in liquidity provision or exogenous variables unrelated to the asset's long-term information, such as feedback trading. These participants react quickly to temporary shocks or changes in market conditions, generating momentary adjustments in the order book slope.

Our analysis integrates the smoothed level mean obtained through the Kalman filter, reflecting the mean of the smoothed level component over time. Additionally, we consider the EGARCH volatility of both permanent and transitory components to capture random fluctuations not explained by the modelled components, offering a comprehensive view of order book dynamics (Rzayev & Ibikunle, 2019).

The model by Kyle (1985) describes how equilibrium prices adapt to asymmetric information among traders, emphasizing that price volatility reflects the rate at which information is incorporated into prices, independent of noise trading. This theoretical framework justifies the use of variances in the permanent and transitory components of SLOPE as indicators of the underlying dynamics of efficient price and uninformed or liquidity trading. Furthermore, studies such as those by Menkveld et al. (2007) and Brogaard et al. (2014) support this methodology by using component variances in the model to analyze informed and uninformed trading activities. These references are incorporated to justify the methodological choices and align the study's approach with established practices in financial market analysis.

We choose to focus on the volatilities of the components rather than the components themselves in the decomposition of SLOPE, as volatilities provide a clearer and more consolidated measure of how information and liquidity fluctuations impact market behavior. This choice allows for better capture of the interaction and cross-influences between components, which is essential for understanding the forces that shape market structure.

This framework is particularly relevant in our research, given that order book variables have significant cumulative long-term effects on mid-price returns, a phenomenon that manifests more pronouncedly and later for variables based on higher levels of the book, as documented by Cenesizoglu et al. (2014), Goettler et al. (2009), and Kalay & Wohl (2009). This adjustment in methodology, therefore, not only enhances our ability to model the inherent complexities of the limit order book but also theoretically grounds the separation between permanent and transitory components, allowing us to more accurately capture the effects of new information and uninformed market dynamics on the order book slope.

The permanent component of the order book slope is modelled using a non-stationary local level model, which reflects the premise that the fundamental level of the slope, representing the accumulated relationship between volumes and prices at different levels, evolves dynamically and can adjust abruptly to capture lasting effects on market structure, such as changes in underlying fundamental information and market participants' expectations. This approach allows for a more flexible and realistic representation of how the long-term informational component in the order book slope can react quickly to new information or market changes, overcoming the limitations of random walk models in capturing these phenomena.

For the transitory component, we identify the optimal order for autoregressive (AR) models in the series data, selecting the one that minimizes each stock's Bayesian Information Criterion (BIC). Subsequently, we apply an unobserved components model to SLOPE, decomposing it into the permanent component while incorporating the identified optimal AR structure. Next, we fit EGARCH models to both components, allowing for the capture of asymmetric volatility dynamics, which are characteristic of financial series. The results include model parameters, variances, and fit statistics.

State equation

We specify a local level model without a control input and without a trend component for the level component, and an autoregressive (AR) component with the optimal number of lags between 1 and 12; to capture the transitory dynamics, the state equation for the permanent and transitory components could be formulated as:

$$x_\tau = \mu_\tau + w_\tau; \quad (12)$$

$$z_\tau = \phi_1 z_{\tau-1} + \phi_2 z_{\tau-2} + \cdots + \phi_p z_{\tau-p} + \epsilon_\tau \quad (13)$$

Where x_τ in equation (12) is the state in bucket τ, representing the permanent component of the LOB slope. μ_τ is the local level at bucket τ, which dynamically adjusts to reflect changes in the underlying information, w_τ is the state process error at bucket τ, normally distributed with a mean of zero and variance Q, i.e., $w_\tau \sim N$ *(0, Q)*. This approach allows for greater flexibility in adapting to abrupt changes in the permanent component, more accurately reflecting the evolution of the informational component in the slope of the limit order book. For the autoregressive (AR) component that models the transitory component, an AR of optimal order (p) is considered for each stock. We identify the optimal order for the autoregressive (AR) model by minimizing the Bayesian Information Criterion (BIC) using equation (13) for an AR(p) model, where z_τ represents the error term of this process, normally distributed with a mean of zero and variance R, i.e., $\epsilon_\tau \sim N(0, R)$.

Observation equation

Equation (14) of observation directly relates the latent state to the actual observation (natural logarithm of the SLOPE):

$$y_\tau = H(x_\tau + z_\tau) + \upsilon_\tau \quad (14)$$

Where y_τ is the actual observation in bucket τ (in this case, the natural logarithm of SLOPE). H is the observation matrix, which in this case would be 1, assuming we directly observe the state. υ_τ is the observation error, normally distributed with a mean of zero and variance R, i.e., $\upsilon_\tau \sim N(0, R)$.

Adjusting for volatility using the E-GARCH models applied to each rescaled component. For the analysis of the components' volatility, an E-GARCH model is applied, which is used to model asymmetries and leverage effects. The formulation of the E-GARCH model for each component is given by equation (15).

$$log(\sigma_\tau^2) = \omega + \sum_{i=1}^{p} \alpha_i \cdot g(z_{\tau-i}) + \sum_{j=1}^{q} \beta_j \cdot log\left(\sigma_{\tau-j}^2\right); \tag{15}$$

$$\varsigma_t = \exp\left(\frac{\log(\sigma_\tau^2)}{2}\right)$$

Where the function $g(z_{\tau-i}) = \theta z_{\tau-i} + \gamma(|z_{\tau-i}| - E[|z_{\tau-i}|])$, $z_{\tau-i} = \frac{x_{\tau-i}}{\sigma_{\tau-i}}$ and σ_τ^2 is the conditional variance. This model is fitted for both the rescaled permanent and transitory components, allowing for a detailed evaluation of the inherent volatility in each of these dynamics in the logarithm of the LOB slope. The parameters ω, α_i, β_j, θ, and γ are estimated from the data. ς_τ is the conditional volatility of each component.

The analysis is complemented by an out-of-sample evaluation to examine the predictive robustness of the model. For each stock, the estimated parameters are calculated, including the optimal AR order, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), the coefficient of determination R^2, and the parameters and variances of the level and AR components, as well as the E-GARCH conditional volatilities for the permanent and transitory components.

These volatilities are conceptually linked to the dynamics of the order book; the volatility of the permanent component is associated with the informed component of the slope, reflecting the arrival of new information to the market, while the volatility of the transitory component is related to liquidity provision[8].

OLS Regression models

We will study the influence of the fundamental information component or efficient price and the uninformed trading component or liquidity trading, identified through the EGARCH components of the slope's permanent and transitory components, on various market quality metrics. A multiple regression analysis will be implemented.

[8] The state-space model has been validated using the Kalman filter on the structure of the limit order book (LOB). This validation confirms the model's ability to accurately decompose the LOB elasticity into its fundamental components across the training sample and maintains its consistency in the out-of-sample validation.

The dependent variables considered are return volatility, conditional volatility (EGARCH) of returns as a robustness measure; VPIN (CDF) (Volume-synchronized Probability of Informed Trading) as a proxy for adverse selection cost; Order Imbalance Ratio (OIR) as a robustness measure; and market depth (DEPTH) as a measure of liquidity. Each variable will be analyzed in a regression model for each stock i. It is important to note that the regressions are controlled for certain dummy variables and the quoted spread.

Dummy variables, SSB and CRASH[9], were introduced to control for the specific effects of short-selling restrictions during the COVID-19 period and the impact of the market crash associated with this period, respectively. The underlying hypothesis was that these interventions and events had a direct and potentially different effect on market metrics compared to the volatility components, equation (16).

$$Y_{i\tau} = \beta_0 + \beta_1 \gamma_{i\tau} + \beta_2 \xi_{i\tau} + \beta_3 \mathrm{SSB}_{i\tau} + \beta_4 \mathrm{CRASH}_{i\tau} + \beta_5 VC_{i\tau} + \epsilon_{i\tau} \tag{16}$$

Where $Y_{i\tau}$ represents the independent variable in bucket τ. $\gamma_{i\tau}$ and $\xi_{i\tau}$ are the permanent and transitory conditional volatilities, respectively. $\mathrm{SSB}_{i\tau}$ is the dummy variable indicating the short-selling restriction period. $\mathrm{CRASH}_{i\tau}$ is the dummy variable capturing the COVID-19 market crash period. In our analysis, when studying the interrelationship between spread, volatility, and the components of the order book slope, we incorporated a specific control variable $VC_{i\tau}$ to isolate the effects of interest. When analyzing volatility as the dependent variable, we used the spread as a control variable to adjust for potential confounding effects associated with transaction costs. Similarly, we controlled for volatility when examining adverse selection costs, represented by the spread, given its potential impact on market structure. The main independent variables are the two components of SLOPE, allowing the analysis to accurately capture their specific relationship with both volatility and spread while adequately controlling for the reciprocal influences of these variables. $\epsilon_{i\tau} \sim N\,(0,\sigma^2)$ e i.i.d. The models were estimated using Ordinary Least Squares (OLS), and robust standard errors were calculated to mitigate the influence of heteroscedasticity.

[9] Pandemic crash (CRASH): From January 21, 2020, to March 17, 2020; Short-selling ban (SSB): From March 18, 2020, to May 18, 2020.

The predictive power of the lags of slope components on stock returns

Finally, to analyze the predictability of returns through the components of the LOB slope, the influence of the order book slope components on realized returns between buckets for IBEX35 stocks is evaluated in equation (17). Lagged variables are incorporated to account for the lags in n = {1, 2,50} for the permanent and transitory components of the order book slope, and dummy indicators for critical market events (SSB and COVID-19). The regression model is specified as follows:

$$R_\tau = \alpha + \sum_{i=1}^{n} \beta_i \gamma_{\tau-i} + \sum_{j=1}^{n} \nu_j \xi_{\tau-j} + \delta_1 SSB_\tau + \delta_2 CRASH_\tau + \delta_3 QS_\tau + \epsilon_\tau \; ; \qquad (17)$$

$$n = \{1, 2, \dots, 50\}$$

Where R_t s the return of the stock in bucket τ. $\gamma_{\tau-i}$ y $\xi_{\tau-j}$ are the permanent and transitory components of the order book lagged by i and j buckets, respectively. QS_τ is the quoted spread, SSB_τ and $CRASH_\tau$ are dummy variables for the short-selling restriction period and the market crash during COVID-19. α, β_i, ν_j, δ_1, δ_2 , δ_3 are the parameters to be estimated. ϵ_τ is the error term. Each model is estimated using Ordinary Least Squares (OLS) with robust standard errors (White correction) to account for heteroscedasticity. This involves collecting the coefficients, standard errors, and p-values for each lag and stock individually. Subsequently, a meta-analysis aggregates these results across all stocks. By weighting individual estimates inversely by their variance, aggregated "weighted mean" coefficients and associated statistical measures are derived, providing a robust perspective on the predictive power of the permanent and transitory components as well as the control variables.

This two-step methodology—individual regression estimation followed by meta-analytic integration—enables detailed analysis of temporal dynamics and the predictive relationships between the LOB slope components and future returns. It provides a robust framework for understanding how informational and liquidity signals, captured by the permanent and transitory components of the LOB slope, influence stock returns at the aggregate market level.

4.5 Results

The study results are presented through a meta-analysis[10] that integrates and synthesizes the regression model estimates. The meta-analysis provides a quantitative and aggregated evaluation of the estimated effects across different categories of company sizes.

We conduct this meta-analysis, as reflected in the literature in the field of financial markets, by considering the use of weighted coefficients for each series with different amounts of data and a p-value through a Z-Score for the mean coefficients. This approach follows studies such as those by Baruník & Křehlík (2018), Mezghani & Boujelbène-Abbes (2021), and Naceur & Zhang (2016), providing a solid basis for analyzing the complexities of the event clock, which, for each component of the IBEX 35, has different buckets according to its events. A weighted mean (among the 33 stocks) of each coefficient is provided based on its inverse standard error, giving more weight to be given to more precise estimates (lower standard error). Subsequently, the z-score is calculated to evaluate the statistical significance of each weighted mean, with an associated p-value that allows for the assessment of the likelihood that each result is due to chance.

Volatility

Table 4.2 synthesizes the results of a meta-analysis that combines the estimated coefficients of the IBEX 35 component stocks, weighted by their standard error, to reveal the impact of the permanent and transitory components of the limit order book (LOB) slope on volatility. The permanent component, associated with fundamental information and reflecting the activity of informed traders, consistently shows an inverse relationship with market volatility, implying a stabilizing effect on prices consistent with Kath (2019), Kiesel & Paraschiv (2017), and Uniejewski et al. (2019). This effect is more pronounced for large-cap stocks (LARGE), as indicated by higher absolute coefficients, reflecting these market's greater liquidity and depth. The effect for medium-cap (MEDIUM) and small-cap (SMALL) stocks is still significant but slightly less pronounced, consistent with lower liquidity and depth in these categories.

In contrast, the transitory component, linked to trading not based on new information, such as algorithmic and liquidity-driven operations, tends to increase volatility. This effect is more pronounced in SMALL stocks, where lower market liquidity makes these markets more

[10] The individual results for each of the IBEX 35 components are presented in Table A.3 of Appendix A.

sensitive to uninformed trading. These findings are revealing in terms of the fundamental role of informed traders in improving the price discovery process and contributing to greater market stability[11].

More specifically, it is observed that the presence of informed traders, who act on the knowledge that eventually reflects in the asset fundamentals, injects informational quality into the LOB, which mitigates uncertainty and favors lower market volatility. Significant negative permanent coefficients support this stabilizing effect of the informational components, suggesting that accurate information helps anchor investors' expectations and reduce price dispersion. The absolute values are higher in LARGE and lower in SMALL, both in conditional volatility and in the absolute value of return residuals[12], consistent with the existing literature that associates informed trading with high-capitalization, high-trading, or so-called "familiar" stocks. The absolute values of γ_τ are higher in LARGE stocks, indicating a stronger stabilizing effect in markets with greater liquidity and trading activity. Although the stabilizing effect persists for SMALL stocks, it is less pronounced due to lower depth and higher sensitivity to market shocks.

In contrast, trading based on factors other than new information—such as immediate liquidity needs or algorithmic trading that responds to non-informative market signals—is associated with increases in volatility. These effects are captured by positive and significant transitory coefficients, emphasizing the influence of liquidity and automated trading in introducing noise and amplifying short-term price fluctuations. These effects are particularly pronounced in SMALL stocks. The lower liquidity in SMALL stocks amplifies the impact of algorithmic and liquidity-driven operations, increasing short-term price fluctuations. The higher market depth for LARGE stocks reduces the sensitivity to uninformed trading, resulting in a more moderate impact of the transitory component on volatility.

This meta-analysis highlights the critical importance of differentiating the effects of informed versus uninformed components of the LOB. The results significantly contribute to understanding market microstructure and provide valuable insights for regulatory entities, who must consider these dynamics when formulating policies that promote market stability and efficiency.

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[11] Coefficients for individual stocks are available in Appendix A. In Table A.4 for RV and in Table A.5 for EV.

[12] A third regression was conducted using the absolute value of returns as a measure of volatility. The results are similar in both value and significance to those of conditional volatility across all categories.

Table 4.2 The effects of the limit order book slope components on volatility

Panel A. The effects of the limit order book slope components on $\boldsymbol{VR_\tau}$.

weighted mean (z-score)	ALL	LARGE	MEDIUM	SMALL
Intercept	2.0472*** (33.7762)	2.1034*** (34.8212)	2.0460*** (34.0988)	1.9934*** (33.9238)
γ_τ	-2.0813*** (-125.3739)	-2.0919*** (-126.4508)	-2.0826*** (-126.7361)	-2.0732*** (-129.2857)
ξ_τ	0.2362*** (64.6453)	0.2388*** (66.0311)	0.2356*** (65.3595)	0.2394*** (65.7690)
SSB_τ	-0.0046 (-0.9248)	-0.0044 (-0.8885)	-0.0089* (-1.8027)	-0.0105** (-2.1545)
$CRASH_\tau$	0.0379*** (31.3232)	0.0391*** (32.2911)	0.0380*** (31.4775)	0.0379*** (31.3877)
QS_τ	0.1060*** (50.4174)	0.1083*** (51.7231)	0.1042*** (50.4537)	0.1007*** (50.0081)
Adj. Squared-R	0.06164	0.0630	0.0611	0.0609

Panel B. The effects of the limit order book slope components on $\boldsymbol{ER_\tau}$

weighted mean (z-score)	ALL	LARGE	MEDIUM	SMALL
Intercept	2.3141*** (196.2392)	2.4386*** (207.4666)	2.2529*** (193.7903)	2.2288*** (195.4082)
γ_τ	-2.0884*** (-661.1404)	-2.1160*** (-671.8064)	-2.0738*** (-665.3530)	-2.0676*** (-679.4652)
ξ_τ	0.1508*** (195.8381)	0.1534*** (199.9443)	0.1530*** (202.0700)	0.1489*** (194.3577)
SSB_τ	0.0896*** (96.0359)	0.0895*** (96.3736)	0.0887*** (96.5860)	0.0828*** (91.1115)
$CRASH_\tau$	0.0545*** (227.3627)	0.0566*** (236.3178)	0.0543*** (227.6547)	0.0545*** (228.1787)
QS_τ	-0.0371*** (-96.2127)	-0.0367*** (-95.3331)	-0.0379*** (-100.9201)	-0.0373*** (-101.3350)
Adj. Squared-R	0.6290	0.6341	0.6289	0.6244

Table 4.2. Regression Coefficients for Each Component: $OLS\ Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3 SSB_{i\tau} + \beta_4 CRASH_{i\tau} + \beta_5 QS_{i\tau} + \epsilon_{i\tau}$, where the dependent variables are volatility measured through return residuals in Panel A and conditional volatility EGARCH in Panel B. The control variables include the Quoted Spread and the dummy variables for the short-selling restriction period and the market crash period defined as COVID-19 CRASH.

In Table 4.2, the coefficient of the control variable SSB (short-selling ban) shows variable significance depending on the market capitalization category. For large-cap stocks (LARGE), the SSB coefficient is not significant in volatility measured by return residuals (VR_τ), as reflected in p-values greater than 0.05 (-0.0046 with z-scores of -0.9248). However, in volatility modelled by EGARCH (ER_τ), the coefficient is significant (p-value < 0.01), with a value of 0.0895 and a z-score of 96.3736. This suggests that short-selling restrictions may introduce conditional volatility, likely due to temporary adjustments in liquidity provision or the persistence of volatility shocks captured by the EGARCH model. For medium-cap stocks (MEDIUM), the SSB coefficient is marginally significant (p-value < 0.10) with a value of -

0.0089 and a z-score of -1.8027 in volatility measured by return residuals (VR_τ). However, in volatility modelled by EGARCH (ER_τ), the coefficient is highly significant (p-value < 0.01) with a value of 0.0896 and a z-score of 96.0359. For small-cap stocks (SMALL), the SSB coefficient is significant in both volatility measures. For VR_τ, the coefficient is -0.0105 (p-value < 0.05, z-score of -2.1545), and for ER_τ, the coefficient is 0.0828 (p-value < 0.01, z-score of 91.1115).

These results suggest that the short-selling ban significantly impacts the volatility of lower-cap stocks (MEDIUM and SMALL). In volatility measured by return residuals (VR_τ), the negative coefficient indicates that short-selling restrictions may stabilize the prices of these stocks. For large-cap stocks, while the SSB coefficient is not significant in VR_τ, the positive and significant coefficient in ER_τ suggests that the short-selling restrictions may introduce conditional volatility, possibly due to adjustments in liquidity provision.

However, in volatility modelled by EGARCH (ER_τ), for medium and small-cap stocks, the positive coefficient suggests that, despite the short-selling restrictions, other market factors continue to introduce volatility in these lower-cap segments.

The Quoted Spread (QS_τ) shows coefficients with opposite signs in the two volatility measures. In volatility measured by return residuals (VR_τ), an increase in the QS_τ is associated with an increase in volatility. This may be due to a wider spread reflecting lower liquidity and greater market uncertainty, resulting in larger short-term price variations. On the other hand, in volatility modelled by EGARCH (ER_τ), an increase in the QS_τ is associated with a decrease in conditional volatility. This result can be interpreted by considering that the EGARCH model captures the persistence of volatility and the effects of news. A wider spread could indicate that past volatility (already high) is being appropriately incorporated into the model, and therefore, future conditional volatility adjusts downward.

In conclusion, the results of the robustness analysis underscore the importance of considering the differences between volatility measures and how variables such as the short-selling ban and the QS_τ affect these measures differently. Short-selling restrictions have a more pronounced impact on lower-cap stocks, and the QS_τ has opposite effects on the two volatility measures, reflecting the complexity and multiple dimensions of market volatility. These findings are crucial for policymakers and regulators seeking to enhance market stability and efficiency.

Adverse selection costs

In Table 4.3, the relationship between the components of the limit order book slope and key adverse selection cost metrics, such as the relative price spread RS_τ and the Order Imbalance Ratio (OIR), is analyzed for the overall market and different market sizes. The permanent component of the order book slope ($\gamma_{i\tau}$) has a significantly negative relationship with RS across all size categories, implying that an increase in the permanent component of the slope is linked to a lower probability of adverse selection costs when the efficient price component increases. The transitory component ($\xi_{i\tau}$) shows a positive and significant effect on RS, indicating that trading based on algorithms, feedback trading, liquidity-driven trading, or responses to short-term events introduces more volatile orders into the LOB.

An interpretation for OIR that emerges from this result is that a steeper slope of the order book could reflect a market where buy or sell orders are more predominant, leading to a more pronounced imbalance.

Table 4.3 The effects of the limit order book slope components on adverse selection costs

Panel A. The effects of the limit order book slope components on the relative spread RS.

Dependent variable: $RS_t \cdot 10^3$ weighted mean (z-score)	ALL	LARGE	MEDIUM	SMALL
Intercept	17.4145*** (278.2498)	17.3426*** (278.7162)	17.4353*** (283.5832)	17.5312*** (286.9087)
γ_τ	-4.5085*** (-260.5878)	-4.4900*** (-260-9007)	-4.5175*** (-266.0910)	-4.5331*** (-269.5703)
ξ_τ	0.0761*** (38.0601)	0.0746*** (38.1445)	0.0750*** (38.1726)	0.0859*** (43.0134)
SSB_τ	0.0495*** (13.9403)	0.0519*** (14.7019)	0.0501*** (14.2741)	0.0427*** (12.2766)
$CRASH_\tau$	0.0145*** (31.6936)	0.01492*** (32.6131)	0.0143*** (31.3013)	-0.0146*** (31.9050)
ER_τ	-0.1710*** -(41.4162)	-0.1698*** (-41.8568)	-0.1745*** (-43.1071)	-0.1723*** (-42.4136)
Adj. Squared-R	0.3097	0.3084	0.3113	0.3117

Table 4.3 The effects of the limit order book slope components on adverse selection costs (continued).

Panel B. The effects of the limit order book slope components on the order imbalance ratio OIR.

Dependent variable: OIR_t: weighted mean (z-score)	ALL	LARGE	MEDIUM	SMALL
Intercept	0.1577*** (38.4680)	0.1560*** (38.1918)	0.1584*** (38.9537)	0.1629*** (40.3911)
γ_{τ}	-0.0154*** (-12.1709)	-0.01513*** (-12.0472)	-0.0151*** (-12.1010)	-0.0164*** (-13.1940)
ξ_{τ}	0.0055 *** (23.6414)	0.0054*** (23.3453)	0.0053*** (22.9750)	0.0054*** (23.1949)
SSB_{τ}	-0.0026*** (-8.3230)	-0.0024*** (-7.6168)	-0.0025*** (-7.9129)	-0.0023*** (-7.5027)
$CRASH_{\tau}$	-0.0009*** (-813.2482)	-0.0008*** (-12.2937)	-0.0009*** (-13.6112)	-0.0010*** (-15.9773)
ER_{τ}	0.0007* (1.8169)	0.0006 (1.4234)	0.0010** (2.5066)	0.0008* (2.0036)
Adj. Squared-R	0.0044	0.0043	0.0043	0.0044

Table 4.3. Regression Coefficients for Each Stock $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3 SSB_{i\tau} + \beta_4 CRASH_{i\tau} + \beta_5 ER_{i\tau} + \epsilon_{i\tau}$ where the dependent variables are the RS in Panel A and OIR in Panel B. The control variables include $ER_{i\tau}$ and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH. Individual stocks coefficients are in tables A.6 for RS_{it} and A.7 for OIR_{it} in Appendix A.

For the permanent component ($\gamma_{i\tau}$), the negative and significant coefficients across all categories suggest that an increase in the fundamental information component reduces order imbalance or asymmetry. This may indicate that when market participants have more dispersed beliefs regarding the fundamental value, there is a tendency toward greater order imbalance, possibly due to more cautious behavior by traders.

The transitory component ($\xi_{i\tau}$) has a positive and significant effect on OIR, suggesting that algorithmic trading, despite its short-term nature, tends to create or increase the imbalance in the order book. We replaced the control variable QS_{τ} with $ER_{i,t}$ for the adverse selection cost measures to avoid multicollinearity issues.

Additionally, we performed a regression on the informed probability variable VPIN (CDF), which indicates an accumulated value of informed trading according to Easley et al. (2012), controlled by the volatility proxy $ER_{i\tau}$, which results can be found in Table 4.4. The results in this case show positive and significant coefficients for both the permanent and transitory components. This would suggest that both components of the order book slope affect accumulated informed trading. The level of accumulated informed trading is influenced by both the fundamental consensus (permanent component) and the transitory component.

