



When volatility is not enough: classical and quantum behaviors in stock investment

F.Xavier Alvarez^a, Hector Sala^{b,c,*} 

^a Departament de Física, Universitat Autònoma de Barcelona, Barcelona, Spain

^b Departament d'Economia Aplicada, Universitat Autònoma de Barcelona, Barcelona, Spain

^c IZA Network at LISER, Bonn, Germany

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ABSTRACT

We introduce two novel metrics—the Zero Bin Ratio (ZBR) and algorithmic price variance (λ)—to analyze investor behavior in high-frequency equity markets. Using nanosecond-level trading data from Nasdaq-100 stocks, we distinguish between classical and quantum patterns of investor behavior. In the classical case, bid-ask spreads are primarily driven by realized volatility, while in the quantum case, they are better explained by algorithmic variance and central distribution dynamics. The ZBR complements this distinction by capturing the role of zero-price-change trades in shaping liquidity. Our framework offers a new lens on market microstructure and investor heterogeneity. We apply it to twelve Nasdaq-100 firms—selected for their structural diversity, trading intensity, and exposure to stock splits—and uncover both persistent behavioral types and sharp regime shifts directly linked to those stock splits. The findings, derived through two empirical specifications tailored to each regime, reveal systematic behavioral heterogeneity with implications for market design, liquidity modeling, and trading strategy.

1. Introduction

Financial markets are commonly described through the lens of volatility, with price fluctuations interpreted as noisy outcomes of random walks punctuated by shocks. Yet this perspective overlooks an essential dimension: the forces that govern how consensus prices emerge, persist, and eventually break down. At tick-level resolution, the vast majority of trades cluster around zero price change, revealing a latent order that standard volatility measures fail to capture. This paper proposes that these microstructural regularities can be better understood through analogies with quantum thermodynamics. By focusing on the concentration of trades at zero price change, we uncover a form of market condensation akin to the tendency of particles in a Bose–Einstein system to occupy the lowest available energy state (Pathria and Beale, 2011). From this starting point, we build a framework to explain how markets transition from stable consensus to re-pricing, and how herding behavior at the micro level shapes macroscopic price dynamics.

Our framework exploits the full informational content of the histogram of stock price changes at high-frequency transaction level—nanosecond trades aggregated into 10-minute intervals. This histogram can be decomposed into three analytically distinct components. First, the central bin captures all trades executed with zero price change. To quantify this clustering, we define the Zero Bin Ratio (ZBR) as the proportion of trades with no price variation relative to the total number of trades. Second, we introduce algorithmic

* Corresponding author at: Departament d'Economia Aplicada, Universitat Autònoma de Barcelona, 08193 Bellaterra (Cerdanyola del Vallès), Spain.

E-mail address: hector.sala@uab.cat (H. Sala).

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variance (λ), defined as the price variance of the best-fitting normal distribution to the central body of returns, explicitly excluding both the zero-change bin and the tails (see Section 4). Finally, the tails represent extreme realizations of 10-minute interval price changes—extreme observations lying outside the fitted normal distribution used to compute λ (see Figs. 2 and 3, and Figs. A1–A3 in the Online Appendix).

Algorithmic variance is conceptually designed as a complement—not a substitute—to realized volatility, which aggregates all variation symmetrically, without distinguishing any of the three components. In contrast, λ isolates the systematic structure of intermediate price responses by abstracting away the extremities (tails) and microstructural stasis (ZBR). This refinement becomes especially salient under market regimes where the traditional volatility measure loses granularity or fails to explain the behavior of the Bid-Ask spread. Indeed, when constructed from high-frequency return data, realized volatility captures not only aggregate price variation but also market microstructure effects and intraday dynamics.