Table 4.4 Natural log of VPIN (CDF) controlled by ER (Volatility)

Coefficients	ALL	LARGE	MEDIUM	SMALL
Intercept	-0.8130***	-0.9151***	-0.7277***	-0.7388***
	(-14.7896)	(-16.7003)	(-13.3395)	(-13.9113)
γ_τ	0.4886***	0.5016***	0.4792***	0.4708***
	(28.6542)	(29.5171)	(28.3968)	(28.5273)
ξ_τ	0.2018***	0.1952***	0.1877***	0.1913***
	(59.2007)	(57.9888)	(55.4798)	(56.3499)
SSB_τ	0.0113**	0.0279***	0.0157***	0.03247***
	(2.8234)	(7.0051)	(3.9634)	(8.3833)
$CRASH_\tau$	-0.04434***	-0.0386***	-0.04656***	-0.0560***
	(-45.8329)	(-39.8933)	(-48.1955)	(-57.9839)
ER_τ	0.2261***	0.2134***	0.2416***	0.2332***
	(42.0749)	(40.1695)	(45.4099)	(44.3866)
Adj. Squared-R	0.0723	0.0712	0.0712	0.0726

Table 4.4. Regression Coefficients for Each Stock: $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3 SSB_{i\tau} + \beta_4 CRASH_{i\tau} + \beta_5 ER_{i\tau} + \epsilon_{i\tau}$ where the dependent variable is the natural logarithm of VPIN (CDF). The control variables include conditional volatility and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH. Coefficients for individual stocks are in table A.8 in Appendix A.

Liquidity

In table 4.5 the permanent component of the LOB slope (γ_τ) has a highly significant positive effect on market depth, indicating that when the slope is influenced by fundamental information (possibly from long-term informed traders), market depth tends to increase. This may be because traders who provide liquidity to the market with limit orders in anticipation of future price movements, without the urgency of short-term liquidity trading, result in a deeper order book. The transitory component related to algorithmic trading not based on fundamental information (ξ_τ) has a negative impact on order book depth. Given the volatile and short-term nature of algorithmic trading, this result could suggest that the increase in algorithmic orders, which can enter and exit the market quickly, reduces depth by making the order book less stable and predictable, consuming liquidity. Table A.9 in Appendix A contains the individual results for each stock.

The negative and significant coefficients for the $CRASH_\tau$ dummy reflect the negative impact of extreme market events, such as the market crash during the COVID-19 crisis, on order book depth. These events led to a withdrawal of liquidity and a reduction in depth, although to a lesser extent than during the short-selling restriction period. The quoted spread variable ($QS_{i,t}$) also has a negative effect on depth, suggesting that market conditions with a larger quoted spread are indicative of lower liquidity and, similarly, a reduction in depth—essentially, reduced liquidity. The SSB coefficient indicates that the short-selling restriction helped mitigate the lack of liquidity in the order book, as evidenced by the significant value of 0.0113.

Table 4.5 The effects of the limit order book slope components on LOB Depth

The effects of the limit order book slope components on natural log depth of LOB				
weighted mean (z-score)	ALL	LARGE	MEDIUM	SMALL
Intercept	0.4644*** (33.8859)	0.4978*** (36.4320)	0.4282*** (31.6250)	0.4240*** (32.1489)
γ_τ	0.8075*** (215.2243)	0.7977*** (213.2142)	0.8170*** (220.4511)	0.8149*** (226.7112)
ξ_τ	-0.2566*** (-319.6900)	-0.2588*** (-324.3445)	-0.2549*** (-324.3347)	-0.2612*** (-326.7228)
SSB_τ	-0.2396*** (-215.1892)	-0.2434*** (-219.7624)	-0.2412*** (-220.3757)	-0.2362*** (-220.9659)
$CRASH_\tau$	-0.0430 *** (-162.6490)	--0.0431*** (-162.8253)	-0.0435*** (-164.6634)	-0.0434*** (-164.5915)
QS_τ	-0.0247*** (-49.2194)	-0.0255*** (-50.8563)	-0.0249*** (-50.5904)	-0.0236*** (-49.5927)
Adj. Squared-R	0.4574	0.4619	0.4609	0.4556

Table 4.5. Coefficients of the regression for each stock OLS $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3 SSB_{i\tau} + \beta_4 CRASH_{i\tau} + \beta_5 QS_{i\tau} + \epsilon_{i\tau}$, where the dependent variable is the natural log of DEPTH. The control variables include the Quoted Spread and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH.

In summary, the components of the limit order book slope play a crucial role in determining market depth. While the informed component increases depth, which could benefit market liquidity, the transitory contributions and the costs associated with a wider spread and crash events significantly reduce market depth.

Return prediction

In this study, we conducted a meta-analysis to investigate the effect of the permanent and transitory components on returns, grouping the results by different lags ranging from 2 to 50 periods. In Table 4.6, we explore how the permanent and transitory components of the order book influence the predictability of market returns, controlling for spread variables, short-selling restrictions, and the context of the COVID-19 crisis period. Our study highlights significant differences in the predictive ability of these components across the initial buckets. See full table A.10 in Appendix A.

In terms of statistical significance, the permanent component showed notable variability across the different lags. The results indicated that the p-values were relatively high for most lags, suggesting a generally low predictive capacity of the reported component. However, low p-values (less than 0.1) were observed in the early lags, suggesting that the transitory component has a statistically significant influence on returns in these intervals.

Table 4.6 Statistical results extract by lag

LAG	$\boldsymbol{\beta_i}$	S.E. $\boldsymbol{\beta_i}$	P value $\boldsymbol{\beta_i}$.	$\boldsymbol{\nu_j}$	S.E. $\boldsymbol{\nu_j}$	P value $\boldsymbol{\nu_j}$	$\boldsymbol{\delta_3}$	S.E. $\boldsymbol{\delta_3}$
1	-4.6800e-07	1.1718e-06	0.6896	7.4152e-05	3.4806e-05	**0.0331**	9.6595e-04	7.3692e-04
2	8.0812e-07	1.1731e-06	0.4909	7.5381e-05	3.5012e-05	**0.0313**	-6.6167e-04	7.0726e-04
3	1.2756e-07	1.1325e-06	0.9103	6.7515e-05	3.4179e-05	**0.0482**	-1.0516e-04	5.7901e-04
4	-1.0498e-06	1.1005e-06	0.3401	6.1856e-05	3.4031e-05	**0.0691**	-1.2427e-03	5.2311e-04
5	-5.4259e-07	1.1905e-06	0.6485	5.9015e-05	3.4082e-05	**0.0834**	9.4475e-05	5.2576e-04
6	-1.1019e-06	1.1737e-06	0.3478	5.9740e-05	3.4008e-05	**0.0790**	-4.6381e-04	4.9937e-04
7	-4.5478e-07	1.0639e-06	0.6690	3.1761e-05	3.3724e-05	0.3463	-6.4013e-04	4.1209e-04
8	-8.8987e-07	1.1008e-06	0.4189	3.1352e-05	3.3703e-05	0.3522	-3.6887e-04	4.2473e-04
9	-2.0142e-06	1.1345e-06	0.0758	3.7480e-05	3.3503e-05	0.2633	-7.7895e-04	4.1699e-04
10	-1.7626e-06	1.0429e-06	0.0910	3.4648e-05	3.3540e-05	0.3016	-7.5198e-04	4.0059e-04
11	-1.9818e-06	1.1312e-06	0.0798	1.4034e-05	3.3288e-05	0.6733	-9.5610e-04	4.2907e-04
...								
50	-2.9594e-07	9.7267e-07	0.7609	8.3011e-06	3.2979e-05	0.8013	-1.9541e-04	3.6896e-04

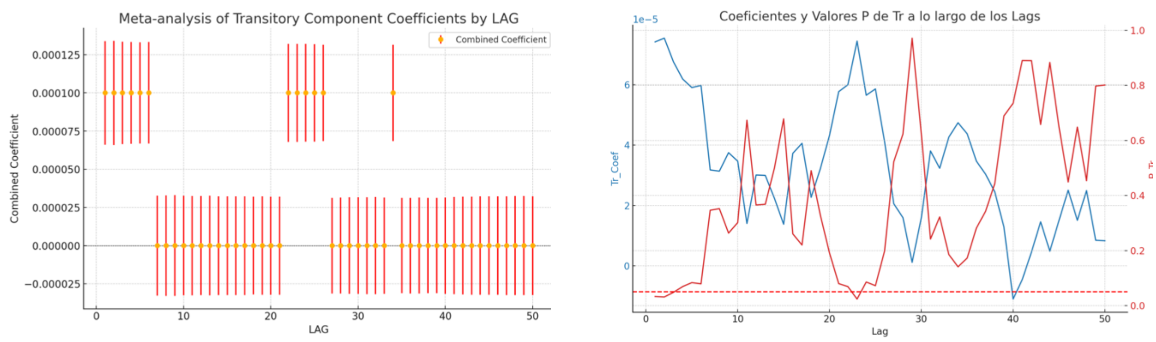
Table 4.6. See full table A.10 in Appendix A. $R_\tau = \alpha + \sum_{i=1}^{n} \beta_i \gamma_{\tau-i} + \sum_{j=1}^{n} \nu_j \xi_{\tau-j} + \delta_1 SSB_\tau + \delta_2 CRASH_\tau + \delta_3 QS_\tau + \epsilon_\tau$; n ={1,2,...,50}

The transitory component demonstrated greater consistency in its predictive ability over returns, particularly in the first 6 lags. The p-values for these lags were consistently low, with an average of approximately 0.0574, reflecting robust statistical significance and a more direct influence on short-term returns.

Figure 4.2 presents the results of the meta-analysis of the transitory component coefficients and the associated p-values across different lags (LAG). In Panel A, the chart shows the weighted coefficients for the transitory component of the 33 stocks at each LAG, weighted according to the variance of each stock. The points indicate the combined coefficient for each specific LAG, and the red error bars represent the standard error associated with these coefficients. The dashed horizontal line at Y=0 serves as a neutral reference point, where coefficients above this line suggest a positive effect, and coefficients below indicate a negative effect. The error bars provide a measure of the uncertainty in the coefficient estimates.

Panel B shows the transitory coefficients and p-values for the transitory component model across different LAGs. The red dashed line indicates the statistical significance threshold at p=0.05. Several lags were identified where the p-values are below 0.05, suggesting a statistically significant relationship between the transitory component and the corresponding lag. These significant lags indicate specific time points where the transitory component has a considerable impact, which is crucial for understanding the temporal dynamics of the phenomenon under study. Multiple points of significance highlight the importance of considering the effect of the transitory component across different time intervals, providing a deeper and more robust understanding of the temporal relationship in the analyzed model.

Figure 4.2 Transitory components



(a) Meta-analysis of the Transitory Component Coefficients by Different Lags (LAG). The points represent the combined coefficients of the stocks, while the error bars indicate the corresponding confidence intervals. The reference line at Y=0 indicates the neutral point.

(b) Coefficients and p-values of the Transitory Component across Different Lags (LAG). The red dashed line indicates the significance threshold at p=0.05. The points and error bars represent the coefficients of the transitory component and the p-values, respectively.

4.6 Conclusion and recommendations

This study has provided a comprehensive assessment of the effects of the permanent and transitory components of the limit order book (LOB) slope on volatility, adverse selection costs (order imbalance), market depth, and return predictability in the components of the IBEX 35. Through a meta-analysis that integrates regression model estimates weighted by their standard errors, it has been demonstrated that the permanent component, associated with fundamental information and the activity of informed traders, has a significant stabilizing effect on prices, reducing market volatility (H1a). This effect is reflected in the reduction of adverse selection costs as measured by the relative price spread and order imbalance (H2a), as well as in an increase in market depth, thereby enhancing liquidity (H3a).

On the other hand, the transitory component, linked to algorithmic trading and liquidity operations not based on new information, tends to increase volatility (H1b) and market noise, raising both adverse selection costs through order imbalance (H2b) and reducing order book depth (H3b). These results underscore the importance of distinguishing between activities related to fundamental information and uninformed trading when evaluating market microstructure. In the case of accumulated informed trading VPIN (CDF), both the fundamental consensus component and the transitory trading component positively affect this variable, indicating that informed limit orders are present in the order book in both fundamental information scenarios and transitory reactions.

The predictive analysis of returns has revealed that the transitory component possesses a greater predictive ability for short-term returns compared to the permanent component (H4). These findings suggest that ultra-short-term trading (1-6 buckets) within the LOB is crucial for forecasting intraday price movements. This study highlights the relevance of considering the informational quality of the LOB and the temporality of its components to improve the price discovery process and mitigate volatility in financial markets.

Regarding the differences between volatility measures (VR and ER), it is evident that the effects of the permanent and transitory components are robust for both metrics. However, VR is more directly associated with short-term price variations, while ER, calculated through EGARCH, better captures the persistence of volatility and shocks over time. This distinction is important for future research on the specific dynamics captured by each component in relation to market behavior.

Additionally, analyzing the effects of the LOB slope during the short-selling restriction periods (SSB) and the market crash (CRASH) due to COVID-19 provides important insights into market dynamics during extreme situations. During these periods, market depth and volatility experienced significant deterioration even with short-selling restrictions.

Specifically, the negative and significant coefficients associated with the SSB component indicate that short-selling restrictions had a negative impact on order book depth. This reduction in depth can be interpreted as a decrease in available liquidity, as investors and traders became more cautious and reluctant to provide liquidity in an environment of high uncertainty and regulatory constraints. Similarly, the CRASH period showed significant negative coefficients, reflecting the adverse impact of the COVID-19 crisis on market depth. The withdrawal of liquidity during this significant market downturn suggests that traders reduced their participation in response to increased volatility and uncertainty.

Moreover, the analysis of the impact of these periods on market volatility revealed that both SSB and CRASH contributed to increases in volatility. The positive and significant coefficients for these variables suggest that short-selling restrictions and the market crash exacerbated volatility, likely due to the reduced ability of traders to implement hedging strategies and the heightened overall market uncertainty.

In summary, this study validated the proposed hypotheses: the informed component of SLOPE reduces volatility (H1a) and adverse selection costs (H2a) while increasing liquidity (H3a). On the other hand, the transitory component increases volatility (H1b), adverse selection costs (H2b), and illiquidity (H3b), in addition to being a significant predictor of intraday returns (H4). In regulatory studies, special attention is recommended to the differences between volatility metrics, such as VR and ER, as each captures specific dynamics in the interaction between informed and uninformed trading. These results enhance the understanding of market microstructure and provide crucial insights for policymakers in promoting market stability and efficiency.

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Appendix A

Table A.1 Market capitalization stock categories

LARGE	ITX	SAN	IBE	BBVA	TEF	AMS	ELE	AENA	NTGY	REP	FER
MEDIUM	GRF	CABK	CLNX	IAG	ACS	SGRE	REE	MAP	MRL	ENG	BKT
SMALL	SAB	BKIA	COL	CIE	ACX	VIS	TL5	MEL	IDR	ENC	MTS

Table A.1. Market capitalization stock categories

Table A.2. Correlation among slope components

STOCK	CORR	BETA	STOCK	CORR	BETA	STOCK	CORR	BETA
SAB	0.0238	0.0111	AMS	0.0319	0.0149	MRL	0.0132	0.0070
CABK	0.0255	0.0128	ELE	0.0250	0.0125	IBE	0.0186	0.0173
REP	0.0156	0.0080	IAG	0.0344	0.0207	ACS	0.0093	0.0072
SAN	0.0180	0.0103	IDR	0.0164	0.0083	MEL	0.0112	0.0053
MAP	0.0132	0.0091	GRF	0.0150	0.0092	ENC	0.0227	0.0095
REE	0.0171	0.0107	CLNX	0.0220	0.010	SGRE	0.0505	0.0236
BBVA	0.0105	0.0085	MTS	0.0112	0.0054	BKIA	0.0222	0.0135
BKT	0.0137	0.0074	NTGY	0.0150	0.0089	COL	0.0278	0.0112
FER	0.0217	0.0149	AENA	0.0109	0.013	ACX	0.0233	0.0111
TEF	0.0123	0.0091	ENG	0.0282	0.0165	CIE	0.0307	0.0140
ITX	0.0240	0.0170	VIS	0.0198	0.0123	TL5	0.0206	0.0151

Table A.2. Correlation among slope components.

Table A.3. Decomposition log slope in local level in permanent and transitory

Stock	lag	AIC	BIC	R^2	Var (υ_τ)	$\overline{\mu_\tau}$	$\overline{\sigma^2_{Tr}}$	$\overline{\sigma^2_{Pr}}$
SAB	12	86785.8789	86803.4365	0.2288	0.3079	7.2856	0.3582	53.2141
CABK	12	36270.7690	36287.4258	0.2244	0.1696	7.4523	0.1881	55.6060
REP	12	32955.7149	32972.1624	0.2463	0.1648	7.5097	0.1901	56.4772
SAN	3	38672.2487	38688.1726	0.2406	0.3432	7.9333	0.3686	63.0664
MAP	12	30649.2923	30665.7829	0.3345	0.1487	7.1090	0.1698	50.6415
REE	2	15680.5931	15695.6437	0.2595	0.1740	7.3911	0.1863	54.7032
BBVA	2	33728.7868	33744.7489	0.3921	0.2605	7.7441	0.2840	60.1668
BKT	12	50893.3320	50910.1162	0.2446	0.2508	7.2576	0.2823	52.7784
FER	2	11610.2137	11625.3936	0.3068	0.1218	7.2211	0.1329	52.2117
TEF	3	28068.9073	28084.6235	0.3467	0.2438	7.8838	0.2562	62.2991
ITX	2	6425.7330	6440.4593	0.3114	0.0947	7.3711	0.1027	54.3884
AMS	12	20793.9145	20809.3521	0.1837	0.1803	7.2679	0.2061	52.8849
ELE	2	12073.4827	12088.7220	0.1868	0.1213	7.1755	0.1276	51.5272
IAG	12	155078.8909	155097.8132	0.3144	0.2561	6.9848	0.2996	48.9493
IDR	12	37975.2120	37992.3427	0.2322	0.1366	6.6124	0.1546	43.7835
GRF	12	24336.3382	24352.5288	0.2937	0.1354	7.1019	0.1623	50.5195
CLNX	12	25810.1698	25826.0167	0.1938	0.1779	7.1824	0.2107	51.6564
MTS	11	97767.2181	97784.6954	0.2211	0.4341	7.1780	0.4877	51.6918
NTGY	12	56736.7664	56754.9518	0.3232	0.1152	7.2413	0.1360	52.5168
AENA	11	9699.6685	9714.8422	0.5814	0.1043	6.7445	0.1119	45.6590
ENG	12	19384.6068	19400.2323	0.2615	0.1501	7.1334	0.1699	50.9599
VIS	12	24664.4770	24680.7719	0.2974	0.1349	6.4501	0.1552	41.6819
MRL	12	27931.7444	27948.5462	0.2804	0.1142	6.7233	0.1376	45.2701
IBE	2	12112.1515	12127.7743	0.4544	0.1033	7.8107	0.1153	61.1127
ACS	12	43420.4946	43437.4266	0.4053	0.1724	7.0827	0.1993	50.3207
MEL	11	97767.2181	97784.6954	0.2211	0.4341	7.1780	0.4877	51.6918
ENC	12	47222.5708	47239.1477	0.1707	0.2578	6.6530	0.2944	44.3416
SGRE	2	9540.9782	9554.7661	0.1574	0.2003	7.1076	0.2170	50.5743
BKIA	12	97509.0424	97527.0118	0.2922	0.2669	7.1002	0.3075	50.5608
COL	1	5449.9057	5463.0837	0.1124	0.1525	6.7196	0.1621	45.1845
ACX	2	24039.2762	24054.2813	0.1833	0.3341	7.1348	0.3522	50.9971
CIE	2	7741.0997	7754.7048	0.1441	0.1791	6.3947	0.1928	40.9351
TL5	12	27905.5168	27920.8597	0.3515	0.3099	6.7962	0.3429	46.3925

Table A.3. Decomposition log slope in local level in permanent and transitory. The table presents the results of decomposing log SLOPE using a state-space model. Variables are defined as: p is the optimal AR order for the transitory component; AIC and BIC are the model selection criteria; $R^2$is the coefficient of determination; Var (υ_τ) is the variance of the observation error; $\overline{\mu_\tau}$ is the mean of the smoothed permanent level; $\overline{\sigma^2_{Tr}}$and $\overline{\sigma^2_{Pr}}$ are the mean conditional variances of the transitory and permanent components from E-GARCH models.

Table A.4. Regression on realized volatility (VR) controlled by quoted spread (QS)

Stock	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_3}$	$\boldsymbol{\beta_4}$	$\boldsymbol{\beta_5}$	SE. $\boldsymbol{\beta_0}$	SE. $\boldsymbol{\beta_1}$	SE. $\boldsymbol{\beta_2}$	SE. $\boldsymbol{\beta_3}$	SE. $\boldsymbol{\beta_4}$	SE. $\boldsymbol{\beta_5}$	$\boldsymbol{R^2}$
SAB	-0.0381	-1.4668	0.1664	0.0312	0.1241	0.1166	0.2235	0.0611	0.0192	0.0231	0.0185	0.0072	0.0380
CABK	1.4492	-1.9230	0.3341	0.1036	0.1131	0.0300	0.4323	0.1188	0.0203	0.0253	0.0199	0.0137	0.0526
REP	1.6040	-1.8736	0.2171	0.0539	0.0083	0.1272	0.4571	0.1240	0.0120	0.0243	0.0203	0.0149	0.0689
SAN	3.0135	-2.1824	0.1962	-0.0837	-0.0054	0.0839	0.4133	0.1038	0.0371	0.0299	0.0251	0.0115	0.0439
MAP	4.9059	-2.8455	0.1978	-0.0194	0.0717	0.0906	0.3533	0.0953	0.0186	0.0312	0.0228	0.0156	0.0845
REE	4.7557	-2.6742	-0.0045	0.0632	-0.0016	0.2384	0.7939	0.2134	0.0484	0.0469	0.0263	0.0203	0.0703
BBVA	2.9682	-2.1530	0.1498	-0.0064	0.1020	0.1245	0.3294	0.0822	0.0220	0.0313	0.0247	0.0135	0.0681
BKT	2.0054	-2.1303	0.2153	-0.1521	0.0430	0.0555	0.4250	0.1159	0.0219	0.0314	0.0195	0.0110	0.0449
FER	5.5572	-2.7405	0.3340	0.0067	0.1103	0.2446	0.7355	0.1993	0.0255	0.0518	0.0283	0.0240	0.1084
TEF	4.1415	-2.4366	0.1045	0.0052	0.0310	0.1460	0.3991	0.0980	0.0287	0.0372	0.0250	0.0152	0.0660
ITX	8.5509	-3.6594	-0.0374	0.0709	0.1119	0.1991	0.9973	0.2680	0.0330	0.0441	0.0319	0.0309	0.0672
AMS	1.8304	-1.9590	0.2240	0.1266	0.0147	0.1277	0.6180	0.1680	0.0248	0.0280	0.0254	0.0185	0.0542
ELE	4.5429	-2.6971	0.1969	0.2964	0.1776	0.1620	0.8657	0.2320	0.0271	0.0393	0.0273	0.0242	0.0734
IAG	0.5735	-1.7154	0.2542	0.0569	0.3601	0.1346	0.1339	0.0380	0.0211	0.0138	0.0182	0.0051	0.0724
IDR	1.9876	-2.1306	0.3809	-0.0248	0.0055	0.0969	0.3808	0.1084	0.0204	0.0288	0.0195	0.0131	0.0558
GRF	3.3730	-2.4583	0.1184	0.0637	0.1565	0.1716	0.5233	0.1481	0.0314	0.0356	0.0243	0.0178	0.0743
CLNX	0.8465	-1.6617	0.2530	0.1050	0.1408	0.2317	0.4900	0.1333	0.0274	0.0367	0.0260	0.0156	0.0586
MTS	0.9160	-1.9201	0.4231	-0.1413	0.0373	0.0101	0.2397	0.0620	0.0409	0.0209	0.0171	0.0070	0.0371
NTGY	3.7730	-2.7661	0.3160	-0.0940	0.0210	-0.0005	0.3624	0.1011	0.0094	0.0217	0.0128	0.0116	0.0930
AENA	1.5457	-1.9058	0.3037	0.0982	0.1272	0.2064	0.4013	0.1123	0.0221	0.0351	0.0301	0.0272	0.0990
ENG	1.2272	-1.8747	0.2553	0.1589	0.0043	0.1193	0.5625	0.1544	0.0245	0.0420	0.0249	0.0192	0.0575
VIS	0.7592	-1.9281	0.2313	0.0243	0.0426	0.1388	0.4649	0.1283	0.0200	0.0339	0.0223	0.0157	0.0528
MRL	4.4283	-2.8536	0.1728	-0.1461	-0.0022	0.0851	0.3742	0.1069	0.0112	0.0231	0.0180	0.0160	0.0619
IBE	2.6273	-2.1013	0.2018	0.2868	0.1431	0.1527	0.5499	0.1581	0.0170	0.0344	0.0244	0.0249	0.0852
ACS	1.4348	-1.9665	0.2987	-0.1241	-0.0454	0.0787	0.2697	0.0753	0.0203	0.0195	0.0159	0.0126	0.0664
MEL	0.7916	-1.8891	0.4192	-0.1341	0.0402	0.0106	0.2359	0.0611	0.0409	0.0205	0.0171	0.0070	0.0371
ENC	0.7064	-1.7422	0.4012	-0.1181	-0.0612	0.0803	0.3564	0.1014	0.0204	0.0368	0.0227	0.0115	0.0454
SGRE	-0.1499	-1.3520	0.1540	0.1025	0.1479	0.1488	0.9662	0.2628	0.0620	0.0921	0.0374	0.0250	0.0289
BKIA	1.3192	-1.9918	0.0740	-0.0903	-0.0100	0.0912	0.2036	0.0576	0.0164	0.0203	0.0149	0.0077	0.0511
COL	2.3653	-1.9200	0.4340	0.0078	0.0000	0.1703	1.1110	0.3057	0.0556	0.0818	0.0013	0.0328	0.0424
ACX	5.5390	-2.8637	0.3364	-0.1993	0.0204	0.1259	0.6541	0.1685	0.0727	0.0592	0.0329	0.0148	0.0631
CIE	-0.0992	-1.4881	0.1298	-0.1403	-0.0619	0.1018	1.2364	0.3465	0.0349	0.0738	0.0423	0.0281	0.0161
TL5	1.5729	-1.8583	0.4210	-0.0425	-0.0242	0.1272	0.3127	0.0910	0.0430	0.0440	0.0332	0.0136	0.1036

Table A.4. OLS $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3\mathrm{SSB}_{i\tau} + \beta_4\mathrm{CRASH}_{i\tau} + \beta_5\mathrm{QS}_{i\tau} + \epsilon_{i\tau}$, where the dependent variable is $RV_{i\tau}$. The control variables include the Quoted Spread and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH.

Table A.5. Regression on conditional volatility (ER) controlled by quoted spread (QS)

Stock	β_0	β_1	β_2	β_3	β_4	β_5	SE. β_0	SE. β_1	SE. β_2	SE. β_3	SE. β_4	SE. β_5	R^2
SAB	-2.0117	-0.8980	0.0873	0.0482	0.0910	0.0207	0.0420	0.0111	0.0030	0.0048	0.0032	0.0013	0.2898
CABK	2.7214	-2.3491	0.1577	0.1693	0.1268	-0.1542	0.0792	0.0218	0.0037	0.0040	0.0030	0.0026	0.5764
REP	-1.0712	-1.1942	0.2442	0.2744	0.0488	-0.0642	0.0755	0.0215	0.0026	0.0031	0.0034	0.0026	0.8240
SAN	3.6920	-2.3021	0.1233	-0.0897	0.0244	-0.0352	0.0654	0.0166	0.0084	0.0048	0.0040	0.0019	0.5983
MAP	3.7078	-2.6664	0.0278	0.2348	0.1698	-0.1011	0.0671	0.0178	0.0034	0.0057	0.0046	0.0031	0.6849
REE	6.8406	-3.2513	0.0454	0.2074	0.0059	-0.0364	0.1070	0.0286	0.0079	0.0067	0.0030	0.0030	0.8080
BBVA	4.9982	-2.6357	0.1665	-0.0465	0.1016	-0.0376	0.0504	0.0125	0.0051	0.0054	0.0041	0.0022	0.7511
BKT	0.3681	-1.6124	0.2150	0.0603	0.0491	-0.0561	0.0694	0.0192	0.0042	0.0051	0.0026	0.0017	0.6269
FER	10.5702	-4.0172	0.3252	0.0828	0.1898	-0.0074	0.1470	0.0418	0.0096	0.0094	0.0052	0.0046	0.8019
TEF	5.5959	-2.7767	0.1392	0.1129	0.0542	-0.0211	0.0507	0.0122	0.0051	0.0047	0.0037	0.0022	0.8336
ITX	11.0782	-4.3244	0.0002	0.1694	0.1736	-0.0858	0.1735	0.0470	0.0056	0.0058	0.0049	0.0050	0.8190
AMS	3.8399	-2.3738	0.2471	0.1017	0.0637	-0.0750	0.1146	0.0315	0.0055	0.0052	0.0034	0.0032	0.6781
ELE	7.7168	-3.5795	0.0225	0.3985	0.1987	-0.0650	0.1646	0.0439	0.0049	0.0082	0.0050	0.0041	0.7623
IAG	-0.1294	-1.3635	0.1216	0.1058	0.3736	0.0913	0.0351	0.0098	0.0053	0.0034	0.0039	0.0012	0.4690
IDR	0.3355	-1.7108	0.1497	0.2301	0.1013	-0.0491	0.0657	0.0183	0.0033	0.0054	0.0032	0.0021	0.5647
GRF	2.4179	-2.0429	0.3580	0.1750	0.1283	-0.0449	0.1067	0.0304	0.0089	0.0074	0.0048	0.0031	0.7265
CLNX	0.0775	-1.4026	0.2175	0.3130	0.1641	0.0291	0.1052	0.0282	0.0061	0.0065	0.0046	0.0029	0.5616
MTS	0.5272	-1.6781	0.0508	-0.0746	0.0548	-0.0395	0.0449	0.0113	0.0078	0.0039	0.0029	0.0012	0.4726
NTGY	2.4376	-2.3594	0.2132	0.0273	0.0342	-0.1396	0.1061	0.0288	0.0023	0.0058	0.0030	0.0032	0.5217
AENA	4.6053	-2.6767	0.1440	0.3173	0.1798	-0.0300	0.0835	0.0224	0.0057	0.0101	0.0053	0.0061	0.7901
ENG	1.0005	-1.7815	0.2260	0.3878	0.0701	-0.0790	0.1057	0.0288	0.0056	0.0076	0.0044	0.0033	0.6983
VIS	0.8376	-1.8433	0.1205	0.0036	0.0025	-0.0268	0.0921	0.0250	0.0042	0.0068	0.0042	0.0030	0.4143
MRL	2.5390	-2.2704	0.1366	-0.0967	0.0339	-0.0639	0.0954	0.0265	0.0024	0.0053	0.0038	0.0036	0.4738
IBE	5.2914	-2.7363	0.1655	0.3865	0.1416	-0.0094	0.0919	0.0267	0.0037	0.0060	0.0043	0.0044	0.7858
ACS	1.2869	-1.8254	0.1738	-0.0883	-0.0565	-0.0393	0.0548	0.0152	0.0045	0.0041	0.0032	0.0027	0.5205
MEL	0.5315	-1.6796	0.0505	-0.0837	0.0615	-0.0399	0.0428	0.0108	0.0078	0.0038	0.0029	0.0012	0.4768
ENC	-0.0363	-1.4890	0.3326	0.0951	0.0300	-0.0644	0.0646	0.0180	0.0042	0.0056	0.0038	0.0019	0.6254
SGRE	3.9098	-2.3614	-0.0560	0.0102	0.1446	0.0171	0.1530	0.0412	0.0101	0.0134	0.0058	0.0038	0.5710
BKIA	-0.0291	-1.5748	0.0530	-0.0640	0.0106	-0.0271	0.0443	0.0123	0.0033	0.0043	0.0027	0.0016	0.3883
COL	8.7728	-3.7564	0.2355	-0.2130	0.0000	-0.0823	0.2000	0.0558	0.0198	0.0198	0.0003	0.0069	0.5589
ACX	5.9088	-3.0272	-0.0816	-0.0749	0.0269	-0.0420	0.1026	0.0265	0.0113	0.0088	0.0044	0.0022	0.7123
CIE	1.7628	-1.7941	0.2550	-0.2197	-0.0725	-0.0421	0.1756	0.0508	0.0104	0.0135	0.0056	0.0042	0.5733
TL5	3.1560	-2.3063	0.2616	0.0527	0.0257	-0.0647	0.0532	0.0162	0.0104	0.0075	0.0067	0.0023	0.8006

TABLE A.5. OLS $Y_{i\tau} = \beta_0 + \beta_1 \gamma_{i\tau} + \beta_2 \xi_{i\tau} + \beta_3 \mathrm{SSB}_{i\tau} + \beta_4 \mathrm{CRASH}_{i\tau} + \beta_5 \mathrm{QS}_{i\tau} + \epsilon_{i\tau}$, where the dependent variable is $E\mathrm{V}_{i\tau}$. The control variables include the Quoted Spread and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH.

Table A.6. Regression on relative spread (RS) controlled by conditional volatility (ER)

Stock	β_0	β_1	β_2	β_3	β_4	β_5	SE. β_0	SE. β_1	SE. β_2	SE. β_3	SE. β_4	SE. β_5	R^2
SAB	0.0214	-0.0052	0.0001	0.0000	0.0001	-0.0000	0.0004	0.0001	0.0000	0.0000	0.0000	0.0000	0.3468
CABK	0.0166	-0.0043	0.0000	0.0001	0.0000	-0.0002	0.0004	0.0001	0.0000	0.0000	0.0000	0.0000	0.3226
REP	0.0164	-0.0042	-0.0000	0.0001	-0.0001	-0.0002	0.0004	0.0001	0.0000	0.0000	0.0000	0.0000	0.3633
SAN	0.0114	-0.0028	0.0001	-0.0000	0.0000	-0.0001	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.2912
MAP	0.0210	-0.0058	0.0001	0.0003	0.0001	-0.0005	0.0005	0.0002	0.0000	0.0000	0.0000	0.0000	0.3513
REE	0.0141	-0.0037	-0.0001	0.0001	-0.0000	-0.0002	0.0009	0.0003	0.0000	0.0000	0.0000	0.0000	0.2308
BBVA	0.0106	-0.0027	0.0002	0.0000	0.0000	-0.0002	0.0002	0.0001	0.0000	0.0000	0.0000	0.0000	0.3291
BKT	0.0180	-0.0048	0.0000	0.0001	0.0000	-0.0003	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.3648
FER	0.0140	-0.0036	0.0000	0.0002	0.0000	-0.0001	0.0006	0.0002	0.0000	0.0000	0.0000	0.0000	0.2667
TEF	0.0086	-0.0020	0.0001	0.0001	0.0000	-0.0000	0.0002	0.0001	0.0000	0.0000	0.0000	0.0000	0.2408
ITX	0.0189	-0.0051	-0.0001	0.0000	0.0000	-0.0003	0.0010	0.0003	0.0000	0.0000	0.0000	0.0000	0.2910
AMS	0.0160	-0.0041	-0.0000	0.0001	-0.0000	-0.0002	0.0006	0.0002	0.0000	0.0000	0.0000	0.0000	0.2525
ELE	0.0167	-0.0045	-0.0000	0.0002	0.0001	-0.0002	0.0007	0.0002	0.0000	0.0000	0.0000	0.0000	0.2537
IAG	0.0229	-0.0057	0.0004	-0.0001	0.0001	-0.0001	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.4106
IDR	0.0254	-0.0068	0.0001	0.0001	-0.0001	-0.0003	0.0005	0.0001	0.0000	0.0000	0.0000	0.0000	0.3143
GRF	0.0206	-0.0056	-0.0001	0.0002	0.0001	-0.0003	0.0010	0.0003	0.0000	0.0000	0.0000	0.0000	0.2575
CLNX	0.0159	-0.0041	0.0000	0.0001	0.0001	-0.0001	0.0006	0.0001	0.0000	0.0000	0.0000	0.0000	0.2743
MTS	0.0202	-0.0050	0.0010	-0.0001	0.0000	-0.0002	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.3790
NTGY	0.0172	-0.0043	-0.0001	-0.0000	-0.0000	-0.0000	0.0004	0.0001	0.0000	0.0000	0.0000	0.0000	0.3614
AENA	0.0122	-0.0027	0.0002	0.0002	-0.0000	0.0001	0.0005	0.0001	0.0000	0.0000	0.0000	0.0000	0.2222
ENG	0.0157	-0.0039	0.0001	0.0001	0.0000	-0.0001	0.0006	0.0002	0.0000	0.0000	0.0000	0.0000	0.3048
VIS	0.0215	-0.0055	0.0002	0.0001	-0.0000	-0.0001	0.0005	0.0001	0.0000	0.0000	0.0000	0.0000	0.3126
MRL	0.0276	-0.0073	0.0001	-0.0001	-0.0000	-0.0002	0.0007	0.0002	0.0000	0.0000	0.0000	0.0000	0.3643
IBE	0.0084	-0.0021	0.0000	0.0000	0.0000	-0.0001	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.3551
ACS	0.0165	-0.0042	0.0000	0.0001	0.0000	-0.0001	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.4008
MEL	0.0203	-0.0051	0.0010	-0.0002	0.0000	-0.0002	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.3801
ENC	0.0314	-0.0079	0.0002	-0.0000	0.0000	-0.0000	0.0008	0.0002	0.0000	0.0001	0.0000	0.0001	0.3096
SGRE	0.0216	-0.0059	0.0001	-0.0001	0.0001	-0.0004	0.0019	0.0005	0.0000	0.0001	0.0000	0.0000	0.2320
BKIA	0.0245	-0.0061	0.0000	0.0001	-0.0000	-0.0001	0.0004	0.0001	0.0000	0.0000	0.0000	0.0000	0.3841
COL	0.0203	-0.0056	0.0002	0.0001	0.0000	-0.0004	0.0010	0.0003	0.0000	0.0001	0.0000	0.0001	0.1637
ACX	0.0225	-0.0061	0.0007	0.0000	-0.0000	-0.0005	0.0009	0.0003	0.0001	0.0001	0.0000	0.0000	0.2903
CIE	0.0352	-0.0090	0.0000	-0.0001	-0.0000	0.0001	0.0021	0.0005	0.0000	0.0001	0.0000	0.0001	0.2725
TL5	0.0251	-0.0071	0.0003	0.0005	0.0003	-0.0006	0.0007	0.0003	0.0001	0.0001	0.0000	0.0001	0.2952

Table A.6. OLS $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3\text{SSB}_{i\tau} + \beta_4\text{CRASH}_{i\tau} + \beta_5 ER_{i\tau} + \epsilon_{i\tau}$, where the dependent variable is the relative spread (RS). The control variables include conditional volatility and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH.

Table A.7. Regression on order imbalance ratio (OIR) controlled by conditional volatility (ER)

Stock	β_0	β_1	β_2	β_3	β_4	β_5	SE. β_0	SE. β_1	SE. β_2	SE. β_3	SE. β_4	SE. β_5	R^2
SAB	0.2209	-0.0362	0.0161	-0.0187	-0.0100	-0.0060	0.0166	0.0045	0.0012	0.0016	0.0012	0.0021	0.0075
CABK	0.0518	-0.0022	0.0000	0.0013	-0.0016	-0.0042	0.0224	0.0063	0.0010	0.0014	0.0010	0.0015	0.0005
REP	0.0202	0.0241	0.0005	-0.0027	-0.0019	0.0096	0.0219	0.0057	0.0007	0.0013	0.0010	0.0021	0.0026
SAN	0.0640	-0.0139	0.0009	-0.0007	-0.0037	-0.0060	0.0135	0.0045	0.0012	0.0009	0.0007	0.0016	0.0021
MAP	0.2547	-0.0248	0.0034	-0.0105	-0.0052	0.0082	0.0286	0.0096	0.0014	0.0025	0.0018	0.0026	0.0027
REE	0.0246	0.0082	0.0075	0.0104	0.0092	-0.0037	0.0473	0.0154	0.0025	0.0028	0.0015	0.0036	0.0051
BBVA	0.1364	-0.0284	0.0017	-0.0049	-0.0023	-0.0054	0.0157	0.0059	0.0009	0.0012	0.0009	0.0020	0.0021
BKT	0.1888	-0.0062	-0.0028	0.0038	-0.0022	0.0117	0.0323	0.0093	0.0017	0.0025	0.0015	0.0029	0.0020
FER	0.0489	-0.0020	0.0008	0.0097	0.0032	-0.0050	0.0482	0.0145	0.0015	0.0030	0.0017	0.0024	0.0011
TEF	0.0953	-0.0048	-0.0026	-0.0043	-0.0011	0.0051	0.0190	0.0069	0.0012	0.0014	0.0009	0.0021	0.0019
ITX	0.2428	-0.0570	-0.0004	-0.0042	0.0003	-0.0053	0.0507	0.0155	0.0013	0.0017	0.0012	0.0025	0.0023
AMS	0.0631	-0.0037	0.0021	0.0060	-0.0006	-0.0021	0.0260	0.0078	0.0011	0.0014	0.0011	0.0021	0.0027
ELE	0.2491	-0.0440	-0.0005	-0.0032	0.0038	0.0006	0.0533	0.0165	0.0016	0.0026	0.0016	0.0033	0.0016
IAG	0.2695	-0.0678	0.0078	-0.0191	-0.0133	-0.0198	0.0124	0.0037	0.0019	0.0012	0.0013	0.0012	0.0079
IDR	0.3400	-0.0171	0.0113	-0.0089	-0.0078	0.0201	0.0368	0.0112	0.0020	0.0030	0.0019	0.0034	0.0046
GRF	0.0122	0.0274	0.0005	-0.0003	0.0047	0.0063	0.0302	0.0091	0.0020	0.0022	0.0016	0.0024	0.0011
CLNX	0.1139	-0.0157	0.0138	-0.0067	-0.0035	-0.0079	0.0266	0.0078	0.0015	0.0021	0.0015	0.0023	0.0040
MTS	0.3193	-0.0456	-0.0045	0.0076	-0.0113	0.0031	0.0227	0.0068	0.0038	0.0020	0.0015	0.0025	0.0071
NTGY	0.2420	0.0067	0.0055	-0.0028	0.0070	0.0203	0.0290	0.0079	0.0009	0.0020	0.0012	0.0015	0.0094
AENA	0.0390	0.0173	0.0023	0.0030	0.0041	0.0038	0.0236	0.0088	0.0013	0.0023	0.0020	0.0028	0.0019
ENG	0.0276	0.0182	0.0055	0.0049	0.0015	0.0016	0.0319	0.0092	0.0016	0.0028	0.0016	0.0029	0.0018
VIS	0.1171	0.0617	0.0170	-0.0035	-0.0018	0.0298	0.0398	0.0119	0.0019	0.0034	0.0022	0.0037	0.0091
MRL	0.3044	-0.0169	0.0102	-0.0067	0.0087	0.0176	0.0330	0.0099	0.0009	0.0021	0.0016	0.0024	0.0133
IBE	-0.0142	0.0136	0.0054	0.0005	0.0046	-0.0033	0.0208	0.0068	0.0008	0.0015	0.0010	0.0019	0.0058
ACS	0.0982	0.0048	0.0054	0.0097	0.0091	0.0033	0.0191	0.0061	0.0015	0.0014	0.0012	0.0020	0.0047
MEL	0.3441	-0.0514	-0.0040	0.0052	-0.0114	0.0033	0.0226	0.0068	0.0038	0.0020	0.0015	0.0025	0.0068
ENC	0.2013	-0.0104	0.0098	-0.0031	-0.0031	0.0068	0.0303	0.0087	0.0019	0.0030	0.0018	0.0033	0.0031
SGRE	0.0520	-0.0217	0.0100	0.0014	0.0044	-0.0183	0.0372	0.0121	0.0025	0.0036	0.0016	0.0032	0.0078
BKIA	0.2427	-0.0123	0.0224	-0.0089	-0.0082	0.0055	0.0201	0.0060	0.0016	0.0021	0.0014	0.0021	0.0060
COL	0.2694	-0.0609	0.0159	-0.0126	0.0000	-0.0127	0.0814	0.0255	0.0036	0.0058	0.0001	0.0045	0.0054
ACX	0.1687	-0.0310	0.0088	0.0016	-0.0015	-0.0075	0.0459	0.0147	0.0048	0.0038	0.0020	0.0036	0.0011
CIE	0.1676	-0.0124	0.0079	0.0073	0.0004	0.0064	0.0712	0.0207	0.0022	0.0049	0.0025	0.0053	0.0116
TL5	0.2257	-0.0320	0.0084	-0.0044	-0.0064	-0.0027	0.0285	0.0114	0.0037	0.0040	0.0027	0.0040	0.0028

Table A.7. OLS $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3\mathrm{SSB}_{i\tau} + \beta_4\mathrm{CRASH}_{i\tau} + \beta_5 ER_{i\tau} + \epsilon_{i\tau}$, where the dependent variable is the order imbalance ratio (OIR). The control variables include conditional volatility and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH.

Table A.8. Regression on natural log of VPIN (CDF) controlled by conditional volatility (ER)

Stock	β_0	β_1	β_2	β_3	β_4	β_5	SE. β_0	SE. β_1	SE. β_2	SE. β_3	SE. β_4	SE. β_5	R^2
SAB	-0.8734	-0.2130	0.8804	-0.5886	-0.4537	-0.2982	0.2629	0.0721	0.0200	0.0210	0.0162	0.0265	0.0858
CABK	-4.6148	0.4873	-0.2176	0.1220	-0.1939	-0.2187	0.5535	0.1593	0.0189	0.0258	0.0183	0.0320	0.0259
REP	0.2090	1.3359	-0.0495	-0.5302	-0.3638	1.1030	0.3988	0.1141	0.0164	0.0239	0.0199	0.0551	0.0677
SAN	1.8707	-0.6625	-0.2699	-0.0204	-0.5702	0.0592	0.3635	0.1158	0.0269	0.0262	0.0255	0.0378	0.0352
MAP	1.5476	0.8939	-0.0504	-0.2815	-0.3943	0.9980	0.3287	0.1141	0.0169	0.0254	0.0227	0.0317	0.0610
REE	-9.0442	1.9308	0.7086	0.8860	0.7257	-0.2240	0.8165	0.2684	0.0490	0.0328	0.0144	0.0572	0.1091
BBVA	4.7902	-1.3780	0.1374	-0.4843	-0.4038	-0.0216	0.3489	0.1176	0.0212	0.0280	0.0283	0.0364	0.0312
BKT	2.9191	0.1389	-0.4087	0.1802	-0.1546	0.8411	0.4451	0.1173	0.0275	0.0275	0.0180	0.0384	0.0365
FER	-7.7720	1.3198	-0.0212	0.9896	0.3227	-0.2362	0.6977	0.2046	0.0214	0.0426	0.0231	0.0354	0.0344
TEF	0.5748	0.8992	-0.2684	-0.5804	-0.1625	0.9470	0.4561	0.1840	0.0307	0.0362	0.0234	0.0646	0.0452
ITX	18.9540	-5.8848	-0.1299	-0.6946	-0.0520	-0.5744	0.9856	0.3062	0.0298	0.0534	0.0342	0.0537	0.0473
AMS	0.0256	-0.4628	0.1851	0.4452	-0.0898	-0.1888	0.5720	0.1591	0.0220	0.0241	0.0252	0.0371	0.0396
ELE	5.2223	-0.5849	-0.1892	-0.3562	0.1182	0.7068	0.6825	0.2162	0.0250	0.0349	0.0224	0.0448	0.0388
IAG	-1.9966	-0.1324	-0.1306	-0.1996	-0.4541	-0.2305	0.1591	0.0489	0.0189	0.0125	0.0131	0.0142	0.0297
IDR	2.1249	2.3629	0.2434	-0.2961	-0.3718	1.8729	0.2587	0.0960	0.0192	0.0199	0.0173	0.0328	0.1443
GRF	-6.6290	1.9835	-0.0636	0.1115	0.3805	0.3823	0.4295	0.1322	0.0251	0.0320	0.0176	0.0346	0.0266
CLNX	-5.0172	0.6197	1.0079	-0.2316	-0.1141	-0.5520	0.5329	0.1387	0.0283	0.0332	0.0188	0.0324	0.0808
MTS	0.7289	0.1116	-0.3931	0.4789	-0.5939	0.4129	0.2060	0.0657	0.0360	0.0155	0.0171	0.0251	0.0858
NTGY	-1.2790	1.4815	0.1052	0.2005	0.1588	0.7994	0.2389	0.0635	0.0080	0.0170	0.0102	0.0169	0.1040
AENA	-5.6566	1.8521	0.0683	0.2464	0.1986	0.3959	0.3356	0.1240	0.0191	0.0269	0.0270	0.0376	0.0367
ENG	-7.7652	2.5958	0.1095	0.4632	0.2647	0.5464	0.4178	0.1333	0.0206	0.0310	0.0183	0.0406	0.0487
VIS	-5.4366	2.8278	0.5966	0.1595	-0.0106	0.7973	0.3162	0.1024	0.0209	0.0242	0.0176	0.0376	0.1442
MRL	0.0667	0.8190	0.5132	-0.0942	0.2912	0.5033	0.2556	0.0826	0.0095	0.0156	0.0130	0.0259	0.1706
IBE	-14.8463	3.5029	0.5224	0.1502	0.5334	-0.0946	0.4268	0.1316	0.0157	0.0291	0.0210	0.0376	0.1738
ACS	-1.3873	-0.0502	-0.1563	0.4750	0.2677	-0.0338	0.2373	0.0791	0.0197	0.0181	0.0161	0.0275	0.0323
MEL	1.7708	-0.1087	-0.3682	0.3997	-0.6054	0.4371	0.2051	0.0658	0.0362	0.0156	0.0172	0.0252	0.0827
ENC	-3.2205	1.2724	0.5632	0.1519	-0.0574	0.3258	0.3216	0.0912	0.0277	0.0251	0.0178	0.0339	0.0703
SGRE	-0.5344	-2.6284	0.8325	0.4460	0.5929	-2.0748	0.7882	0.2730	0.0724	0.0567	0.0303	0.0830	0.1529
BKIA	-0.1950	0.4254	0.7890	-0.2186	-0.2301	0.2372	0.1921	0.0567	0.0152	0.0147	0.0122	0.0209	0.0716
COL	6.6971	-2.2237	0.3171	-0.3570	0.0000	-0.2466	1.3729	0.4212	0.0599	0.0569	0.0010	0.0724	0.0167
ACX	6.8747	-2.6912	0.1729	-0.1266	-0.3081	-0.5147	0.6270	0.2101	0.0637	0.0464	0.0382	0.0562	0.0223
CIE	0.8878	0.7852	0.5565	0.3245	0.0146	0.7367	0.6961	0.2179	0.0455	0.0445	0.0360	0.0717	0.1737
TL5	2.6486	-0.3304	0.3556	-0.1692	-0.4239	0.3455	0.2746	0.1190	0.0371	0.0297	0.0389	0.0426	0.0570

Table A.8. OLS $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3\mathrm{SSB}_{i\tau} + \beta_4\mathrm{CRASH}_{i\tau} + \beta_5 ER_{i\tau} + \epsilon_{i\tau}$, where the dependent variable is the natural log of VPIN (CDF). The control variables include conditional volatility and the dummy variables for the short-selling restriction period and the market crash period defined as the COVID-19 CRASH.

Table A.9. Regression on natural log of depth of the limit order book controlled by quoted spread (QS)

Stock	β_0	β_1	β_2	β_3	β_4	β_5	SE. β_0	SE. β_1	SE. β_2	SE. β_3	SE. β_4	SE. β_5	R^2
SAB	-0.2364	1.0261	-0.4198	-0.0036	-0.0946	0.0282	0.0577	0.0158	0.0054	0.0068	0.0044	0.0019	0.3602
CABK	0.6790	0.8591	-0.2643	-0.1972	0.0179	0.0198	0.1154	0.0316	0.0050	0.0084	0.0047	0.0040	0.3184
REP	0.4363	0.8081	-0.2988	-0.1695	0.1168	-0.0512	0.1298	0.0354	0.0033	0.0063	0.0062	0.0045	0.5591
SAN	2.6235	0.1847	-0.4622	-0.0896	0.0566	-0.0566	0.1539	0.0386	0.0178	0.0137	0.0090	0.0041	0.1329
MAP	1.8145	0.5102	-0.1605	-0.3710	-0.0644	-0.0309	0.0756	0.0200	0.0036	0.0074	0.0060	0.0038	0.4296
REE	-0.4562	1.0200	-0.1321	-0.3647	-0.0346	-0.0857	0.1961	0.0520	0.0082	0.0111	0.0051	0.0051	0.5281
BBVA	3.3387	-0.0505	-0.5324	-0.0948	-0.1476	-0.0731	0.0936	0.0229	0.0095	0.0122	0.0062	0.0040	0.4071
BKT	-0.7669	1.1305	-0.2130	-0.2884	-0.0627	-0.0293	0.0875	0.0238	0.0039	0.0060	0.0042	0.0025	0.5815
FER	2.7358	0.1272	-0.3534	-0.4419	-0.0440	-0.0765	0.1775	0.0495	0.0071	0.0108	0.0068	0.0067	0.6166
TEF	4.0626	-0.2124	-0.3461	-0.3899	-0.1570	-0.1130	0.1029	0.0255	0.0114	0.0114	0.0072	0.0048	0.4134
ITX	-3.4415	1.7766	-0.0842	-0.1840	-0.1879	-0.1833	0.2315	0.0628	0.0076	0.0111	0.0068	0.0088	0.5159
AMS	-0.1112	0.9592	-0.2203	-0.3189	-0.0609	-0.0535	0.1410	0.0396	0.0066	0.0059	0.0069	0.0049	0.5165
ELE	-2.2301	1.5790	-0.1170	-0.5937	-0.1576	-0.0435	0.2219	0.0597	0.0054	0.0096	0.0070	0.0066	0.6336
IAG	-0.9221	1.1982	-0.3336	0.1045	-0.2429	-0.0129	0.0389	0.0107	0.0059	0.0051	0.0042	0.0014	0.2758
IDR	1.6838	0.5088	-0.2328	-0.3666	-0.0423	-0.0483	0.0830	0.0234	0.0037	0.0057	0.0039	0.0029	0.4429
GRF	-0.2790	1.0470	-0.0089	-0.2632	-0.1310	-0.0749	0.1098	0.0309	0.0059	0.0068	0.0044	0.0041	0.4193
CLNX	-3.2191	1.7644	-0.3020	-0.3592	-0.1526	-0.0076	0.1043	0.0287	0.0072	0.0072	0.0049	0.0041	0.6105
MTS	-0.3154	0.9426	-0.5094	-0.1740	-0.0554	-0.0069	0.0484	0.0125	0.0087	0.0038	0.0032	0.0015	0.3969
NTGY	-1.6776	1.5109	-0.1289	-0.3917	-0.0642	0.0588	0.0798	0.0221	0.0017	0.0041	0.0028	0.0027	0.6194
AENA	3.5548	-0.0155	-0.2693	-0.2761	-0.0845	-0.0812	0.1051	0.0297	0.0049	0.0081	0.0077	0.0078	0.4168
ENG	0.0996	0.9112	-0.2985	-0.3945	-0.0242	-0.0214	0.1444	0.0398	0.0060	0.0094	0.0057	0.0051	0.5337
VIS	1.0287	0.6845	-0.2697	-0.2640	-0.0033	-0.0153	0.0957	0.0262	0.0043	0.0067	0.0044	0.0034	0.5119
MRL	2.3569	0.2349	-0.2289	-0.1835	-0.1581	-0.1033	0.0792	0.0233	0.0024	0.0044	0.0040	0.0035	0.5121
IBE	5.9868	-0.6486	-0.3674	-0.4459	-0.1935	-0.0770	0.1568	0.0465	0.0068	0.0102	0.0058	0.0078	0.5804
ACS	0.8816	0.7528	-0.1943	-0.2386	0.0230	-0.0282	0.0573	0.0163	0.0044	0.0041	0.0041	0.0034	0.4423
MEL	-0.3121	0.9417	-0.5092	-0.1773	-0.0615	-0.0072	0.0469	0.0122	0.0087	0.0037	0.0032	0.0015	0.3989
ENC	0.7578	0.7281	-0.5465	-0.1741	-0.0011	0.0179	0.0795	0.0232	0.0070	0.0068	0.0045	0.0031	0.4989
SGRE	-2.3625	1.5785	-0.1736	-0.3526	-0.1124	-0.0400	0.1969	0.0546	0.0138	0.0141	0.0071	0.0062	0.4593
BKIA	0.6918	0.7750	-0.3085	-0.1893	0.0422	0.0022	0.0432	0.0122	0.0034	0.0045	0.0028	0.0018	0.4817
COL	2.9341	0.1808	-0.1550	-0.3116	0.0000	-0.0388	0.2046	0.0566	0.0108	0.0132	0.0003	0.0077	0.1881
ACX	1.7519	0.4225	-0.3161	-0.4281	-0.0472	-0.0611	0.1575	0.0408	0.0163	0.0120	0.0069	0.0036	0.3560
CIE	-0.5093	1.1658	-0.1316	-0.3409	-0.0318	-0.0403	0.2463	0.0693	0.0062	0.0129	0.0078	0.0055	0.5717
TL5	-0.8492	1.1534	-0.2118	0.0072	0.0087	-0.0208	0.0561	0.0167	0.0084	0.0076	0.0066	0.0030	0.4681

Table A.9. OLS $Y_{i\tau} = \beta_0 + \beta_1\gamma_{i\tau} + \beta_2\xi_{i\tau} + \beta_3\mathrm{SSB}_{i\tau} + \beta_4\mathrm{CRASH}_{i\tau} + \beta_5 QS_{i\tau} + \epsilon_{i\tau}$, where the dependent variables is DEPTH. With the control variables of the quoted spread and the dummies of the short selling restriction period and the fall of the period defined as COVID-19 CRASH.

Table A.10 Statistical results extract by lag

LAG	$\boldsymbol{\beta_i}$	SE. $\boldsymbol{\beta_i}$	$\boldsymbol{\nu_j}$	SE. $\boldsymbol{\nu_j}$	$\boldsymbol{\delta_1}$	SE $\boldsymbol{\delta_1}$	$\boldsymbol{\delta_2}$	SE $\boldsymbol{\delta_2}$	$\boldsymbol{\delta_3}$	SE $\boldsymbol{\delta_3}$
1	-4.6800e-07	1.1718e-06	7.4152e-05	3.4806e-05	-9.2790e-05	1.6353e-05	-1.3494e-04	7.8829e-05	9.6595e-04	7.3692e-04
2	8.0812e-07	1.1731e-06	7.5381e-05	3.5012e-05	-9.3419e-05	1.6325e-05	-1.3916e-04	7.9316e-05	-6.6167e-04	7.0726e-04
3	1.2756e-07	1.1325e-06	6.7515e-05	3.4179e-05	-9.5971e-05	1.6350e-05	-1.3911e-04	7.9473e-05	-1.0516e-04	5.7901e-04
4	-1.0498e-06	1.1005e-06	6.1856e-05	3.4031e-05	-9.4209e-05	1.6310e-05	-1.3976e-04	8.0008e-05	-1.2427e-03	5.2311e-04
5	-5.4259e-07	1.1905e-06	5.9015e-05	3.4082e-05	-9.7172e-05	1.6472e-05	-1.4407e-04	8.0563e-05	9.4475e-05	5.2576e-04
6	-1.1019e-06	1.1737e-06	5.9740e-05	3.4008e-05	-9.2365e-05	1.6409e-05	-1.4100e-04	8.0732e-05	-4.6381e-04	4.9937e-04
7	-4.5478e-07	1.0639e-06	3.1761e-05	3.3724e-05	-9.1703e-05	1.6262e-05	-1.4404e-04	8.0421e-05	-6.4013e-04	4.1209e-04
8	-8.8987e-07	1.1008e-06	3.1352e-05	3.3703e-05	-9.2980e-05	1.6267e-05	-1.4612e-04	8.0671e-05	-3.6887e-04	4.2473e-04
9	-2.0142e-06	1.1345e-06	3.7480e-05	3.3503e-05	-9.0414e-05	1.6322e-05	-1.4616e-04	8.0978e-05	-7.7895e-04	4.1699e-04
10	-1.7626e-06	1.0429e-06	3.4648e-05	3.3540e-05	-9.1391e-05	1.6283e-05	-1.4768e-04	8.0746e-05	-7.5198e-04	4.0059e-04
11	-1.9818e-06	1.1312e-06	1.4034e-05	3.3288e-05	-9.1718e-05	1.6395e-05	-1.4946e-04	8.1178e-05	-9.5610e-04	4.2907e-04
12	-1.5426e-06	1.0201e-06	3.0078e-05	3.3223e-05	-9.2572e-05	1.6278e-05	-1.4803e-04	8.0926e-05	-5.9794e-04	3.5556e-04
13	-1.7606e-06	1.0303e-06	2.9949e-05	3.3263e-05	-9.5380e-05	1.6305e-05	-1.4828e-04	8.1088e-05	-4.3592e-04	3.6547e-04
14	-1.4640e-06	1.0299e-06	2.2352e-05	3.3127e-05	-9.5706e-05	1.6320e-05	-1.4743e-04	8.1241e-05	-5.4449e-04	3.4465e-04
15	-2.5230e-06	1.0387e-06	1.3781e-05	3.3211e-05	-9.3182e-05	1.6343e-05	-1.4883e-04	8.1254e-05	-1.1848e-03	4.0122e-04
16	-1.6431e-06	1.0216e-06	3.7246e-05	3.3099e-05	-9.5883e-05	1.6332e-05	-1.5055e-04	8.1225e-05	-2.9610e-04	3.2233e-04
17	-1.5721e-06	1.0036e-06	4.0571e-05	3.3086e-05	-9.6932e-05	1.6327e-05	-1.5091e-04	8.1414e-05	-5.1335e-04	3.2444e-04
18	-1.0948e-06	9.9320e-07	2.2690e-05	3.2884e-05	-9.0944e-05	1.6325e-05	-1.5045e-04	8.1568e-05	-2.6950e-04	3.3951e-04
19	-1.2034e-06	1.0307e-06	3.2180e-05	3.2925e-05	-9.6467e-05	1.6316e-05	-1.5115e-04	8.1685e-05	-6.7978e-04	4.4701e-04
20	-1.3854e-06	1.0099e-06	4.3198e-05	3.3028e-05	-9.6911e-05	1.6317e-05	-1.5140e-04	8.1547e-05	-3.3619e-04	3.8019e-04
21	-1.1089e-06	1.0086e-06	5.7681e-05	3.2913e-05	-9.8915e-05	1.6298e-05	-1.5180e-04	8.1832e-05	-1.3586e-04	3.1795e-04
22	-7.6984e-07	1.0106e-06	5.9941e-05	3.2960e-05	-9.7486e-05	1.6304e-05	-1.5246e-04	8.2038e-05	2.2735e-04	2.8567e-04
23	-1.6600e-06	9.9231e-07	7.4413e-05	3.2887e-05	-9.8247e-05	1.6263e-05	-1.5458e-04	8.2263e-05	-4.0151e-04	3.3223e-04
24	-6.6348e-07	1.0150e-06	5.6485e-05	3.2869e-05	-9.5805e-05	1.6298e-05	-1.5371e-04	8.2232e-05	-6.1121e-05	3.6196e-04
25	-3.4214e-07	9.9209e-07	5.8581e-05	3.2582e-05	-9.6218e-05	1.6285e-05	-1.5306e-04	8.2430e-05	-1.6030e-04	3.3825e-04
26	-1.0842e-06	1.0005e-06	4.1100e-05	3.1957e-05	-9.5961e-05	1.6317e-05	-1.5270e-04	8.2312e-05	-2.4959e-04	3.0551e-04
27	-1.3662e-06	9.8781e-07	2.0567e-05	3.2153e-05	-9.1993e-05	1.6294e-05	-1.5306e-04	8.2383e-05	-6.1395e-04	3.0673e-04

Table A.10 Statistical results extract by lag (continued)

LAG	$\boldsymbol{\beta_i}$	SE. $\boldsymbol{\beta_i}$	$\boldsymbol{\nu_j}$	SE. $\boldsymbol{\nu_j}$	$\boldsymbol{\delta_1}$	SE $\boldsymbol{\delta_1}$	$\boldsymbol{\delta_2}$	SE $\boldsymbol{\delta_2}$	$\boldsymbol{\delta_3}$	SE $\boldsymbol{\delta_3}$
28	-6.9240e-07	1.0016e-06	1.5948e-05	3.2451e-05	-9.1168e-05	1.6296e-05	-1.5218e-04	8.2504e-05	-5.0549e-04	3.8200e-04
29	-1.3512e-06	9.9081e-07	1.1619e-06	3.2465e-05	-9.1693e-05	1.6298e-05	-1.5076e-04	8.2590e-05	-3.7241e-04	3.0868e-04
30	-1.1630e-06	9.7000e-07	1.5895e-05	3.2433e-05	-9.0727e-05	1.6278e-05	-1.5209e-04	8.2656e-05	-4.8322e-04	3.4106e-04
31	-1.3186e-06	9.8252e-07	3.8047e-05	3.2500e-05	-9.6980e-05	1.6283e-05	-1.5459e-04	8.2684e-05	-5.4936e-04	3.9882e-04
32	-4.1469e-07	9.7835e-07	3.2315e-05	3.2630e-05	-9.4385e-05	1.6288e-05	-1.5340e-04	8.2768e-05	2.1284e-04	3.5490e-04
33	-3.0729e-07	9.7130e-07	4.2625e-05	3.2186e-05	-9.3218e-05	1.6261e-05	-1.5592e-04	8.2864e-05	-3.8739e-04	3.2820e-04
34	-9.2754e-07	9.7195e-07	4.7381e-05	3.2182e-05	-9.6690e-05	1.6279e-05	-1.5232e-04	8.2796e-05	-4.8996e-04	3.4910e-04
35	-1.4041e-06	9.7962e-07	4.3707e-05	3.2061e-05	-9.4317e-05	1.6281e-05	-1.5206e-04	8.2828e-05	-8.0610e-04	3.3464e-04
36	-8.8945e-07	9.6984e-07	3.4664e-05	3.2193e-05	-9.5189e-05	1.6259e-05	-1.4844e-04	8.3890e-05	-5.2522e-04	3.0523e-04
37	-8.2923e-07	9.7964e-07	3.0352e-05	3.1958e-05	-9.5941e-05	1.6233e-05	-1.4990e-04	8.3911e-05	-4.7735e-05	3.5063e-04
38	-1.7982e-06	9.6577e-07	2.4510e-05	3.1947e-05	-9.4230e-05	1.6234e-05	-1.4899e-04	8.4145e-05	-5.9568e-04	2.9959e-04
39	-1.1160e-06	9.6855e-07	1.2895e-05	3.2205e-05	-9.4591e-05	1.6231e-05	-1.5002e-04	8.4040e-05	4.3037e-05	3.1751e-04
40	-6.8844e-07	9.6561e-07	-1.0989e-05	3.2455e-05	-9.0735e-05	1.6236e-05	-1.4808e-04	8.4292e-05	-2.9213e-04	3.4640e-04
41	-1.5835e-07	9.6969e-07	-4.5110e-06	3.2716e-05	-9.1653e-05	1.6203e-05	-1.4873e-04	8.4320e-05	1.7537e-04	3.2222e-04
42	-2.9438e-07	9.7032e-07	4.5564e-06	3.2917e-05	-9.1722e-05	1.6174e-05	-1.4920e-04	8.4397e-05	2.1295e-04	3.6363e-04
43	-1.1455e-06	9.6791e-07	1.4588e-05	3.2920e-05	-9.0624e-05	1.6168e-05	-1.4809e-04	8.4469e-05	-9.4127e-04	3.3442e-04
44	-1.5123e-06	9.6655e-07	4.8433e-06	3.3020e-05	-9.1024e-05	1.6150e-05	-1.4817e-04	8.4453e-05	-4.7996e-04	3.0323e-04
45	-8.2200e-07	9.6142e-07	1.5022e-05	3.3032e-05	-8.9962e-05	1.6134e-05	-1.4942e-04	8.4552e-05	-1.7489e-04	3.7206e-04
46	-2.1262e-07	9.7911e-07	2.5066e-05	3.3097e-05	-9.1518e-05	1.6162e-05	-1.5239e-04	8.4461e-05	-5.0505e-04	3.5341e-04
47	-1.2407e-06	9.5761e-07	1.5088e-05	3.3084e-05	-8.8176e-05	1.6139e-05	-1.5131e-04	8.4540e-05	-1.0421e-03	3.5203e-04
48	-6.2077e-07	9.8329e-07	2.4942e-05	3.3260e-05	-9.0007e-05	1.6159e-05	-1.5367e-04	8.4540e-05	-4.8141e-04	3.3361e-04
49	-5.5333e-07	9.7034e-07	8.4685e-06	3.3008e-05	-8.9402e-05	1.6177e-05	-1.5495e-04	8.4566e-05	-5.4105e-04	3.5612e-04
50	-2.9594e-07	9.7267e-07	8.3011e-06	3.2979e-05	-8.9500e-05	1.6171e-05	-1.5216e-04	8.4745e-05	-1.9541e-04	3.6896e-04

Table A. 10. $R_\tau = \alpha + \sum_{i=1}^{n} \beta_i \gamma_{\tau-i} + \sum_{j=1}^{n} \nu_j \xi_{\tau-j} + \delta_1 SSB_\tau + \delta_2 CRASH_\tau + \delta_3 QS_\tau + \epsilon_\tau$; n ={1,2,...,50} The table reports the weighted means, standard errors, and p-values for each variable across all stocks, reflecting the impact of permanent $\gamma_{\tau-i}$ and transitory $\xi_{\tau-j}$ components, short-selling restrictions SSB_τ, market crash $CRASH_\tau$, and quoted spread QS_τ on returns (R_τ).

5. Resumen y conclusiones

La microestructura de mercado se ha consolidado como un ámbito de estudio esencial para comprender las dinámicas subyacentes de los mercados financieros modernos. En un entorno marcado por la automatización, el trading algorítmico (AT) y la negociación de alta frecuencia (HFT), los mercados han evolucionado significativamente, introduciendo nuevas complejidades que plantean desafíos críticos para la estabilidad, la eficiencia y la calidad del mercado. Estos cambios han motivado investigaciones que exploran cómo medidas basadas en datos de alta frecuencia, como la probabilidad de negociación informada acumulada (VPIN) o medidas relacionadas con el libro de órdenes limitadas (LOB) interactúan con variables clave como la volatilidad, la liquidez, o influyen en la formación y descubrimiento de precio sobre respecto a los precios fundamentales (Carmona & Webster, 2013; Easley et al., 2012). Esta tesis doctoral se desarrolla en este marco conceptual, explorando cómo estas medidas avanzadas pueden ofrecer una comprensión más profunda de las dinámicas del mercado, especialmente en contextos extremos como la crisis de la COVID-19.

El pilar metodológico de esta investigación es el uso de datos de alta frecuencia, tanto en las transacciones ejecutadas *tick* a *tick*, como en la variación del flujo de órdenes obtenidos del libro de órdenes limitadas completo. Se analizan los cambios en el LOB que proporciona instantáneas detalladas cada vez que ocurre una transacción, se introduce una nueva orden o se modifica o cancela una existente. Este nivel de granularidad permite capturar dinámicas que serían imperceptibles con datos agregados o de menor resolución temporal (Hasbrouck, 1991).

La presente investigación adopta un enfoque progresivo y metodológicamente estructurado para analizar la microestructura del mercado durante la crisis del COVID-19, avanzando desde un análisis granular a nivel *tick* a *tick* hacia modelos más complejos que descomponen dinámicas subyacentes no observables. Para ello, se utiliza un enfoque que combina el reloj de calendario y el reloj de eventos, aplicando métodos como pruebas de Wilcoxon, regresiones de panel, modelos vectoriales de corrección de errores (VECM), contrastes de causalidad Granger y un modelo de espacio de estados. El objetivo es revelar la interrelación entre variables de calidad de mercado (liquidez, volatilidad y descubrimiento de precio), la negociación informada, el trading de alta frecuencia y el flujo de órdenes en el LOB, conectando el mundo visible de las transacciones ejecutadas y la dinámica invisible del flujo de órdenes, especialmente en escenarios de alta volatilidad y fluctuaciones extremas.

Se inicia el análisis empleando datos de alta frecuencia del libro de órdenes completo, capturando cada variación instantánea del mismo. Esto permite explorar cómo la pendiente del LOB funciona como una medida de la capacidad de resiliencia del mercado y un proxy del nivel de consenso de las creencias de los inversores sobre el valor fundamental de los activos. Adicionalmente, se examinan las principales medidas de calidad de mercado —como liquidez, volatilidad y eficiencia y descubrimiento de precios— y la prevalencia de la actividad de alta frecuencia (HFT), proporcionando una visión detallada de las interacciones dinámicas entre estas variables. También se evalúa el impacto de la restricción de ventas en corto[13] aplicada durante la crisis, identificando efectos significativos en la elasticidad y profundidad del LOB, así como en la actividad de HFT. En este contexto, la pendiente del LOB emerge como una medida particularmente informativa para anticipar la estabilidad del mercado, especialmente en mercados con diferentes niveles de capitalización y en momentos de alta incertidumbre.

Con el objetivo de analizar el impacto de la restricción de ventas en corto y la actividad HFT en la calidad del mercado español, el segundo capítulo de la tesis analiza el efecto de la prohibición de ventas en corto (*Short-Selling Restriction*, SSR) impuesta por la Comisión Nacional del Mercado de Valores (CNMV) durante la primera ola de la pandemia de COVID-19 en varias medidas de calidad del mercado de los componentes del índice IBEX 35. Con datos de alta frecuencia que abarcan del 20 de noviembre de 2019 al 13 de julio de 2020, se realiza un estudio detallado empleando un reloj de calendario, en los periodos de pre-pandemia (W0); crash pandémico (W1); prohibición de venta en corto (W2); y primera fase de desescalada (W3); para capturar la evolución de la volatilidad, la liquidez y la eficiencia de precios, así como la prevalencia de la HFT.

Los hallazgos indican que la SSR logró reducir parcialmente la volatilidad intradía, si bien a costa de un deterioro en la liquidez, particularmente en el lado de venta del libro de órdenes limitadas. Esta contracción se ve acrecentada por la disminución de la actividad HFT, cuyos participantes suelen actuar como proveedores de liquidez y facilitar el descubrimiento de precios (Foley et al., 2022). Asimismo, se observa que la elasticidad y la profundidad del LOB se vieron afectadas, incrementando los costes de transacción para los participantes. Aunque la pendiente del LOB ("*slope*") no es la variable principal en este capítulo, se introduce como un proxy secundario de la elasticidad y capacidad de resiliencia del libro de órdenes limitadas, sirviendo de base para análisis posteriores.

[13] En la tesis se usará indistintamente SSR y SSB para hacer referencia al periodo de restricción o veto de posiciones netas de venta de acciones en corto.

Para descubrir las relaciones entre negociación informada, consenso en las creencias acerca del valor y volatilidad, en el tercer capítulo se explora la relación entre el *trading* informado, la liquidez y la volatilidad de mercado a partir de datos de alta frecuencia, haciendo hincapié en la distribución de creencias en el libro de órdenes y en los efectos de la prohibición de ventas en corto aplicada a determinados valores del IBEX-35 durante la crisis de la COVID-19. Para ello, se combinan distintos enfoques econométricos (modelos de panel, VAR, análisis de causalidad de Granger, Tablas de Probabilidad Condicional) con métricas de asimetría informativa como VPIN y su variación, así como con la pendiente del LOB como indicador del consenso en torno al precio.

Los resultados muestran, en primer lugar, que el trading informado tiende a fomentar la alineación de expectativas —aunque también reduce la profundidad en el LOB— y, en segundo lugar, que el consenso medido por la pendiente del LOB emerge como un predictor más robusto de la volatilidad futura que las propias métricas de trading informado. Este hallazgo cobra especial relevancia en mercados con menor liquidez, donde la concentración de órdenes alrededor del precio se torna fundamental para estabilizar la rentabilidad. En última instancia, el capítulo contribuye a entender cómo la presencia de operadores informados y las condiciones de liquidez influyen en la formación de precios y la volatilidad, ofreciendo claves para la gestión de riesgos y la formulación de políticas regulatorias en escenarios de alta inestabilidad.

Tras los resultados prometedores de la pendiente del LOB ("*slope*") como medida relevante de consenso de las creencias del valor y con el objetivo de desagregar el impacto de estos componentes en medidas clave de la calidad del mercado, como la volatilidad, la liquidez y los costes de selección adversa, en el cuarto capítulo se analizan sus componentes para comprender las dinámicas del mercado. El análisis se realiza mediante la descomposición de la pendiente en dos elementos distintos pero interconectados: un componente permanente, relacionado con cambios estructurales de largo plazo y la incorporación de información eficiente al mercado, y un componente transitorio, asociado a fluctuaciones de corto plazo impulsadas principalmente por actividades de *trading* no informado, como la provisión algorítmica de liquidez y el *feedback trading*.

El componente permanente de la pendiente del LOB refleja la información eficiente integrada en el mercado. Este componente representa el consenso colectivo entre los negociadores informados sobre el valor intrínseco de un activo, funcionando como un factor estabilizador en el mercado. Al incorporar información relevante de largo plazo, este aspecto de la pendiente acerca los precios de los activos a sus valores fundamentales, mejorando la eficiencia del mercado y reduciendo la incertidumbre. Los hallazgos empíricos destacan este rol estabilizador, revelando que el componente permanente mitiga la volatilidad intradía y fomenta una mayor profundidad de la liquidez al anclar las expectativas y reducir la dispersión de creencias entre los participantes del mercado.

Por otro lado, el componente transitorio captura dinámicas efímeras impulsadas por comportamientos de *trading* de corto plazo. Estas dinámicas suelen ser reactivas y no fundamentales, originadas en actividades como el *trading* algorítmico, tanto HFT como por ajustes de liquidez. Si bien estas operaciones contribuyen al funcionamiento inmediato del mercado, también amplifican la volatilidad y erosionan la liquidez a corto plazo. Los resultados indican que las fluctuaciones transitorias introducidas por este componente incrementan los costes de selección adversa, elevando los riesgos y las ineficiencias asociadas al *trading* en estas condiciones.

Este capítulo también introduce un análisis pionero sobre la capacidad predictiva del componente transitorio en relación con los rendimientos intradía. Los resultados sugieren que este componente posee un poder predictivo modesto pero significativo en términos de rentabilidad en el corto plazo. Este hallazgo resulta particularmente relevante tanto para los negociadores de alta frecuencia como para los reguladores del mercado, ya que resalta la compleja interacción entre las dinámicas transitorias del flujo de órdenes y los movimientos de precios a lo largo del día de negociación.

En conjunto, los hallazgos de esta tesis tienen un interés significativo tanto para los reguladores, quienes pueden evaluar la eficacia de medidas como la prohibición de ventas en corto, como para los participantes del mercado, que pueden desarrollar nuevas medidas para control de riesgo y que buscan optimizar estrategias de inversión y cobertura en escenarios de estrés financiero extremo.

5.1 Resumen y conclusiones del capítulo 2: Calidad del mercado y prohibición de las ventas en corto durante la pandemia de COVID-19: un enfoque de datos de alta frecuencia.

Introducción, revisión de la literatura e hipótesis de investigación

La prevalencia del trading algorítmico (TA) y, en particular, de la actividad de alta frecuencia (HFT), ha crecido significativamente en los últimos años (Baron et al., 2019; Borch, 2016; Cvitanic & Kirilenko, 2012; Dall'Amico et al., 2019; Golub et al., 2012; Hasbrouck & Saar, 2013; Jovanovic & Menkveld, 2012). La literatura financiera ha analizado en profundidad los parámetros de calidad del mercado y su relación con el TA y HFT, aunque los hallazgos relacionados con la volatilidad, liquidez, eficiencia de precios y costes de transacción siguen siendo inconcluyentes respecto al impacto y comportamiento del HFT (Virgilio, 2019). Sin embargo, puede concluirse que las tecnologías y las estrategias emergentes de TA y HFT han transformado significativamente la microestructura de los mercados (O'Hara, 2015).

La Directiva MiFID II establece claramente las definiciones de TA y HFT en un mercado financiero. El TA es descrito como "la negociación de instrumentos financieros en la que un algoritmo informático determina automáticamente parámetros individuales de las órdenes, como si iniciar la orden, el momento, el precio o la cantidad de la misma, o cómo gestionarla tras su envío, con intervención humana limitada o nula" (artículo 4(1)(39), MiFID II). Por otro lado, el HFT se define como "una técnica de TA caracterizada por: (a) infraestructuras diseñadas para minimizar latencias, incluyendo co-ubicación, alojamiento en proximidad o acceso electrónico directo de alta velocidad; (b) determinación del sistema para la iniciación, generación, enrutamiento o ejecución de órdenes sin intervención humana; y (c) altas tasas intradía de mensajes" (artículo 4(1)(40), MiFID II).

El impacto de la crisis del COVID-19 en los mercados financieros presentó una oportunidad única para analizar las medidas intervencionistas en un contexto de mercados altamente automatizados. Durante la primera ola de la pandemia, la Autoridad Europea de Valores y Mercados (ESMA) impulsó a seis autoridades europeas a prohibir las ventas en corto en las acciones más líquidas. En España, la Comisión Nacional del Mercado de Valores (CNMV) implementó esta prohibición el 17 de marzo de 2020, basada en los artículos 23 y 24 del Reglamento Europeo de Ventas en Corto (Reglamento 236/2012), debido a la "extrema volatilidad que afectaba los mercados de valores europeos, incluyendo España" (CNMV

Restricción de Cortos, 2020.). Esta medida se levantó el 18 de mayo de 2020 a medida que mejoraron las condiciones del mercado.

La prohibición de ventas en corto (SSR, por sus siglas en inglés) proporciona un marco idóneo para analizar su impacto en la calidad del mercado. Aunque el mercado español no se clasifica como un lugar de negociación HFT, cuenta con infraestructuras de baja latencia y servicios de co-ubicación, lo que lo convierte en un entorno relevante para estudiar el impacto de la SSR en la microestructura y calidad del mercado.

El objetivo principal de este capítulo es analizar las medidas de calidad del mercado y la prevalencia del HFT en los valores del IBEX 35 durante cuatro subperiodos: el período pre-pandemia, el inicio de la crisis por COVID-19, la ventana de prohibición de ventas en corto y la fase inicial de desescalada. Utilizando un conjunto de datos con actualizaciones *tick* a *tick* del libro de órdenes (LOB), este estudio identifica los cambios en la microestructura y evalúa el impacto de la SSR en un contexto automatizado. Se emplean proxies basados en tráfico de mensajes para identificar la actividad de alta frecuencia, revisando medidas de liquidez, eficiencia de precios y volatilidad, y se aplica un modelo de panel para analizar causalidad de Granger entre la volatilidad realizada de 1 minuto y la pendiente del LOB. Por último, en este capítulo se formulan las siguientes hipótesis:

H1: La efectividad de las restricciones a las ventas en corto para reducir la volatilidad extrema es limitada.

H2: La calidad del mercado se deteriora durante el período de la SSR.

H3: La prohibición de ventas en corto reduce drásticamente la actividad de alta frecuencia.

H4: El deterioro del libro de órdenes no es simétrico; afecta más al lado vendedor.

H5: La actividad de alta frecuencia y la pendiente del LOB causan volatilidad realizada.

Datos, metodología y resultados del capítulo 2

A continuación, se integran todos los datos, metodologías (incluyendo las pruebas de contraste de medianas por cuartiles, Diferencias en Diferencias (DID), VECM con cointegración de variables I (1) y análisis de impulso-respuesta) y resultados obtenidos en el estudio. No incluiremos la notación matemática e invitamos a lector a consultarla en el capítulo 2, de modo que se facilite la lectura sin perder detalle de los cálculos.

Se utilizaron bases de datos *tick* a *tick* que contienen tanto los mensajes del libro de órdenes (LOB) como información de las transacciones de acciones ordinarias negociadas en la plataforma electrónica del mercado español. Los datos fueron proporcionados por BME MarketData. El periodo de análisis abarca 184 días, divididos en cuatro ventanas temporales: Pre-pandemia (W0), del 20 de noviembre de 2019 al 20 de enero de 2020. Crisis pandémica (W1), del 21 de enero de 2020 al 17 de marzo de 2020. Prohibición de posiciones cortas (W2), del 18 de marzo de 2020 al 18 de mayo de 2020. Desescalada (W3), del 19 de mayo de 2020 al 13 de julio de 2020.

La prohibición parcial de cortos del día 13 de marzo se considera puntual y, por no haberse comunicado con mayor alcance, no se incluyó en W2. La muestra analizada consta de 35 valores que componen el IBEX 35, subdivididos en cuatro cuartiles según la capitalización bursátil a diciembre de 2019.

Los datos del LOB, proporcionados por BME DATA FEED Services, incluyen las veinte mejores posiciones de compra y de venta, que se actualizan con cada nuevo mensaje que llega al Sistema de Interconexión Bursátil Español (SIBE). Para cada nivel del LOB y para cada activo, se dispone de las cotizaciones, el número de órdenes visibles y la profundidad (cantidad de acciones disponibles). Cada operación ejecutada se puede vincular con exactitud con los mensajes y modificaciones del libro de órdenes, pues se genera un número de secuencia único para cada orden de compra, venta, cancelación o modificación que llega al SIBE. No se facilita información sobre profundidad oculta ni órdenes iceberg. Dado que los primeros y últimos minutos de negociación son relevantes para este trabajo, se incluyen también los mensajes de pre-subasta y subasta.

Medidas de actividad algorítmica y de negociación de alta frecuencia (HFT)

La identificación exacta de la presencia de HFT es compleja, pues no existe un método único que dé una estimación exacta del porcentaje de negociación HFT. Desde MiFID II (2018), BME DATA FEED Services facilita información detallada del LOB y de las transacciones, pero no incluye etiquetas que identifiquen a las HFT; sí dispone de un indicador (Algorithmic Trade Indicator) que marca si la orden fue introducida por un algoritmo. Por ello, se establecen proxys indirectos de actividad HFT que se calculan combinando el tráfico de mensajes y la negociación.

La regulación (EU) 2017/565 (Artículo 19) entiende por alta frecuencia de mensajes el envío de 2 o más mensajes por segundo para un solo instrumento, o 4 o más mensajes por segundo para todos los instrumentos, siempre que exista mercado líquido. Como no se dispone de datos de bróker para diferenciar quién rebasa ese umbral, se analizan los cambios en el número de mensajes por segundo y por operación. El Smart SIBE, vigente desde 2012, ofrece servicios de proximidad al SIBE para minimizar latencias, facilitando la negociación de alta frecuencia en el mercado español.

Las medidas que se emplean incluyen el flujo de mensajes, la ratio de mensajes por operación y los cambios frecuentes en el precio medio (MIDPRICE). También se usa la ratio de mensajes por cada 100 euros negociados. Un aumento de estas medidas se asocia a mayor presencia de negociadores de alta frecuencia. A continuación, se detallan las medidas utilizadas:

Porcentaje de trading algorítmico (ALGO_TR). Se calcula tomando el número de órdenes enviadas por algoritmos (flag AlgorithmicTradeIndicator) y dividiéndolo entre el total de órdenes enviadas, multiplicando luego por 100 para expresarlo en porcentaje.

Tamaño medio de la operación (AVGSIZE). Se obtiene tomando el volumen total (en acciones) que se negocia a lo largo del día y dividiéndolo entre el número de operaciones ejecutadas en esa jornada, resultando un promedio de acciones por operación.

Mensajes por segundo (MESSAGES_SEC). Se contabiliza cuántos mensajes (órdenes, cancelaciones, modificaciones) llegan al LOB y se divide por el número de segundos de la sesión bursátil, reflejando la intensidad de actividad en el libro.

Mensajes por operación (MESSAGES_TRADE). Se calcula dividiendo el número total de mensajes recibidos en el LOB por la cantidad de operaciones ejecutadas en ese mismo periodo. Es otra forma de captar la intensidad de actualizaciones por cada transacción efectiva.

Cambios en el precio intermedio (MIDPRICE_CHANGES). Se mide cuántas veces varía el precio que está en la mitad entre la mejor cotización de compra (BID) y la mejor cotización de venta (ASK). Solo se cuentan los cambios cuando el nuevo precio intermedio difiere del inmediatamente anterior.

Mensajes por 100 euros negociados (MESSAGES_€100). Se toma el total de mensajes del LOB y se divide entre el importe monetario total negociado en el día; luego se normaliza multiplicando o dividiendo para obtener la ratio por cada 100 euros.

Medidas de liquidez

La liquidez constituye un indicador crucial de la calidad de mercado (Ma et al., 2018). Se han calculado parámetros como el volumen negociado, el *spread* entre el mejor precio de compra y de venta, el *spread* relativo (*spread* dividido entre el precio medio), la profundidad del LOB (sumando los veinte mejores niveles tanto de compra como de venta), y la ratio de Amihud. A continuación, se detallan las medidas utilizadas:

Volumen medio negociado (AVGVOL). Se considera la negociación total diaria de acciones. En un solo día puede estimarse simplemente como el total negociado de ese activo.

Spread (SPREAD). Se computa restando el mejor precio de compra al mejor precio de venta. Refleja la diferencia que afronta un inversor que quiera comprar (pagando la mejor venta) o vender (recibiendo la mejor compra).

Spread relativo (RELATIVE_SPREAD). Se divide el doble del *spread* anterior entre la suma de la mejor compra y venta. Esto dimensiona el coste de transacción en términos porcentuales del precio.

Profundidad en LOB (DEPTH). Se miden las cantidades (acciones) acumuladas a lo largo de los veinte primeros niveles de compra y de los veinte primeros de venta, y luego se hace el promedio entre ambas cifras, describiendo la liquidez disponible en el LOB.

Ratio de Amihud (AMIHUD). En cada operación, se toma el valor absoluto del retorno (por ejemplo, el cambio porcentual de precio respecto a la operación previa) y se divide por el volumen monetario de la operación. Al promediar estos cocientes intradía se obtiene un indicador de cuánto cambia el precio en función del volumen negociado. Cuanto más elevado, menor es la liquidez.

Los contrastes estadísticos se realizan sobre las medianas diarias de estas distribuciones debido a que los datos no siguen la normalidad. Se aplican test no paramétricos pareados (prueba de la t no paramétrica y prueba de la mediana de Wilcoxon).

Resiliencia del LOB y eficiencia de precios

Para las medidas de la resiliencia del LOB y la eficiencia en la formación del precio usamos las siguientes medidas con datos de alta frecuencia:

Pendiente del LOB (SLOPE), a partir del método descrito por (Næs & Skjeltorp, 2006), se estima como el grado de concentración o dispersión de las órdenes en el libro. Para cada escalón en el lado de la compra y de la venta, se analiza cuánta variación de precio supone y cuántas acciones hay acumuladas. Una mayor pendiente sugiere que los volúmenes se concentran cerca de los mejores precios; una pendiente reducida indica más dispersión de órdenes.

Posteriormente, se compara la pendiente media de la parte compradora con la de la parte vendedora. Dicha comparación se expresa como un cociente (ELOB) que muestra la *asimetría entre la demanda y la oferta*: si está por encima de 1, el lado comprador puede estar más "inclinado" (más concentrado), mientras el vendedor podría dispersarse o viceversa.

Volatilidad realizada tanto a un minuto (RVol_1m) como a 30 minutos (RVol_30min). La primera se obtiene tomando todos los rendimientos de cada minuto y calculando su desviación estándar; la segunda se obtiene análogamente, pero con datos de 30 minutos. Si el mercado fuera eficiente, la volatilidad a 1 minuto, escalada a 30 minutos multiplicándola por la raíz de 30, debería ser similar a la volatilidad directamente medida a 30 minutos. Cuando hay discrepancias, podrían deberse a ineficiencias o al ruido de alta frecuencia.

El coeficiente de volatilidad (COEF_VOL) resulta de comparar la volatilidad a 1 minuto escalada frente a la de 30 minutos reales. Si la ratio se desvía mucho de 1, indica divergencias respecto al modelo ideal de mercado eficiente.

La *autocorrelación* (AUTOCORR) de primer orden a un minuto se calcula correlacionando los rendimientos de un minuto con los de su minuto siguiente. A frecuencias muy altas, con precios con componente de ruido, suele aparecer autocorrelación negativa (ROLL, 1984).

Dado que existen patrones intradía típicos (formas en "U" en liquidez y volatilidad), y también efectos día de la semana, se comprobó la influencia de *dummies* para martes, miércoles, jueves y viernes (considerando el lunes en la intersección). El resultado mostró poca significancia de ese factor en la mayoría de las variables, excepto casos puntuales en los que viernes o jueves adquieren relevancia.

Diferencia en diferencias (DID), modelo de efectos fijos en panel y Análisis de causalidad en panel (VECM y test de Dumitrescu y Hurlin)

Para estimar el efecto de la restricción de cortos en la volatilidad, se toma la volatilidad realizada a 1 minuto del IBEX 35 (grupo tratado) y se compara contra la volatilidad implícita VDAX de Alemania (grupo control, donde no hubo prohibición). Tras escalar el VDAX a frecuencia de un minuto, la metodología DID aísla la parte de la volatilidad debida a la prohibición de cortos de la parte que se explica por la propia incertidumbre de la COVID-19.

Para cada medida, se regresa su valor diario frente a *dummies* de los cuatro subperiodos (W0, W1, W2 y W3), con el fin de aislar cómo cada fase afectó a la liquidez, la volatilidad y la actividad HFT, entre otras variables.

Se evalúa si existen relaciones de causalidad de Granger entre las variables, en particular entre la volatilidad realizada a 1 minuto (REALIZED_VOL) y un proxy de actividad HFT (mensajes por operación), así como entre la volatilidad realizada y la pendiente (SLOPE). Para ello, se examina la presencia de raíz unitaria y estacionariedad en panel (Hadri, 2000). Si ambas variables son I(1) y cointegran, se aplica el test de Johansen para hallar relaciones de largo plazo. Se estiman entonces VECM (modelos de corrección de error vectorial) para analizar la causalidad de corto y largo plazo. Se examinan las funciones impulso-respuesta para ver cómo la volatilidad responde ante un shock en la actividad HFT o en la pendiente del LOB.

Resultados principales

En la transición del periodo pre-COVID (W0) a la crisis (W1), se observó un marcado aumento de las medidas asociadas a negociación de alta frecuencia (mensajes por segundo, cambios en el precio intermedio, etc.), lo que sugiere mayor prevalencia de negociadores algorítmicos y HFT en un entorno de volatilidad creciente. Al entrar en vigor la prohibición de ventas en corto (W2), dichos indicadores se redujeron de forma significativa, sugiriendo que parte importante de la actividad HFT cesó o disminuyó al restringirse las posiciones bajistas y, por ende, ciertas estrategias. Una vez levantada la prohibición (W3), los indicadores de alta frecuencia se recuperaron, aunque no siempre al nivel previo.

En referencia a los resultados de la liquidez, incrementos significativos de la ratio de Amihud mostraron que la liquidez se deterioró fuertemente con la prohibición. El *spread* y el *spread* relativo también se ampliaron durante la prohibición, mientras que la profundidad del LOB se redujo de manera pronunciada. Esto confirma que el veto a las posiciones cortas puede drenar parte de la liquidez, al privar al mercado de participantes que contribuyen con órdenes limitadas o que asumen riesgo vendiendo en corto para ofrecer contrapartida.

Para la volatilidad, aplicando la metodología DID, se vio que, sin la restricción, la volatilidad española habría sido aún mayor, por lo que la prohibición cumplió en parte el objetivo de contener la volatilidad. No obstante, la volatilidad realizada a 1 minuto sí experimentó un fuerte aumento en W1 y se mantuvo alta en W2. Es decir, aunque el veto mitigó parcialmente los picos de volatilidad, no evitó el entorno turbulento del mercado.

En relación con la eficiencia de precios; la pendiente del LOB (SLOPE) se redujo drásticamente durante la prohibición, denotando mayor dispersión de la oferta frente a una demanda más concentrada. Al levantarse la prohibición, volvió a niveles más equilibrados, aunque sin llegar en todos los casos a la situación anterior. Se apreció también un deterioro en la autocorrelación y en el coeficiente de volatilidad, lo que sugiere menor eficiencia de los precios durante la prohibición (rentabilidades más predecibles o más afectadas por ruido).

Las pruebas VECM mostraron, por un lado, que la actividad HFT (mensajes por operación) causa unidireccionalmente la volatilidad a 1 minuto: cuando aumenta la actividad de este tipo, la volatilidad tiende a reaccionar, primero con una ligera reducción instantánea durante los primeros 1-2 minutos, seguida de una exacerbación que se manifiesta entre los 2 y 8 minutos. Finalmente, en torno al minuto 10, la volatilidad comienza a estabilizarse, corrigiendo aproximadamente un 10 % de la desviación respecto al equilibrio de largo plazo en cada minuto. Por otro lado, la pendiente del LOB y la volatilidad se causan bidireccionalmente. Una mayor pendiente puede reducir inicialmente la volatilidad de manera significativa en los primeros 4 minutos, mientras que choques de volatilidad pueden, a su vez, reconfigurar la pendiente del libro de órdenes de forma persistente, con un impacto que se extiende más allá de los 10 minutos y evidencia un ajuste más lento que el de la volatilidad.

Las funciones impulso-respuesta confirman que la volatilidad intradía es muy sensible tanto a la actividad de alta frecuencia como a la estructuración de órdenes en el LOB. Ambos factores interactúan de forma dinámica: la actividad HFT genera impactos más inmediatos y de corto plazo sobre la volatilidad, mientras que la pendiente del LOB, aunque más lenta en su recomposición, refleja una interacción prolongada que puede generar ineficiencias temporales en los mercados. Estas diferencias en los plazos de ajuste destacan la necesidad de considerar los impactos tanto inmediatos como persistentes en la dinámica de precios y órdenes intradía.

Conclusiones

El análisis intradía con datos de alta frecuencia durante la prohibición de posiciones cortas en el mercado español por la COVID-19 evidencia que esta medida logró moderar parcialmente la volatilidad extrema, pero a costa de un deterioro significativo en la liquidez y en la eficiencia de precios. La ampliación del *spread*, la reducción de profundidad del libro de órdenes (LOB) y el aumento de la autocorrelación negativa en la rentabilidad reflejan los altos costes implícitos que estas restricciones generan para los gestores e inversores en un contexto intradía.

Aunque la prohibición de ventas en corto redujo parcialmente la volatilidad intradía, no logró eliminar la inestabilidad derivada de caídas abruptas durante el periodo de crisis. La actividad de alta frecuencia (HFT), que incrementa la volatilidad realizada a corto plazo, disminuyó durante la prohibición, regresando a niveles previos una vez que la restricción fue levantada. Esto confirma que los negociadores de alta frecuencia dependen en parte de estrategias asociadas a las ventas cortas, y su ausencia afecta la dinámica intradía del mercado.

La restricción de posiciones cortas mantuvo los precios alejados de los valores fundamentales, deteriorando el equilibrio entre precio y valor. Esto se refleja en una pendiente del LOB más baja y en una mayor dispersión de las órdenes de venta en comparación con las de compra. Dichos efectos desaparecen una vez eliminadas las restricciones, destacando la asimetría de su impacto en ambos lados del mercado.

En términos de eficiencia de precios, las restricciones exacerbaron la volatilidad y aumentaron la ineficiencia, generando costes de transacción más altos y dificultando la negociación automatizada. Los resultados muestran que las medidas regulatorias, como la prohibición de cortos, pueden tener efectos contraproducentes, penalizando a los inversores con costes implícitos elevados y deteriorando la calidad del mercado. Aunque estas medidas buscan proteger al inversor, en la práctica pueden facilitar comportamientos especulativos o desestabilizadores al reducir la liquidez y alterar la relación entre precios y valores fundamentales.

Desde un punto de vista metodológico, sería interesante profundizar en el análisis de estas dinámicas. Por ejemplo, emplear un enfoque dinámico como el de Tilfani et al. (2021) permitiría visualizar la evolución temporal de las relaciones entre las variables analizadas en lugar de obtener cifras aisladas para cada subperiodo. Además, agrupar los activos según la prevalencia de HFT/AT en cada uno de ellos podría revelar diferencias en el deterioro de las medidas de calidad del mercado, como sugieren Chakrabarty y Pascual (2022). También podría ser útil dividir las jornadas bursátiles en franjas horarias para analizar si los efectos de las restricciones varían entre momentos de alto y bajo volumen de negociación.

Finalmente, futuras investigaciones podrían explorar fenómenos como el efecto de momentum intradía, ya observado en otros mercados como el de divisas, para comprender mejor las dinámicas del mercado continuo español durante este periodo excepcional.

5.2 Resumen y conclusiones del capítulo 3: El papel de la negociación informada y el consenso en el LOB sobre la volatilidad del mercado.

Introducción y objetivos de la investigación

La negociación informada es un tema de gran relevancia debido a su impacto significativo en múltiples aspectos de los mercados financieros, incluyendo la dinámica de mercado, los movimientos de precios, la integración de la información y la calidad del mercado. Se entiende como el uso de información no pública y materialmente relevante por parte de los agentes financieros para tomar decisiones de negociación que influyen en los precios de los activos. La literatura ha demostrado que la presencia de *trading* informado en los mercados puede acelerar la incorporación de información específica de una empresa a los precios, pero al mismo tiempo, puede ralentizar la integración de la información a nivel de mercado debido a los costes de transacción asociados a la asimetría de información. Además, el *trading* informado afecta la calidad informativa del mercado y ha sido objeto de análisis en el ámbito de la microestructura del mercado y las políticas regulatorias.

Una de las principales preocupaciones de la literatura ha sido su relación con la volatilidad del mercado. Mientras algunos estudios sugieren que la negociación informada incrementa la volatilidad al generar un desequilibrio entre agentes informados y no informados, otros argumentan que este tipo de negociación reduce la volatilidad en mercados con alta capitalización, al permitir una integración más rápida y eficiente de la información. Sin embargo, la relación entre ambas variables no es concluyente, ya que puede verse influida por factores como la asimetría de información y el nivel de liquidez del mercado. En este contexto, comprender los mecanismos a través de los cuales la negociación informada afecta la volatilidad resulta esencial para evaluar la estabilidad del mercado y su eficiencia informativa.

Uno de los indicadores más utilizados para cuantificar la actividad del trading informado y la asimetría de información es la probabilidad de negociación informada sincronizada con el volumen (*Volume-Synchronized Probability of Informed Trading,* conocida como *VPIN*), una métrica dinámica del desequilibrio del flujo de órdenes que ha sido empleada en la literatura para anticipar eventos extremos, como los "*flash crashes*" en mercados de alta frecuencia. No obstante, su validez ha sido debatida, ya que se ha encontrado que altos valores de VPIN están correlacionados con el sentimiento del inversor y con problemas de liquidez que pueden exacerbar la volatilidad. En este sentido, se ha utilizado la toxicidad del mercado, medida a través de umbrales en la función de distribución acumulada (CDF) de la VPIN, para anticipar momentos de volatilidad extrema.

El impacto de la negociación informada en la liquidez del mercado es otro aspecto fundamental. En situaciones de información asimétrica, los agentes con información privilegiada pueden optar por ejecutar órdenes de mercado para beneficiarse de su ventaja informativa, lo que tradicionalmente se ha asociado con el consumo de liquidez. Sin embargo, estudios recientes han demostrado que los *traders* informados también pueden utilizar órdenes limitadas estratégicamente, lo que implica que su impacto sobre la liquidez puede ser más complejo de lo previamente considerado. En particular, la estructura del libro de órdenes (LOB) ofrece información detallada sobre las intenciones de los participantes del mercado, y métricas como la pendiente del LOB han sido propuestas como indicadores del grado de consenso sobre el valor fundamental de un activo.

Desde una perspectiva de microestructura del mercado, la pendiente del LOB captura la relación entre la profundidad del libro de órdenes y la distancia de las órdenes respecto al precio de mercado. Un LOB con mayor pendiente indica un alto grado de consenso entre los participantes, mientras que una pendiente baja sugiere una mayor dispersión de creencias y, por ende, una mayor incertidumbre en la valoración de los activos. Se ha argumentado que una mayor dispersión en el LOB puede ser percibida por los creadores de mercado como un indicador de volatilidad esperada, lo que los lleva a ajustar sus estrategias.

El impacto de la negociación informada en la liquidez y la volatilidad podría ser distinto dependiendo del tamaño de la empresa y el nivel de cobertura informativa. En acciones de gran capitalización, donde la disponibilidad de información es mayor y los analistas proporcionan evaluaciones constantes del valor fundamental, se espera que la negociación informada incremente la eficiencia del mercado y fomente un mayor consenso. En cambio, en empresas de mediana y pequeña capitalización, donde la liquidez es más limitada y la asimetría de información es mayor, el efecto de la negociación informada podría exacerbar la volatilidad y reducir la estabilidad del mercado.

Este estudio persigue tres objetivos fundamentales. En primer lugar, analiza el efecto de la negociación informada sobre el consenso de creencias en el libro de órdenes y su relación con la liquidez externa (medida por el *spread* relativo) y la liquidez interna (medida por la profundidad del LOB). En segundo lugar, examina de qué manera la negociación informada, el consenso en el LOB y la volatilidad del mercado se influyen mutuamente, tanto de forma bidireccional como unidireccional, a través de pruebas de causalidad de Granger. Finalmente, valora la capacidad de la pendiente del LOB para complementar o superar al VPIN en la predicción de la volatilidad, incorporando tanto variaciones de corto plazo de la negociación informada como periodos de elevada actividad de inversores informados, capturados mediante la CDF del VPIN.

En función de este planteamiento, la primera hipótesis (H1a) postula que la negociación informada mejora el consenso acerca del valor fundamental en el LOB, mientras que la segunda (H1b) sostiene que dicha negociación consume tanto la liquidez externa como la interna. La hipótesis (H2a) evalúa si la negociación informada causa positivamente el consenso en acciones con mayor cobertura, y (H2b) propone una relación bidireccional negativa entre consenso en el LOB y volatilidad. Por otro lado, la hipótesis (H2c) sugiere que la negociación informada reduce la volatilidad en condiciones normales, pero puede incrementarla en momentos extremos al afectar la disponibilidad de liquidez. Por último, la hipótesis (H3) considera que la dispersión de creencias en el LOB (medida por la pendiente del LOB) es un predictor más sólido de la volatilidad que el propio trading informado.

Este análisis adquiere especial relevancia durante la pandemia de COVID-19, cuando los mercados financieros en general —y el IBEX 35 en particular— experimentaron volatilidades sin precedentes en un contexto de elevada incertidumbre, asimetría de información y restricciones regulatorias. Estas condiciones ofrecen una oportunidad única para investigar la interacción entre trading informado, liquidez y consenso del mercado, así como su impacto en la formación de precios y la volatilidad.

Finalmente, el uso de relojes de volumen para trabajar con datos intradía, junto con técnicas de alta frecuencia y datos *tick* a *tick* que abarcan todos los niveles del LOB, facilita un análisis minucioso de la dinámica del mercado. Al estudiar cómo actúan los agentes informados en situaciones de estrés, la investigación aporta evidencia empírica para impulsar la eficiencia y la estabilidad de los mercados, generando recomendaciones que promuevan una mayor resiliencia durante episodios de volatilidad extrema.

A lo largo del capítulo se explora en detalle la relación entre la negociación informada, la formación del consenso en el LOB y la volatilidad del mercado, prestando especial atención a los efectos diferenciados según la capitalización bursátil de los activos analizados. El capítulo se estructura de la siguiente manera: en primer lugar, se presenta una revisión de la literatura relevante; posteriormente, se describen los datos utilizados y la metodología aplicada; en la sección de resultados, se exponen los principales hallazgos del estudio, y finalmente, se presentan las conclusiones y las implicaciones de los resultados obtenidos.

Revisión de la literatura

El análisis de la volatilidad debida a la información y la volatilidad inducida por la liquidez es esencial para comprender la compleja interacción entre estas dos fuentes de inestabilidad en los mercados financieros. La volatilidad causada por información surge cuando nueva información modifica la percepción del valor de los activos, mientras que la volatilidad inducida por liquidez se debe a cambios en la oferta y demanda de activos sin que exista otra nueva información. Ambas formas de volatilidad pueden coexistir y amplificarse mutuamente, especialmente en períodos de tensión en los mercados, cuando la escasez de liquidez limita la capacidad de los participantes para ajustar los precios de manera eficiente (Drechsler et al., 2021). Esta interacción es particularmente relevante en el contexto de la negociación informada, ya que los agentes informados pueden influir en la estabilidad del mercado y en la dirección de los ajustes de precios, afectando así a la volatilidad general (Hameed et al., 2010).

Diversos estudios han explorado la relación entre la información privada y la volatilidad del mercado, mostrando que la influencia de la negociación informada varía según la capitalización bursátil de los activos. En mercados con alta capitalización y amplia liquidez, el impacto de la negociación informada puede ser absorbido sin generar grandes fluctuaciones en los precios. Sin embargo, en activos con menor capitalización y liquidez fragmentada, la presencia de agentes informados tiende a amplificar la volatilidad, ya que la escasez de liquidez impide que el mercado se ajuste de manera eficiente a la nueva información (Jena et al., 2021; Salisu et al., 2018).

Para medir la presencia de negociación informada y su impacto en la volatilidad, una de las herramientas más utilizadas en la literatura es la medida VPIN. Este indicador cuantifica la probabilidad de que los volúmenes negociados sean impulsados por agentes informados, proporcionando una medida dinámica del desequilibrio en el flujo de órdenes (Easley et al., 2012). En entornos de alta frecuencia, VPIN se ha empleado como un indicador adelantado de eventos extremos, como caídas abruptas del mercado o episodios de iliquidez. Sin embargo, su aplicación ha sido objeto de debate, ya que algunos estudios sugieren que altos valores de VPIN pueden estar correlacionados con problemas de toxicidad del mercado y reducciones abruptas de la liquidez (Rzayev & Ibikunle, 2019).

Otra variable fundamental para analizar el impacto de la negociación informada en los mercados es la pendiente del libro de órdenes (LOB). Este indicador mide la distribución de las órdenes en distintos niveles de precios y se ha observado que refleja el consenso entre los participantes del mercado. Una pendiente del LOB elevada indica una mayor concentración de órdenes en torno a ciertos precios, lo que sugiere un mayor consenso sobre el valor fundamental del activo y una menor volatilidad esperada (Jain & Jiang, 2014). En contraste, una pendiente más plana implica una mayor dispersión de órdenes y mayor incertidumbre, lo que suele traducirse en una volatilidad más elevada.

Desde una perspectiva de microestructura de mercado, la pendiente del LOB también ha sido interpretada como una medida de la elasticidad del mercado ante cambios en los precios. Un libro de órdenes con una pendiente pronunciada permite ajustes de precio más suaves y predecibles, ya que los participantes del mercado convergen en una interpretación similar del valor de los activos. Por el contrario, cuando la pendiente del LOB es baja y la liquidez está fragmentada, la formación de precios puede volverse errática y ser susceptible a movimientos abruptos (Wang et al., 2020).

La combinación de la medida VPIN y la pendiente del LOB ofrece un marco sólido para evaluar cómo la negociación informada afecta al comportamiento del mercado. Mientras que VPIN proporciona una medida del grado de desequilibrio en el flujo de órdenes, la pendiente del LOB captura la forma en que los participantes distribuyen sus creencias sobre el valor de los activos. En mercados de alta frecuencia, donde la liquidez puede desaparecer rápidamente, la interacción entre estas dos variables es clave para comprender la estabilidad del mercado y anticipar episodios de volatilidad extrema.

Finalmente, la literatura existente destaca que el impacto de la negociación informada en la volatilidad del mercado es un fenómeno complejo y dependiente del contexto. En mercados con alta liquidez y participación de analistas, la información privada se incorpora rápidamente a los precios, favoreciendo la estabilidad del mercado. Sin embargo, en entornos con menor liquidez y alta asimetría de información, la negociación informada puede exacerbar la volatilidad y generar desajustes en la formación de precios (Cenesizoglu et al., 2014; Frey & Sandås, 2017; Kang & Zhang, 2013). Comprender estas dinámicas es esencial para diseñar estrategias que permitan mitigar los efectos adversos de la negociación informada sobre la estabilidad del mercado.

Datos y medidas

El estudio se basa en una muestra de 18 acciones pertenecientes al índice IBEX 35, seleccionadas en función de su capitalización bursátil y volumen de negociación para representar tres categorías: gran capitalización, mediana capitalización y pequeña capitalización. Siguiendo la metodología de Abad y Yagüe (2012), se conformaron tres carteras de seis valores cada una, asegurando la representatividad de cada segmento. Las acciones de gran capitalización incluyen: Amadeus IT Group (AMS), Repsol YPF (REP), Telefónica (TEF), Banco Bilbao Vizcaya Argentaria (BBVA), Caixabank (CABK) e Iberdrola (IBE). Para la mediana capitalización se seleccionaron: Gamesa Corporación Tecnológica (SGRE), ACS (ACS), Red Eléctrica de España (REE), Banco de Sabadell (SAB), Mapfre (MAP) e International Consolidated Airlines Group (IAG). Finalmente, la categoría de pequeña capitalización está compuesta por: Acerinox (ACX), Gestevisión Telecinco (TL5), CIE Automotive (CIE), Viscofan (VIS), Indra Sistemas (IDR) y Bankia (BKIA).

La ventana temporal del estudio abarca desde el 20 de noviembre de 2019 hasta el 13 de julio de 2020, un período que cubre distintas fases de la crisis de COVID-19. Se definen cuatro períodos diferenciados: el período pre-pandemia (W0) del 20 de noviembre de 2019 al 20 de enero de 2020; la caída del mercado por la pandemia (W1) del 21 de enero al 17 de marzo de 2020; la prohibición de ventas en corto (W2) del 18 de marzo al 18 de mayo de 2020; y la fase de desescalada (W3) del 19 de mayo al 13 de julio de 2020. La elección de estos períodos permite evaluar los efectos de la negociación informada en diferentes condiciones de mercado, incluyendo momentos de alta incertidumbre y restricciones regulatorias.

Los datos de alta frecuencia provienen de Bolsas y Mercados Españoles (BME) e incluyen información detallada sobre volúmenes de negociación, el libro de órdenes completo y datos intradía con una precisión de milisegundos. El sistema de negociación es el Sistema de Interconexión Bursátil Español (SIBE), que permite la negociación continua de 9:00 a 17:30 horas, excluyendo los períodos de subasta de apertura y cierre. Esta exclusión garantiza que el análisis se centre exclusivamente en la actividad de negociación continua, evitando distorsiones derivadas de la fijación de precios en subastas.

Para estructurar el análisis de alta frecuencia, se adopta un enfoque basado en el reloj de eventos, en línea con la metodología de Easley et al. (2011). En lugar de emplear intervalos de tiempo fijos, el análisis segmenta la actividad de mercado en contenedores definidos por volumen de negociación. Este enfoque permite capturar la dinámica del mercado de manera más precisa, ya que ajusta el muestreo a la actividad de negociación en lugar de a una escala temporal arbitraria.

El estudio emplea una serie de métricas para evaluar la interacción entre la liquidez, la negociación informada y la volatilidad. La primera medida clave es VPIN, que cuantifica el nivel de negociación informada a través del desequilibrio en el flujo de órdenes de compra y venta. Siguiendo la metodología de Easley et al. (2011), se establece un tamaño de contenedor de volumen igual a un quincuagésimo del volumen promedio diario en 2019. A partir de él, se agrupan las operaciones hasta completar cada contenedor y se calcula VPIN en base a la diferencia entre volúmenes de compra y venta.

Para evaluar la liquidez, se utilizan dos medidas principales. El *spread* relativo cotizado (RS) mide la liquidez externa del mercado, reflejando los costes asociados a la ejecución inmediata de transacciones. Por otro lado, la profundidad del LOB (*DEPTH*) se emplea como proxy de la liquidez interna, representando la cantidad de órdenes acumuladas en distintos niveles de precios dentro del libro de órdenes.

La dispersión de creencias en el mercado se analiza a través de la pendiente del LOB (*SLOPE*), que mide la relación entre la profundidad del libro de órdenes y la distancia de los precios respecto al mejor *bid-ask*. Una mayor pendiente del LOB indica un mayor consenso entre los participantes del mercado, mientras que una pendiente baja sugiere una mayor dispersión de creencias y, por ende, mayor incertidumbre en la valoración de los activos.

Por último, la volatilidad se mide a través del valor absoluto de los retornos en cada contenedor de volumen y mediante modelos de volatilidad condicional como EGARCH. Este enfoque permite evaluar cómo responde la volatilidad a la presencia de negociación informada y a la evolución de las condiciones de liquidez en distintos segmentos del mercado.

El uso combinado de estas métricas proporciona una visión integral de la interacción entre la negociación informada, la liquidez y la volatilidad en distintos períodos y categorías de capitalización bursátil. La inclusión de VPIN y la pendiente del LOB como indicadores clave permite una evaluación más detallada de los efectos de la negociación informada en la estructura de precios y la estabilidad del mercado.

Metodología y resultados

En primer lugar, el análisis de la relación entre la negociación informada, la liquidez y la dispersión de creencias en el libro de órdenes (LOB) se lleva a cabo mediante un enfoque basado en relaciones no contemporáneas. Se investigan las hipótesis H1a y H1b, evaluando el impacto de la negociación informada sobre el consenso en el LOB y sobre las medidas de liquidez. Para ello, se emplean modelos de datos de panel que permiten identificar patrones a lo largo del tiempo y entre diferentes categorías de capitalización bursátil.

El modelo sigue el marco teórico propuesto por Hendershott et al. (2011) y Yildiz et al. (2020), controlando variables clave que pueden influir en la dinámica del mercado, como el nivel de actividad, la volatilidad y los eventos de mercado. Se incorpora el número de órdenes en cada contenedor de volumen como un indicador del nivel de transacciones diarias, dado que un mayor número de operaciones puede indicar una mayor liquidez y menores costes de transacción. Asimismo, la volatilidad se introduce como variable de control, ya que mercados más volátiles tienden a presentar mayores costes de transacción y menor liquidez percibida, especialmente en períodos de estrés financiero, cuando los agentes informados pueden reducir la liquidez disponible, afectando a la estructura del mercado. Adicionalmente, se emplean variables ficticias para capturar los efectos regulatorios y de crisis, diferenciando entre el colapso del mercado por COVID-19, la prohibición de ventas en corto y la fase de desescalada, permitiendo una segmentación del impacto de cada período sobre las relaciones analizadas.

Las variables dependientes incluyen el consenso en el LOB, medido a través de la pendiente del LOB (*SLOPE*), y las medidas de liquidez, tanto externa (RS) como interna (*DEPTH*). La variable explicativa clave es la negociación informada, representada por la distribución acumulada del VPIN (CDFVPIN), que permite capturar períodos de alta asimetría de información en el mercado. Para abordar la heterocedasticidad y la naturaleza no equilibrada de los datos, se emplea la técnica de Panel EGLS con ponderaciones por sección cruzada y *clustering* por período, garantizando una estimación robusta de los coeficientes. Además, se aplica el test de Hausman para confirmar la idoneidad de los efectos fijos en la especificación del modelo. Como parte del análisis de robustez, se realizan pruebas utilizando diferentes medidas de volatilidad como variables de control, incluyendo la volatilidad absoluta de la rentabilidad, la volatilidad de los residuos de la rentabilidad y la volatilidad condicional estimada mediante un modelo EGARCH. Estos enfoques permiten determinar la sensibilidad de los resultados al método empleado para medir la volatilidad y proporcionar una visión más completa del impacto de la negociación informada.

El análisis revela que la presencia de negociación informada afecta significativamente al consenso en el LOB, aunque la dirección de esta relación varía según el tamaño de la empresa. En el caso de las empresas de gran capitalización, se encuentra una relación positiva entre

VPIN y pendiente del LOB, lo que sugiere que la negociación informada contribuye a alinear las expectativas de los inversores y a reducir la dispersión de creencias. La alta liquidez y cobertura analítica facilitan la rápida integración de la información, permitiendo una menor incertidumbre en la formación de precios. En las de mediana capitalización, se observa un efecto variable, con algunas empresas mostrando un incremento del consenso al aumentar la negociación informada, mientras que en otras el impacto es más débil. La menor liquidez en comparación con las de gran capitalización hace que el efecto de la negociación informada sea más dependiente de las condiciones específicas del mercado. En el caso de las empresas de pequeña capitalización, la relación es más heterogénea, con algunas empresas mostrando una mejora en el consenso mientras que en otras se detecta un aumento de la dispersión de creencias, sugiriendo que en entornos con menor profundidad en el LOB, la presencia de agentes informados puede incrementar la incertidumbre en la formación de precios.

En cuanto a la liquidez, los resultados muestran un impacto dual de la negociación informada. En términos de liquidez externa, se observa que la negociación informada tiende a reducir el *spread* cotizado, lo que indica una mejora en las condiciones de ejecución de las operaciones. Este hallazgo contradice parcialmente la hipótesis H1b, ya que implica que la negociación informada no siempre consume liquidez, sino que en mercados con suficiente profundidad puede contribuir a reducir los costes de transacción. Sin embargo, cuando se analiza la liquidez interna, medida a través de la profundidad del LOB, los resultados confirman que la negociación informada reduce la cantidad de órdenes en los distintos niveles del LOB en todas las categorías de capitalización bursátil. Este efecto es más pronunciado en empresas de mediana y pequeña capitalización, donde la asimetría de información genera mayor aversión al riesgo entre los proveedores de liquidez, lo que puede llevar a una disminución en la profundidad del mercado y una mayor sensibilidad a cambios en la estructura del LOB.

Los análisis agrupados permiten observar tendencias generales que refuerzan los hallazgos obtenidos en las regresiones individuales. En el agregado, la negociación informada muestra un efecto positivo sobre el consenso en el LOB en entornos de alta capitalización y liquidez, mientras que su impacto es más incierto en mercados con menor liquidez. Las pruebas de robustez utilizando diferentes medidas de volatilidad confirman que los resultados son consistentes, aunque se observa que la relación entre negociación informada y consenso en el LOB es más pronunciada cuando se emplea volatilidad condicional EGARCH, lo que sugiere que los efectos de la negociación informada en el consenso son más evidentes en períodos de volatilidad persistente. En cuanto a la liquidez, las pruebas de robustez muestran que la disminución de la profundidad del LOB es más severa en entornos de volatilidad alta y sostenida, mientras que el impacto sobre la liquidez externa puede variar dependiendo de la proxy de volatilidad utilizada.

Estos hallazgos sugieren que la negociación informada desempeña un papel ambivalente en la estructura del mercado. En mercados con alta liquidez y profundidad, puede contribuir a la eficiencia en la formación de precios y a la reducción de la dispersión de creencias, mientras que en mercados menos líquidos, su impacto puede ser más volátil, con posibles efectos adversos sobre la profundidad del LOB. El análisis agrupado permite concluir que el impacto de la negociación informada varía según la categoría de capitalización, con efectos más previsibles en mercados con mayor liquidez y más inciertos en entornos con menor profundidad en el LOB. Este estudio enfatiza la importancia de considerar el contexto de mercado al evaluar las implicaciones de la negociación informada y la necesidad de desarrollar estrategias regulatorias y de gestión de riesgos que equilibren la eficiencia en la formación de precios con la estabilidad de la liquidez en mercados con diferentes niveles de capitalización y asimetría de información.

La relación entre la negociación informada, el consenso en el libro de órdenes y la volatilidad es una de las cuestiones centrales en la microestructura del mercado. Para abordar esta relación, en segundo lugar se emplea un modelo VAR (Vector Autoregresivo) que permite evaluar las interacciones dinámicas entre estas variables en diferentes segmentos de capitalización bursátil.

El análisis se desarrolla en tres niveles: en primer lugar, se evalúan los coeficientes del modelo VAR para identificar la relación entre las variables de estudio; en segundo lugar, se realiza un test de causalidad de Granger para determinar la direccionalidad de las relaciones observadas; finalmente, se utilizan funciones de impulso-respuesta acumuladas para analizar el efecto de un shock en una variable sobre las demás a lo largo del tiempo.

Resultados del Modelo VAR

Los coeficientes estimados en el modelo VAR revelan patrones diferenciados en la relación entre la negociación informada, el consenso en el LOB y la volatilidad en función del tamaño de las empresas. Para las empresas de gran capitalización, la volatilidad presenta una alta persistencia, con coeficientes positivos y significativos en los retardos de la variable de volatilidad, lo que indica que los shocks en la volatilidad tienen efectos prolongados. Además, el consenso en el LOB muestra una relación negativa con la volatilidad, lo que sugiere que un mayor acuerdo acerca del valor fundamental en el libro de órdenes contribuye a estabilizar el mercado. La negociación informada también está negativamente correlacionada con la volatilidad, lo que indica que la integración eficiente de información reduce la incertidumbre en los precios.

En las empresas de mediana capitalización, la relación entre la negociación informada y la volatilidad es más dinámica, con coeficientes negativos y significativos en retardos cercanos a cero, pero sin un efecto sostenido en el tiempo. El consenso en el LOB juega un papel clave en la estabilidad del mercado, con coeficientes significativamente negativos respecto a la volatilidad. A diferencia de las empresas de grand capitalización, en las que la negociación informada está vinculado a una mayor estabilidad, en las de mediana capitalización su efecto es más dependiente de la estructura de liquidez en el mercado.

Para las empresas de pequeña capitalización, la relación entre la negociación informada y la volatilidad es opuesta a la observada en los segmentos de mayor tamaño. Aquí, la volatilidad impulsa la negociación informada, con coeficientes positivos y significativos en retardos tempranos, lo que indica que los aumentos en la volatilidad generan oportunidades de arbitraje para los agentes informados. El consenso en el LOB también reduce la volatilidad, aunque su efecto es menor que en las categorías de mayor capitalización.

Tests de causalidad de Granger

Los resultados del test de causalidad de Granger refuerzan estos hallazgos. En las empresas de gran capitalización, la negociación informada Granger-causa el consenso en el LOB, lo que indica que la presencia de órdenes informadas en el mercado mejora el acuerdo en el libro de órdenes. Sin embargo, el consenso en el LOB no Granger-causa la negociación informada, lo que sugiere que el efecto de retroalimentación es débil. En cuanto a la volatilidad, se observa una relación bidireccional con el consenso en el LOB, lo que implica que una mayor volatilidad desordena el mercado, pero un libro de órdenes bien estructurado puede reducir la volatilidad.

Para las empresas de mediana capitalización, la negociación informada y el consenso en el LOB muestran una relación bidireccional significativa, lo que sugiere que estos factores se retroalimentan mutuamente para estabilizar el mercado. La volatilidad también es Granger-causada tanto por el consenso en el LOB como por la negociación informada, lo que refuerza la idea de que ambos factores contribuyen a la estabilidad del mercado en este segmento.

En las empresas de pequeña capitalización, la volatilidad Granger-causa la negociación informada, pero no ocurre lo contrario. Esto implica que la incertidumbre en los precios genera actividad de *trading* informado, lo que a su vez no contribuye de manera significativa al consenso en el libro de órdenes. Dicho consenso en el LOB también es Granger-causado por la volatilidad, lo que sugiere que estos mercados dependen más de la estabilidad externa que de la actividad de los agentes informados.

Análisis de impulso-respuesta acumulada

Las funciones de impulso-respuesta proporcionan una representación gráfica del impacto acumulado de un shock en una variable sobre las demás a lo largo del tiempo. En las empresas de gran capitalización, un shock en la negociación informada genera un aumento inmediato en el consenso en el LOB, que se estabiliza en el tiempo. Esto confirma que la presencia de órdenes informadas contribuye a un mayor acuerdo en el libro de órdenes. La volatilidad responde negativamente a un shock en el consenso en el LOB, reduciendo su nivel de manera progresiva, lo que indica que un libro de órdenes estructurado disminuye la incertidumbre en el mercado.

Para las empresas de mediana capitalización, un shock en la negociación informada también genera un incremento en el consenso en el LOB, aunque de menor magnitud que en las de gran capitalización. La volatilidad responde negativamente tanto a shocks en la negociación informada como en el consenso, pero su reducción es más pronunciada cuando el shock proviene del consenso en el LOB, lo que resalta su rol estabilizador en estos mercados.

En las empresas de pequeña capitalización, la respuesta de la volatilidad a un shock en el consenso en el LOB es más débil y menos sostenida en el tiempo, lo que sugiere que la estructura del mercado limita la capacidad estabilizadora del consenso en el LOB. Además, un shock en la volatilidad genera un incremento en la negociación informada, reflejando que la incertidumbre en el mercado crea oportunidades para los *traders* informados, en lugar de que estos contribuyan a la estabilidad del mercado.

El análisis a través del modelo VAR, el test de causalidad de Granger y las funciones de impulso-respuesta acumuladas permite identificar diferencias sustanciales en la relación entre la negociación informada, el consenso en el LOB y la volatilidad en función del tamaño de las empresas. En las de gran capitalización, la negociación informada mejora el consenso en el LOB y contribuye a reducir la volatilidad, en tanto que en las de mediana capitalización se observa una relación bidireccional entre estos factores. En las empresas de pequeña capitalización, la volatilidad impulsa la negociación informada, pero ésta no incrementa el acuerdo en el LOB ni contribuye a reducir la volatilidad, reflejando las limitaciones de liquidez y profundidad en estos mercados. Estos resultados subrayan la importancia de considerar la segmentación del mercado en la formulación de estrategias de regulación y gestión de riesgos.

La última fase de este estudio evalúa la hipótesis H3, que postula que la dispersión de creencias en el LOB es un mejor predictor de la volatilidad del mercado que la negociación informada. Para ello, se utiliza un análisis de Probabilidad Condicional Conjunta mediante Tablas de Probabilidad Condicional (CPTs), que permiten representar asociaciones complejas de manera no lineal y ofrecer predicciones probabilísticas detalladas. Esta metodología permite examinar la dinámica entre la negociación informada, el nivel de consenso en el LOB y la volatilidad en función de la capitalización bursátil de los activos.

El análisis se basa en tres métricas principales: la variación de VPIN entre intervalos, utilizada para medir cambios a corto plazo en la negociación informada; la función de distribución acumulada (CDF) de VPIN, que evalúa la acumulación de negociación informada en el tiempo; y la pendiente del LOB, que mide el grado de consenso del mercado. A través de estas medidas, se busca determinar cuál de estas variables tiene un mayor poder predictivo sobre la volatilidad del mercado en las categorías de capitalización alta, media y baja.

Resultados del análisis de probabilidad condicional

Los resultados para las acciones de gran capitalización revelan que una pendiente baja en el LOB en el periodo previo está asociada con una menor probabilidad de volatilidad reducida en el siguiente intervalo. En los casos donde la pendiente del LOB es baja (40.6 - 705.17), solo el 50.72% de las rentabilidades se encuentran en el rango de volatilidad baja (0.0 - 0.01). En cambio, en los intervalos con mayor pendiente (4901.66 - 10926.13), el 90.72% de las rentabilidades se concentran en el rango de volatilidad baja, con solo un 0.11% en niveles más altos. Este patrón es aún más marcado en las acciones de pequeña capitalización, donde, en los valores más altos de la pendiente del LOB (2763.78 - 5631.29), el 97.51% de las rentabilidades se encuentran en el rango de volatilidad baja. En las acciones de capitalización media, la tendencia es similar: en los niveles más bajos de la pendiente del LOB (22.0 - 405.32), el 52.93% de las rentabilidades caen en el rango de volatilidad baja, mientras que en los niveles más altos de pendiente (3157.23 - 6013.6), la concentración de rentabilidades en el rango de baja volatilidad aumenta al 87.58%.

En contraste, el impacto de la variación de VPIN sobre la volatilidad es mínimo. Para las acciones de gran capitalización, una variación positiva de VPIN entre 0.0 y 0.04 resulta en un 80.57% de las rentabilidades en el rango de baja volatilidad, mientras que una variación negativa similar arroja un porcentaje casi idéntico del 80.50%. En las acciones de mediana capitalización, los porcentajes oscilan entre el 82.99% y el 84.47%, sin una relación observable entre la variación de VPIN y la concentración de rentabilidades en el rango de baja volatilidad. En las acciones de pequeña capitalización, los valores correspondientes son del 93.86% y 92.79%, respectivamente, lo que indica que la variación de VPIN no tiene un impacto significativo en la volatilidad del mercado.

La evaluación de la CDF de VPIN sugiere que este indicador tampoco predice de manera efectiva la volatilidad en los diferentes segmentos de capitalización. En las acciones de pequeña capitalización, la concentración de rentabilidades en el rango de baja volatilidad permanece alta en todos los niveles de CDF de VPIN, con una ligera disminución en los rangos más altos (de 93.46% a 91.03%). En las acciones de mediana capitalización, la concentración de rentabilidades en el rango de baja volatilidad aumenta de 79.26% en los niveles más bajos de CDF de VPIN a 83.89% en los niveles más altos. En las acciones de gran capitalización, la concentración de rentabilidades en el rango de baja volatilidad disminuye ligeramente de 80.87% en los niveles más bajos de CDF de VPIN a 78.98% en los niveles más altos.

Estos resultados demuestran que la pendiente del LOB es un predictor más efectivo de la volatilidad del mercado en comparación con las métricas de negociación informada, como la variación de VPIN o la CDF de VPIN. La pendiente del LOB captura la disposición agregada de los participantes del mercado a negociar a diferentes precios, reflejando la organización del libro de órdenes y proporcionando una medida más directa de la estabilidad del mercado. Un valor alto de la pendiente indica una concentración de órdenes en torno al precio actual, lo que sugiere un consenso fuerte sobre el valor del activo y, en consecuencia, menor volatilidad.

Por otro lado, la variación de VPIN, aunque útil para evaluar cambios en la actividad de trading informado en el corto plazo, no se correlaciona de manera significativa con la volatilidad en ninguna de las categorías de capitalización. La CDF de VPIN puede identificar volatilidad inducida por problemas de liquidez en condiciones extremas del mercado, pero en general, no muestra una relación predictiva consistente con la volatilidad del mercado. Estos hallazgos contrastan con estudios previos que destacaban la utilidad de la negociación informada para predecir eventos adversos en el mercado, subrayando la necesidad de un enfoque más integral que incorpore la estructura del mercado y las dinámicas colectivas de los participantes.

El análisis probabilístico conjunto proporciona evidencia empírica robusta de que la pendiente del LOB es un mejor predictor de la volatilidad del mercado que las métricas tradicionales de trading informado. En todas las categorías de capitalización, una mayor pendiente del LOB se asocia con una menor volatilidad, destacando el papel del consenso en la estabilidad del mercado. Estos resultados refuerzan la importancia de considerar la estructura del libro de órdenes y la profundidad del mercado como indicadores clave en la predicción de la volatilidad, más allá de la información contenida en las órdenes ejecutadas. Finalmente, los hallazgos resaltan la necesidad de reevaluar la dependencia de métricas basadas en negociación informada en modelos predictivos de volatilidad y sugieren que las características estructurales del mercado pueden proporcionar información más relevante para evaluar su estabilidad y riesgo.

Conclusiones

Este estudio ha analizado la interacción entre la negociación informada, el consenso en el libro de órdenes (LOB), la liquidez del mercado y la volatilidad en un conjunto de empresas del IBEX 35, categorizadas en grupos de gran, mediana y pequeña capitalización. El objetivo era comprender cómo estas dinámicas varían según la capitalización bursátil en condiciones normales y extraordinarias, como la crisis del COVID-19 y la prohibición de ventas en corto en España. Los resultados obtenidos ofrecen una visión matizada del impacto de la negociación informada sobre la calidad del mercado, el consenso en el LOB, la liquidez y la volatilidad.

Los hallazgos confirman la Hipótesis H1a, que postula que la presencia de *traders* informados aumenta la alineación de creencias en el LOB en todas las capitalizaciones. Los agentes informados tienden a mejorar el consenso del mercado mediante la incorporación de información superior en órdenes limitadas, aumentando la eficiencia del libro de órdenes. No obstante, el grado de este efecto varía según el tamaño de la empresa, lo que sugiere que factores como la liquidez y la asimetría informativa influyen en la magnitud del impacto.

En contraste con la Hipótesis H1b, se encontró que la negociación informada generalmente reduce el *spread bid-ask*, mejorando la liquidez externa. Este resultado sugiere que los agentes informados pueden proporcionar liquidez al colocar órdenes limitadas que reducen el *spread*, probablemente buscando maximizar su ventaja informativa en condiciones de menor coste. Sin embargo, respecto a la liquidez interna, el estudio confirma que la negociación informada reduce la profundidad del libro de órdenes, disminuyendo la oferta de liquidez en múltiples niveles de precios. Este efecto es más pronunciado en empresas de mediana y pequeña capitalización, donde la menor profundidad del mercado amplifica la sensibilidad de la liquidez interna a la actividad de los *traders* informados.

Para las empresas de gran capitalización, se confirma una relación unidireccional en la que la negociación informada influye positivamente en el consenso dentro del LOB, apoyando la Hipótesis H2a. Esta mejora en el consenso contribuye a una reducción temporal de la volatilidad al mejorar la eficiencia en la formación de precios. Sin embargo, en empresas de pequeña capitalización, la negociación informada no influye significativamente en el consenso ni viceversa, lo que confirma la ausencia de una relación causal.

En las empresas de mediana capitalización, se observa una relación recíproca entre la negociación informada y el consenso en el LOB, lo que sugiere una interacción dinámica en la que los participantes del mercado ajustan sus expectativas en función de la nueva información y el consenso predominante. Esta retroalimentación mutua contribuye a la estabilidad del mercado al reducir la volatilidad a lo largo del tiempo, resaltando la importancia del consenso y la negociación informada en la calidad del mercado para este segmento.

Además, los resultados demuestran una relación bidireccional negativa entre el consenso y la volatilidad en todas las categorías de capitalización, lo que respalda la Hipótesis H2b. Un mayor consenso en el LOB se asocia con una menor volatilidad, mientras que un aumento en la volatilidad tiende a "desordenar" el consenso de los inversores. En las empresas de gran capitalización, en las que la liquidez es alta, el consenso actúa como una fuerza estabilizadora. Sin embargo, en empresas más pequeñas, esta relación es menos pronunciada debido a la menor liquidez y profundidad de mercado, lo que dificulta el mantenimiento de un consenso constante.

Los resultados también ofrecen evidencia parcial en favor de la Hipótesis H2c en empresas de pequeña capitalización. Se observa que la volatilidad del mercado atrae la negociación informada, lo que indica que, en mercados menos líquidos, niveles elevados de volatilidad pueden intensificar la actividad de negociación informada. La limitada profundidad y liquidez de estas empresas las hace más susceptibles a los impactos de la negociación informada en la volatilidad de los precios.

Finalmente, se encuentra una fuerte evidencia en apoyo de la Hipótesis H3, que plantea que la dispersión de creencias en el LOB, medida a través de la pendiente del libro de órdenes, es un predictor más efectivo de la volatilidad que métricas de negociación informada como VPIN. Valores elevados de la pendiente del LOB, que indican un fuerte consenso del mercado, están asociados con una mayor concentración de rentabilidades en rangos de baja volatilidad en todas las capitalizaciones. Este efecto es más pronunciado en empresas de pequeña capitalización, donde la menor liquidez amplifica el impacto del consenso en la estabilización de precios. En cambio, aunque VPIN y su función de distribución acumulada (CDF) pueden predecir picos de volatilidad en condiciones de estrés extremo, su poder predictivo general es limitado en condiciones de mercado normales.

Estos hallazgos tienen implicaciones relevantes para inversores, operadores y reguladores. La pendiente del LOB se posiciona como un indicador fiable de la volatilidad, lo que permite a los participantes del mercado ajustar sus estrategias para gestionar mejor el riesgo. Los reguladores pueden utilizar esta métrica para promover prácticas que favorezcan el consenso del mercado y estabilicen los mercados, especialmente en segmentos menos líquidos como las empresas de pequeña capitalización.

Si bien el estudio proporciona hallazgos significativos, presenta ciertas limitaciones. El análisis se ha centrado en un subconjunto del IBEX 35 durante un período excepcional marcado por la pandemia del COVID-19 y la prohibición de ventas en corto en el mercado español, lo que puede limitar la generalización de los resultados a entornos de mercado más estables. Futuras investigaciones podrían ampliar el análisis a diferentes períodos temporales, mercados o incluir una gama más amplia de valores. Además, la exploración de métricas alternativas de trading informado y consenso podría proporcionar información complementaria sobre estas dinámicas complejas.

En conclusión, este estudio destaca el papel multifacético de la negociación informada en los mercados financieros. Aunque puede mejorar la calidad del mercado mediante un mayor consenso y una formación de precios más eficiente, también plantea desafíos en términos de liquidez y volatilidad, particularmente en mercados menos líquidos. La pendiente del LOB emerge como una herramienta valiosa para predecir la volatilidad, con beneficios prácticos para los participantes del mercado y consideraciones regulatorias. Al enfatizar la interacción entre la negociación informada, el consenso del mercado y la volatilidad en diferentes niveles de capitalización se contribuye a una comprensión más profunda de la microestructura del mercado y se sientan las bases para futuras investigaciones en este ámbito financiero crítico.

5.3 Resumen y conclusiones del capítulo 4: Análisis de los componentes de la pendiente del libro de órdenes limitadas a través de un modelo de espacio de estados: impacto en el mercado

Introducción, revisión de la literatura e hipótesis de investigación

En este estudio aplicamos un modelo de espacio de estados a la pendiente del libro de órdenes limitadas (LOB), utilizando datos de alta frecuencia del libro de órdenes completo. Este enfoque permite descomponer la pendiente en dos componentes no observables: el componente permanente, asociado con información eficiente de largo plazo, y el componente transitorio, influenciado por operaciones no informadas, como provisión de liquidez, *trading* algorítmico o *feedback trading*.

La pendiente del LOB es un indicador integrado que refleja tanto la dinámica del mercado como el consenso sobre el valor de los activos y las expectativas de los participantes. Estudios previos (Næs & Skjeltorp, 2006; Tripathi et al., 2020) destacan que una pendiente más pronunciada se asocia con mayor consenso sobre el valor fundamental, lo que estabiliza el mercado al reducir la volatilidad y la actividad. Sin embargo, el distinto impacto de los componentes permanente y transitorio sobre variables clave del mercado, como la volatilidad, los costes de selección adversa y la liquidez, no ha sido explorado.

Nuestro objetivo es analizar cómo los distintos componentes de la pendiente del LOB afectan la calidad del mercado. Para ello, el estudio se lleva a cabo basándonos en el uso de relojes de eventos en lugar de relojes de calendario, lo que permite capturar dinámicas significativas del mercado con mayor precisión (Carmona & Webster, 2013; Ling, 2017). Además, utilizamos un modelo de espacio de estados con filtro de Kalman para descomponer la pendiente, separando las señales eficientes de las fluctuaciones transitorias. Este enfoque aporta un análisis innovador dentro de la teoría de microestructura de mercado.

Proponemos varias hipótesis que exploran cómo los componentes de la pendiente del LOB influyen en la calidad del mercado:

H1a: El componente eficiente reduce la volatilidad.

H1b: El componente transitorio incrementa la volatilidad.

H2a: El componente eficiente reduce los costes de selección adversa.

H2b: El componente transitorio aumenta los costes de selección adversa.

H3a: El componente eficiente reduce la iliquidez.

H3b: El componente transitorio incrementa la iliquidez.

H4: El componente transitorio es un predictor significativo de la rentabilidad intradía.

Con este estudio, buscamos aportar una comprensión más profunda sobre cómo los distintos tipos de órdenes afectan la estabilidad y la eficiencia en la formación de precios. Al analizar la pendiente del LOB, destacamos el papel estabilizador de la información eficiente y los riesgos que generan las operaciones no fundamentadas.

Datos, medidas y metodología

Se analizaron datos de alta frecuencia correspondientes al período 2019-2020, proporcionados por el Sistema de Interconexión Bursátil Español (SIBE) de los componentes del IBEX 35. Su horario de negociación abarca desde las 9:00 a.m. hasta las 5:30 p.m. (GMT+1), con períodos de negociación ininterrumpida. Se han eliminado las subastas de apertura y cierre para la investigación.

Los datos recopilados permiten un análisis detallado del Libro de Órdenes Limitadas (LOB), que contienen hasta 20 niveles de profundidad de oferta y demanda. Esta información se actualiza en tiempo real con cada nueva orden, modificación o cancelación, reflejando dinámicas precisas de la formación de precios y la provisión de liquidez en un mercado que opera sin creadores de mercado oficiales. Se registran variables clave como el precio, el volumen y las cotizaciones más competitivas justo antes de cada transacción. Para preservar la validez del análisis, se excluyen operaciones especiales, como las relacionadas con subastas, centrándonos únicamente en transacciones estándar. Además, un identificador secuencial común permite sincronizar con precisión los datos de transacciones con las instantáneas del LOB, asegurando una reconstrucción fiel de las condiciones del mercado en cada momento.

Se excluyen del análisis aquellas acciones que tuvieron una presencia menor por cambios o sustitución en el índice. La muestra final incluye 33 acciones del índice IBEX 35, lo que garantiza la representatividad de la actividad del mercado bursátil español en los años analizados. El LOB, como registro público de las intenciones de compra y venta, no solo documenta las órdenes pendientes de ejecución, sino que también evidencia la dispersión de expectativas entre los participantes del mercado. Estas órdenes, al no ejecutarse de inmediato, reflejan tanto necesidades de liquidez como estrategias de captura de valor fundamentadas en información que afectará al activo en el medio o largo plazo.

La figura incluida en este apartado detalla la estructura y dinámica del LOB en un momento específico, representando la disposición de las órdenes de compra (*bid*) y venta (*ask*). En el eje horizontal se ubican los niveles de precio en el mercado, mientras que en el eje vertical se observa el volumen acumulado de órdenes. Las curvas escalonadas reflejan acumulaciones de compra a la izquierda y de venta a la derecha, convergiendo en el punto medio del precio de mercado (PM). Esta representación en la figura 1 ayuda a comprender la profundidad del mercado y la liquidez disponible en diferentes niveles de precio. La pendiente de estas curvas escalonadas proporciona una medida directa del consenso entre los inversores sobre el valor intrínseco del activo: pendientes más pronunciadas indican un mayor consenso.

El análisis de la pendiente del LOB se lleva a cabo tanto para el lado de la oferta como para el de la demanda, siguiendo la metodología propuesta por Næs y Skjeltorp (2006). Se calcula la pendiente en cada cambio significativo del mercado, en lugar de utilizar promedios diarios, para capturar variaciones inmediatas en la elasticidad del libro de órdenes.

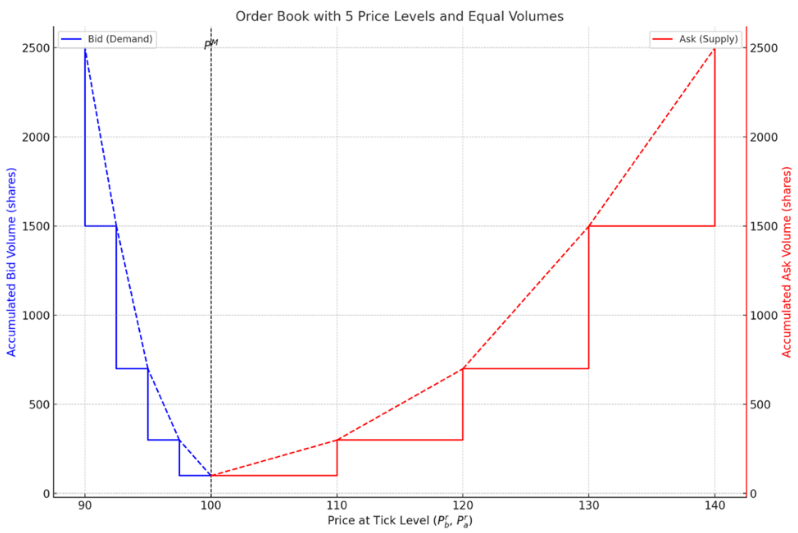

Figura 1: Representación del libro de órdenes (LOB) mostrando la acumulación de volúmenes de compra (*bid*) y venta (*ask*) con cinco niveles de precios.

Abordamos varias medidas clave para analizar la calidad del mercado, incluyendo volatilidad, costes de selección adversa y liquidez, utilizando datos de alta frecuencia del LOB. La volatilidad de las rentabilidades se evalúa prestando especial atención al patrón intradía en forma de "U", que refleja alta volatilidad al inicio y cierre de las sesiones de negociación. Para normalizar los efectos estacionales intradía y aislar las dinámicas subyacentes, se utiliza un reloj de eventos, lo que permite examinar las fluctuaciones de precios de manera más precisa, eliminando la influencia de discrepancias relacionadas con el momento del día o el volumen de transacciones.

La metodología para estimar la volatilidad se basa en un modelo de regresión lineal, siguiendo el enfoque de Jones et al. (1994). Este modelo permite analizar la influencia de los retardos de la rentabilidad en la actual, seleccionando el número óptimo de retardos mediante el Criterio de Información de Akaike (AIC). Los residuos del modelo proporcionan una primera aproximación a la volatilidad, representada como el valor absoluto de los errores no explicados por la autocorrelación. Para refinar este análisis, se incorpora un modelo EGARCH, el cual captura no solo la persistencia de la volatilidad, sino también su respuesta asimétrica a shocks positivos y negativos. Este modelo permite identificar agrupamientos de volatilidad y evaluar cómo los eventos pasados impactan en la variabilidad de las rentabilidades, ofreciendo así una perspectiva de las dinámicas del mercado más detallada.

En cuanto a los costes de selección adversa, se utiliza el indicador VPIN (*Volume-synchronized Probability of Informed Trading*) para cuantificar la asimetría informativa en el mercado. Este indicador se calcula como el desequilibrio promedio entre órdenes de compra y venta durante un intervalo de tiempo, normalizado por el volumen total de transacciones. Este enfoque permite evaluar la probabilidad de que las órdenes negociadas contengan información que favorezca a una de las partes, incrementando así los costes de transacción. Como complemento, se incluye la ratio de desequilibrio de órdenes (*Order Imbalance Ratio,* OIR), que mide la presión compradora o vendedora relativa sobre el volumen total de órdenes. Ambas métricas ofrecen una evaluación robusta de cómo la asimetría informativa afecta a la eficiencia del mercado.

Para analizar la liquidez, se utilizan medidas de liquidez tanto interna como externa. La profundidad del LOB (DEPTH) se emplea como métrica estándar para evaluar la liquidez interna, definida como el volumen promedio de órdenes en todos los niveles del libro. Una mayor profundidad indica que las transacciones tienen un menor impacto en los precios, reflejando un mercado más líquido. Como medida de liquidez externa se utiliza el *spread* relativo (RS), calculado como el *spread* cotizado dividido por el precio medio. Estas métricas se complementan con variables de control, como las variables *dummy* correspondientes a eventos específicos, como las restricciones de ventas en corto (SSB) y los períodos de *crash* durante la pandemia de la COVID-19, para garantizar un análisis más completo de las dinámicas del mercado.

La metodología utilizada para descomponer la pendiente del LOB se basa en un modelo de espacio de estados, que permite distinguir entre dos dinámicas fundamentales: un componente permanente, asociado a la información eficiente, y un componente transitorio, vinculado a desequilibrios temporales de liquidez y *trading* no informado. El componente permanente se modeliza como un proceso no estacionario de nivel local, diseñado para capturar cambios de largo plazo que reflejan ajustes estructurales en la pendiente del LOB, consistentes con la llegada de nueva información relevante. Este componente captura el consenso informado entre los participantes del mercado sobre el valor intrínseco del activo. Por otro lado, el componente transitorio, modelado como un proceso autorregresivo estacionario, representa fluctuaciones de corto plazo relacionadas con la provisión de liquidez y actividades no informadas, que responden a desequilibrios temporales y ajustes tácticos sin incorporar información fundamental.

La estimación de ambos componentes se realiza mediante el filtro de Kalman, una herramienta eficaz para generar estimaciones dinámicas optimizadas de factores latentes. Se llevaron a cabo pruebas comparativas entre modelos alternativos, como el camino aleatorio y el nivel local no estacionario, seleccionando la configuración más adecuada mediante los criterios de información de Akaike (AIC) y Bayesiano (BIC). La validez del modelo se confirma a través del análisis de los residuos, asegurando la ausencia de autocorrelación y consistencia con los supuestos teóricos.

La pendiente del LOB se modeliza como la suma de un componente permanente no estacionario y un componente transitorio estacionario. Este enfoque refleja cómo los participantes informados generan cambios duraderos en el mercado, mientras que las actividades de *trading* no informado generan fluctuaciones temporales. En estas actividades, los proveedores de liquidez y los algoritmos de *trading* ajustan el volumen disponible en respuesta a pequeños movimientos de precio, generando variaciones en la elasticidad del LOB que son reversibles y de corto plazo. Esta distinción es clave para distinguir las contribuciones de ambos tipos de *trading* a la dinámica de la pendiente.

El análisis se complementa mediante un modelo E-GARCH para evaluar las volatilidades condicionales de ambos componentes. Este enfoque permite identificar asimetrías y patrones de agrupamiento de volatilidad, proporcionando una visión más detallada de cómo las dinámicas del mercado afectan a la pendiente del LOB. La volatilidad del componente permanente se asocia con shocks informativos, que producen cambios duraderos en la elasticidad de la pendiente, mientras que la volatilidad del componente transitorio captura las fluctuaciones generadas por actividades no informadas, como ajustes temporales en el volumen y el precio.

Este modelo metodológico, inspirado en trabajos de microestructura del mercado (Glosten & Milgrom, 1985; Hasbrouck, 1991), ofrece una visión integral de cómo las dinámicas del LOB afectan a métricas clave como la volatilidad, los costes de selección adversa y la liquidez. Al distinguir entre negociación informada y no informada, proporciona un análisis detallado de cómo las fuerzas informativas y de liquidez moldean la estructura del mercado.

Este análisis estudia la influencia del componente relacionado con la negociación informada, asociado al precio eficiente, y del componente vinculado al *trading* no informado, relacionado con la provisión de liquidez y el *feedback trading*, sobre diversas métricas de calidad del mercado. Para este propósito, se emplean las volatilidades EGARCH de los componentes permanente y transitorio de la pendiente del LOB como variables explicativas principales. El análisis se lleva a cabo mediante un modelo de regresión múltiple, diseñado para evaluar cómo cada componente afecta a dinámicas clave del mercado. Para garantizar un análisis exhaustivo, se realizan regresiones específicas para cada acción del índice IBEX 35, lo que permite evaluar las dinámicas particulares de cada activo. El análisis de las regresiones se complementa con variables de control diseñadas para captar factores externos relevantes durante el período de estudio. Entre estas se incluyen la variable *dummy* SSB, que representa las restricciones de ventas en corto implementadas durante la pandemia de la COVID-19, y la variable *dummy* CRASH, que captura los efectos específicos del crash del mercado asociado a la crisis sanitaria. Además, el *spread* cotizado se incorpora como una variable adicional para controlar su influencia en la liquidez y la formación de precios.

El análisis se complementa con un meta-análisis diseñado para integrar y sintetizar las estimaciones obtenidas en los modelos de regresión. Este enfoque proporciona una evaluación cuantitativa agregada de los efectos estimados en diferentes categorías de tamaños de empresa, clasificadas en gran capitalización (LARGE), mediana capitalización (MEDIUM) y pequeña capitalización (SMALL). Para ello, se utiliza el cálculo de medias ponderadas basadas en el error estándar inverso, asignando mayor peso a las estimaciones más precisas (con menor error estándar). Posteriormente, se calcula un z-score para evaluar la significancia estadística de cada media ponderada, asociando un valor p para determinar la probabilidad de que los resultados sean atribuibles al azar.

La metodología se fundamenta en estudios previos de la literatura financiera, como Baruník y Křehlík (2018), Mezghani y Boujelbène-Abbes (2021) y Naceur y Zhang (2016), que abordan las complejidades analíticas en mercados de alta frecuencia y en entornos de reloj de eventos.

Cada componente del IBEX 35 presenta diferentes intervalos de análisis según sus eventos, lo que permite ajustar el análisis a las dinámicas específicas de cada acción.

Adicionalmente, se evalúa el poder predictivo de los componentes de la pendiente del LOB sobre la rentabilidad intradía, incorporando variables retardadas tanto del componente permanente como del transitorio. Este enfoque permite explorar cómo las dinámicas de la pendiente influyen en el comportamiento de los precios en intervalos definidos, capturando tanto los impactos de largo plazo como las fluctuaciones temporales. Para garantizar la robustez de los resultados, se incluyeron nuevamente las variables *dummy* relacionadas con eventos críticos como las restricciones de ventas en corto y el impacto del crash del mercado. Este diseño analítico busca identificar si las dinámicas reflejadas en los componentes del modelo tienen un impacto estadísticamente significativo en la rentabilidad intradía, proporcionando una comprensión más profunda de cómo las dinámicas del libro de órdenes pueden influir en la formación de precios a corto plazo.

Resultados

El análisis de resultados se presenta mediante un meta-análisis que integra y sintetiza los coeficientes estimados de los modelos de regresión para las acciones del IBEX 35. Este enfoque emplea coeficientes ponderados por el error estándar para priorizar estimaciones más precisas y garantizar una evaluación robusta de los efectos de los componentes de la pendiente del libro de órdenes limitadas (SLOPE) sobre métricas clave del mercado: volatilidad, costes de selección adversa, liquidez y capacidad predictiva de los rendimientos.

Volatilidad

El componente permanente, asociado con información fundamental y que refleja la actividad de operadores informados, muestra consistentemente una relación inversa con la volatilidad del mercado, implicando un efecto estabilizador en los precios, coherente con Kath (2019), Kiesel y Paraschiv (2017) y Uniejewski et al. (2019). En contraste, el componente transitorio, vinculado a operaciones de *trading* no basadas en nueva información, como operaciones algorítmicas y orientadas a la liquidez, tiende a aumentar la volatilidad. Estos hallazgos son reveladores en términos del papel fundamental de los operadores informados en mejorar el proceso de descubrimiento de precios y contribuir a una mayor estabilidad del mercado.

Específicamente, se observa que la presencia de operadores informados, que actúan sobre conocimiento que eventualmente se refleja en los valores fundamentales del activo, inyecta calidad informativa en el LOB, lo que mitiga la incertidumbre y favorece una menor volatilidad del mercado. Este efecto estabilizador del componente informacional está respaldado por coeficientes permanentes negativos significativos, sugiriendo que la información precisa ayuda a anclar las expectativas de los inversores y reducir la dispersión de precios. Los valores absolutos son mayores en empresas de gran capitalización y menores en las de pequeña capitalización, tanto en la volatilidad condicional como en el valor absoluto de los residuos de la rentabilidad, lo que es coherente con la literatura existente que asocia la negociación informada con acciones de alta capitalización y alto volumen de negociación.

Por el contrario, el componente transitorio, vinculado al *trading* algorítmico y operaciones de liquidez no informadas, tiende a aumentar la volatilidad. Estos efectos son capturados por coeficientes transitorios positivos y significativos, enfatizando la influencia de la liquidez y el *trading* automatizado en la amplificación de fluctuaciones de precios a corto plazo. Los resultados contribuyen significativamente a la comprensión de la microestructura del mercado y proporcionan valiosos conocimientos a las entidades reguladoras, que deben considerar estas dinámicas al formular políticas que promuevan la estabilidad y eficiencia del mercado.

En el estudio, el coeficiente de la variable de control correspondiente al periodo de prohibición de ventas en corto (SSB) muestra significatividad variable dependiendo de la categoría de capitalización de mercado. Para las acciones de gran capitalización, el coeficiente SSB no es significativo en ninguna de las dos medidas de volatilidad (absoluta o condicional). Sin embargo, para acciones de mediana y pequeña capitalización, SSB tiene un impacto significativo, sugiriendo que las restricciones a las ventas en corto afectan más a las empresas de menor capitalización.

La variable de control del *spread* cotizado muestra coeficientes con signos opuestos en las dos medidas de volatilidad. En la volatilidad medida por los residuos de la rentabilidad, un aumento en el *spread* cotizado se asocia a un incremento en la volatilidad, reflejando menor liquidez y mayor incertidumbre. En cambio, en la volatilidad modelizada por EGARCH, un aumento en este *spread* cotizado se asocia con una disminución en la volatilidad condicional, posiblemente porque el modelo EGARCH captura la persistencia de la volatilidad y ajusta la volatilidad futura a la baja.

Costes de selección adversa

Finalmente se analiza la relación entre los componentes de la pendiente del LOB y métricas clave de costes de selección adversa, como el *spread* relativo de precios y la ratio de desequilibrio de órdenes (OIR). El componente permanente tiene una relación negativa y significativa con el *spread* relativo en todas las categorías de tamaño, implicando que un aumento en este componente reduce la probabilidad de costes de selección adversa. El componente transitorio muestra un efecto positivo y significativo sobre este *spread* relativo, indicando que el *trading* algorítmico y orientado a la liquidez introduce más volatilidad en el LOB. En cuanto al OIR, el componente permanente reduce el desequilibrio de órdenes, mientras que el transitorio lo aumenta. Esto sugiere que la información fundamental contribuye a un mercado más equilibrado, mientras que la negociación no informada tiende a crear desequilibrios.

Adicionalmente, se realiza una regresión sobre VPIN (CDF), medida de probabilidad acumulada de negociación informada, que muestra que ambos componentes de la pendiente del LOB afectan positivamente a esta variable. Esto sugiere que tanto el consenso relacionado con información fundamental como las fluctuaciones transitorias impactan directamente en el nivel de negociación informada.

Liquidez

En el caso de la liquidez, el componente permanente de la pendiente del LOB tiene un efecto positivo y significativo sobre la profundidad del mercado, indicando que la información fundamental aumenta la liquidez. El componente transitorio tiene un impacto negativo, sugiriendo que el *trading* algorítmico reduce la profundidad del libro de órdenes, posiblemente al introducir volatilidad y reducir la estabilidad.

Las variables de control SSB y CRASH muestran coeficientes negativos y significativos, indicando que las restricciones a las ventas en corto y eventos extremos, como el periodo de la COVID-19, reducen tanto la profundidad del mercado como la liquidez.

Predicción de rentabilidad

Finalmente, se realiza un meta-análisis para evaluar los efectos de los componentes permanente y transitorio sobre la rentabilidad intradía, considerando retardos de 2 a 50 períodos. Los resultados muestran que el componente transitorio tiene una mayor capacidad predictiva para la rentabilidad a corto plazo, especialmente en los primeros 6 retardos, con valores *p* significativos. Esto sugiere que el *trading* de muy corto plazo contenido en el LOB es crucial para pronosticar movimientos de precios intradía.

El análisis segmentado por categorías de capitalización bursátil (LARGE, MEDIUM, SMALL) revela diferencias significativas en el impacto de los componentes de la pendiente del LOB sobre las métricas de mercado. En las acciones de gran capitalización (LARGE), el componente permanente mostró un efecto estabilizador más pronunciado, reduciendo la volatilidad y los costes de selección adversa, además de incrementar la liquidez, gracias a la mayor profundidad y liquidez inherente de estos mercados. Por el contrario, en las acciones de pequeña capitalización (SMALL), el componente transitorio amplifica la volatilidad y aumenta los costes de selección adversa, reflejando la mayor sensibilidad de estos mercados al ruido generado por el *trading* algorítmico. Las acciones de mediana capitalización (MEDIUM) presentan un comportamiento intermedio entre estas dos categorías.

Durante eventos extremos, como las restricciones a las ventas en corto (SSB) y la crisis del COVID-19 (CRASH), se observa que las acciones SMALL fueron las más afectadas, registrando una disminución pronunciada en la liquidez y un incremento significativo en la volatilidad.

Conclusiones

Este estudio ha proporcionado una evaluación integral de los efectos de los componentes permanente y transitorio de la pendiente del libro de órdenes (LOB) sobre la volatilidad, los costes de selección adversa, la profundidad del mercado y la predictibilidad de los rendimientos en los componentes del IBEX 35. A través de un meta-análisis que integra estimaciones de modelos de regresión ponderados, se observa que el componente permanente, asociado con información fundamental, tiene un efecto estabilizador significativo en los precios, reduciendo la volatilidad del mercado (H1a). Este efecto se refleja en la reducción de los costes de selección adversa y en un aumento en la profundidad del mercado, mejorando la liquidez (H3a).

Por otro lado, el componente transitorio, relacionado con *trading* algorítmico y operaciones de liquidez no fundamentadas en información eficiente, incrementa la volatilidad (H1b), eleva los costes de selección adversa y reduce la profundidad del LOB (H3b). Estos resultados subrayan la importancia de distinguir entre actividades relacionadas con información fundamental y *trading* por liquidez o no informado al evaluar la microestructura del mercado.

El análisis predictivo de la rentabilidad ha revelado que el componente transitorio posee una mayor capacidad predictiva para los rendimientos a corto plazo en comparación con el componente permanente (H4). Estos hallazgos sugieren que el *trading* de ultra-corto plazo contenido dentro del LOB es crucial para pronosticar movimientos de precios intradía.

Adicionalmente, el análisis de los efectos del LOB durante los períodos de restricciones a las ventas en corto (SSB) y el crash del mercado debido al COVID-19 proporciona claves acerca de las dinámicas del mercado durante situaciones extremas. Durante estos períodos, la profundidad del mercado y la volatilidad experimentaron deterioros significativos, incluso con restricciones a las ventas en corto en vigor.

En resumen, este estudio valida las hipótesis propuestas: el componente informado de la pendiente del LOB reduce la volatilidad (H1a) y los costes de selección adversa (H2a) mientras aumenta la liquidez (H3a). Por otro lado, el componente transitorio aumenta la volatilidad (H1b), los costes de selección adversa (H2b) y la iliquidez (H3b), además de ser un predictor significativo de la rentabilidad intradía (H4). Estos resultados mejoran la comprensión de la microestructura del mercado y proporcionan observaciones clave para las políticas que busquen promover la estabilidad y calidad del mercado.

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6. Conclusiones de la tesis

La presente investigación ofrece una exploración detallada de la microestructura del mercado en el contexto del IBEX 35, con especial énfasis en el impacto de la negociación informada, las restricciones de venta en corto (SSR) y la descomposición de los componentes de la pendiente del libro de órdenes (LOB) en torno al periodo de la pandemia de COVID-19. La tesis aborda preguntas fundamentales sobre cómo estas variables afectan a la calidad del mercado, centrándose en la volatilidad, la liquidez y la eficiencia en la formación de precios. Al articular las conclusiones de los tres capítulos principales, se establece una comprensión integral de las complejas relaciones entre la negociación informada y los parámetros del mercado en un entorno de alta frecuencia y condiciones extraordinarias.

Un objetivo adicional era evaluar los efectos de intervenciones regulatorias y comportamientos del mercado sobre la calidad de los precios, aportando una base empírica para reguladores y participantes del mercado interesados en promover la estabilidad y eficiencia de los mercados financieros. A continuación, se presenta una síntesis de las conclusiones clave de cada capítulo y un análisis integrador que subraya las contribuciones de esta investigación a la literatura.

El segundo capítulo de la tesis analiza cómo las restricciones de ventas en corto (SSR) implementadas durante la pandemia afectaron a la calidad del mercado del IBEX 35. Este estudio se centra en evaluar la volatilidad intradía, la liquidez y la eficiencia de precios bajo un enfoque de alta frecuencia.

Se observa que las SSR, aunque lograron reducir la volatilidad intradía, no alcanzaron su objetivo de eliminar la inestabilidad extrema causada por el colapso de los precios durante el confinamiento (Hipótesis 1). Además, estas restricciones generaron un deterioro significativo en la liquidez y la eficiencia de precios, aumentando los costes implícitos para los inversores a nivel intradía (Hipótesis 2). Durante el periodo de SSR, la actividad de alta frecuencia (HFT) disminuyó drásticamente, lo que confirmó su papel crucial en la formación de precios y la liquidez del mercado (Hipótesis 3).

Otro hallazgo relevante es la asimetría en los efectos de las SSR sobre el libro de órdenes, dispersando las órdenes de venta más allá de sus valores fundamentales en mayor medida que las de compra (Hipótesis 4). Por último, el análisis de causalidad de Granger revela que la actividad HFT causa unidireccionalmente volatilidad intradía, subrayando su influencia en la calidad del mercado (Hipótesis 5).

En conjunto, este capítulo demuestra que las restricciones regulatorias, aunque bien intencionadas, pueden generar consecuencias no deseadas, deteriorando la calidad del mercado y penalizando a los inversores con altos costes implícitos. Estos resultados subrayan la importancia de diseñar políticas regulatorias equilibradas que consideren tanto los beneficios como el impacto no deseado.

El tercer capítulo profundiza en la interacción entre la negociación informada, el consenso en el libro de órdenes (LOB), la liquidez y la volatilidad en 18 compañías del IBEX 35, clasificadas en carteras de gran, mediana y pequeña capitalización. Se analiza un período marcado por la pandemia de COVID-19 y la prohibición de ventas en corto, factores que incrementaron la incertidumbre y pusieron a prueba la estabilidad del mercado.

Los hallazgos obtenidos respaldan la Hipótesis H1a, al evidenciar que la presencia de negociación informada alinea las creencias en el LOB y contribuye a una mayor cohesión informativa, tal como se ha señalado también en estudios previos. Sin embargo, este efecto varía entre las distintas capitalizaciones, siendo más pronunciado en empresas de gran capitalización, donde la cobertura por parte de analistas y la mayor profundidad del mercado facilitan la formación de consenso.

En contraposición a la Hipótesis H1b, se observa que la negociación informada reduce el *spread bid-ask*, mejorando la liquidez externa. Esta conducta coincide con trabajos, que señalan que los agentes informados pueden colocar órdenes limitadas para aprovechar su ventaja informativa con menores costes de ejecución. No obstante, se confirma que la negociación informada disminuye la profundidad interna del LOB, lo que sugiere que sí consume liquidez en niveles de precio menos competitivos, coherente con la literatrura sobre la desincentivación que generan los agentes informados en participantes no informados. Este efecto es más notorio en empresas de menor capitalización, más sensibles a cambios en la estructura de liquidez.

Respecto a la Hipótesis H2a, en las empresas de gran capitalización se detecta una relación unidireccional positiva entre la negociación informada y el consenso en el LOB, lo que reduce temporalmente la volatilidad al agilizar la incorporación de nueva información en los precios. Sin embargo, en las empresas de pequeña capitalización no se registra una influencia significativa: ni la negociación informada Granger-causa el consenso ni el consenso Granger-causa la negociación informada.

En el caso de las empresas de mediana capitalización, se encuentra una relación recíproca: la falta de consenso atrae la actividad informada, que a su vez refuerza el consenso, generando un ciclo de retroalimentación que disminuye la volatilidad a lo largo del tiempo. El resultado valida parte de la Hipótesis H2b, según la cual el consenso actúa como fuerza estabilizadora, mientras que la volatilidad puede quebrar ese consenso en mercados menos líquidos.

Asimismo, los resultados dan un respaldo parcial a la Hipótesis H2c en las empresas de pequeña capitalización, ya que se detecta que la volatilidad incentiva la negociación informada, lo que a su vez puede magnificar los movimientos de precios en mercados con menor profundidad. El limitado consenso que se logra en este entorno restringe su capacidad para estabilizar el mercado, subrayando los desafíos de estas empresas frente a episodios de alta volatilidad.

Por último, el estudio confirma la Hipótesis H3, al mostrar que la pendiente del LOB (o dispersión de creencias) constituye un predictor más sólido de la volatilidad que métricas de trading informado, como VPIN o su CDF. Un valor elevado en la pendiente del LOB —indicativo de un alto grado de consenso— se asocia de forma consistente con menores niveles de volatilidad futura. Este hallazgo resulta particularmente relevante en las empresas de menor capitalización, donde la liquidez limitada exacerba el peso del consenso en la formación de precios. Por el contrario, aunque VPIN puede alertar sobre crisis de liquidez puntuales, su utilidad predictiva sobre la volatilidad en condiciones normales resulta limitada.

En conjunto, estos resultados ponen de manifiesto la importancia de tener en cuenta el consenso como un indicador esencial de la estabilidad del mercado. La pendiente del LOB ofrece, además, una herramienta valiosa para predecir la volatilidad y ajustar estrategias de gestión del riesgo. Por otro lado, se hace evidente que el papel de la negociación informada no es uniforme: en entornos con mayor profundidad puede mejorar la calidad del mercado, mientras que en segmentos con menor liquidez puede exacerbar la volatilidad. Estas conclusiones abren la puerta a políticas regulatorias y estrategias de inversión más focalizadas, especialmente en los tramos de mercado con menor capitalización, con el fin de propiciar una mayor estabilidad y eficiencia en la formación de precios.

El cuarto capítulo profundiza en los efectos de los componentes permanente y transitorio de la pendiente del LOB sobre la volatilidad, los costes de selección adversa, la profundidad del mercado y la capacidad predictiva sobre la rentabilidad. Se demuestra que el componente permanente, asociado con información fundamental y negociadores informados, estabiliza significativamente los precios, reduce la volatilidad (Hipótesis H1a) y disminuye los costes de selección adversa (Hipótesis H2a), al tiempo que incrementa la liquidez (Hipótesis H3a).

Por otro lado, el componente transitorio, vinculado al *trading* algorítmico y operaciones de liquidez, aumenta la volatilidad (Hipótesis H1b) y los costes de selección adversa (Hipótesis H2b), y reduce la profundidad del mercado (Hipótesis H3b). Este componente también demuestra ser un predictor más efectivo de la rentabilidad intradía (Hipótesis H4), destacando la relevancia del *trading* a ultra-corto plazo en la formación de precios.

Durante los periodos de restricciones de venta en corto y colapsos de mercado, se observa que ambos componentes contribuyeron a la volatilidad y al deterioro de la liquidez. Estos resultados subrayan la importancia de distinguir entre actividades informadas y no informadas al evaluar la microestructura del mercado.

Esta investigación representa una contribución significativa al estudio de la microestructura de los mercados financieros, particularmente en contextos de alta frecuencia y condiciones extraordinarias como las observadas durante la pandemia de COVID-19. A través de un enfoque metodológico robusto, se han alcanzado las siguientes aportaciones clave:

Evidencia de órdenes informadas en el LOB: Los resultados confirman la existencia de órdenes informadas en el libro de órdenes limitadas, así como su capacidad para influir en la calidad del mercado mediante la mejora del consenso de creencias y la reducción de la volatilidad en condiciones específicas.

Comprensión ampliada del LOB: La descomposición de la pendiente del LOB en un componente permanente y uno transitorio permite un análisis más detallado de las dinámicas subyacentes al comportamiento del mercado, diferenciando el impacto de actividades informadas frente a no informadas.

Impacto de las restricciones a las ventas en corto: Los resultados destacan cómo las restricciones regulatorias, a pesar de sus objetivos de estabilización, pueden generar efectos contraproducentes al afectar negativamente la liquidez y eficiencia del mercado.

Herramientas predictivas: La validación de la pendiente del LOB como un indicador fiable de la volatilidad, combinado con su utilidad complementaria frente a medidas tradicionales como VPIN, establece un nuevo estándar para evaluar la estabilidad del mercado y facilita su uso en la gestión de riesgos.

Implicaciones regulatorias: Los hallazgos ofrecen una base empírica valiosa para el diseño de políticas regulatorias más efectivas, equilibrando la necesidad de estabilidad con la preservación de la eficiencia y liquidez del mercado.

En suma, esta tesis aporta nuevas perspectivas para reguladores, inversores y académicos interesados en la estabilidad y eficiencia de los mercados financieros. Además, se abren múltiples vías de investigación futura, incluyendo la aplicación de estos enfoques en mercados internacionales y contextos normativos diversos. También se subraya el potencial de incorporar tecnologías avanzadas como el aprendizaje automático y la inteligencia artificial para optimizar herramientas predictivas y explorar dinámicas más complejas en la formación de precios.

De cara a investigaciones futuras, resulta fundamental explorar con mayor profundidad las interacciones entre las variables de consenso del libro de órdenes, la negociación informada y el comportamiento de los inversores en mercados financieros. Estas dinámicas podrían analizarse en diferentes mercados y periodos de inestabilidad financiera para evaluar cómo influyen en la formación de precios y la volatilidad. Además, sería valioso investigar cómo el consenso en el LOB puede actuar como mediador en la relación entre negociación informada y comportamiento gregario, identificando posibles patrones causales que podrían proporcionar nuevas herramientas para predecir eventos extremos en los mercados. Finalmente, integrar modelos avanzados basados en inteligencia artificial y aprendizaje profundo permitirá capturar las complejidades subyacentes a estas relaciones y diseñar estrategias más eficaces para la gestión de riesgos y la estabilidad financiera.