We classify investor behavior at the company level as either classical or quantum based on the empirical dominance of the distinct market microstructure characteristics we define through our newly introduced metrics. A company exhibits classical behavior when two conditions are met: first, the bid-ask spread is primarily governed by realized volatility—captured through standard measures of price variance—indicating that liquidity and transaction costs are closely tied to the magnitude of price fluctuations over time. Second, as a consequence, there is a low ZBR—reflecting little concentration of trades at unchanged prices—, suggesting that price formation is primarily driven by more extreme price changes, with trading activity dominated by Low Frequency Traders (LFTs) that do not operate mainly through algorithmic speed.¹

In contrast, a company displays quantum behavior when the bid-ask spread is better explained by algorithmic variance. This signals that liquidity conditions are shaped not by extreme trading behavior but by interactions occurring in the central part of the price change distribution. In this regime, trading is led by High Frequency Traders (HFTs), whose actions are less reactive and more diffusely distributed across price levels. Additionally, the quantum regime is characterized by a high ZBR, indicating that a dense concentration of zero-price-change transactions may reflect a form of herding behavior. Note that in the extreme case of ZBR = 1, price volatility disappears. These two dimensions—volatility source and ZBR interpretation—jointly characterize the distinct microstructural dynamics of classical and quantum investor behavior. Fig. 1 summarizes our approach.

LFTs typically hold positions over extended horizons, ranging from days to years, guided by strategic decision-making and fundamental analysis aimed at capturing broader market trends. Their trading activity is relatively sparse, and position adjustments are infrequent, often tied to shifts in macroeconomic conditions, firm-level fundamentals, or portfolio rebalancing needs. In contrast, HFTs operate on ultrashort time scales, executing large volumes of orders within milli, micro, or nanoseconds to exploit transitory price discrepancies. HFT requires continuous market engagement and heavy investment in advanced technological infrastructure, including co-location services and low-latency systems, to maintain a speed advantage. The distinction between the two groups is thus twofold: first, in technological intensity, with HFT relying on substantial capital expenditures that are largely absent in LFT activity; and second, in trading intensity, as LFTs place relatively few orders compared to the extremely high turnover rates that characterize HFT.

The behavior observed in the stock market does not depend on changes in individual investor strategies, but rather on the relative proportions of HFTs and LFTs.² When dominant, HFTs impart quantum-like behavior to the market, while LFTs confer classical behavior. Our results show that such dominance is essentially determined by the stock price. Because HFT strategies operate within limited price variations, the relative price fluctuation becomes smaller for high-priced stocks, reducing the profitability of investing in them. This effect is particularly evident in high-ratio stock splits, where the relative abundances of HFTs and LFTs can even be inverted.

In a nutshell, by introducing algorithmic variance and the ZBR, we extend the traditional market microstructure toolkit with a framework that allows for a cleaner identification of distinct investment strategies—such as the contrast between LFTs and HFTs—alongside the detection and quantification of herding behavior. These two dimensions are interrelated, as competition for profitability in HFT is primarily driven by execution speed, which pushes traders toward convergent strategies. This framework thereby expands the informational content of the histogram of price changes beyond the aggregate measure of realized volatility, disentangling the microstructural forces that shape price dynamics.

The contributions of this paper are thus fourfold. First, we shift the analytical focus from the tails of the price change distribution—where realized volatility typically dominates—to its center, where most trading activity occurs. Second, we propose two novel empirical measures, the ZBR and algorithmic variance, which provide insight into liquidity and investor behavior within the central part of the distribution. Third, we introduce a quantum-theoretic framework that complements what we call the classical approach to market microstructure. Fourth, we conduct a detailed empirical analysis of a selection of Nasdaq-100 stocks, classifying

¹ What we call classical setting is not only extensively documented in the literature (Roll, 1984; Glosten and Milgrom, 1985; Hasbrouck, 2009; Comerton-Forde et al., 2010), but also closely aligned with the foundations of classical statistics—particularly the Gaussian characterization of price changes. By contrast, the Bose–Einstein distribution offers an instructive tool for capturing the condensation phenomena associated with quantum behavior (Staliūnas, 2005; Wang et al., 2019).

² Investor strategies are naturally heterogeneous and may be conditioned on factors that influence volatility (Kacperczyk et al., 2025). Even within a given investor type, strategic variation is well documented—for example, Menkveld and Zoican (2017) distinguish between HFTs acting as market makers and those engaging in short-term speculative activity ('high-frequency bandits'). In this study, however, our focus is narrower: we emphasize the correspondence between the relative dominance of HFT activity, associated with quantum-like price dynamics, and the relative dominance of LFT activity, associated with more classical price behavior. In a related spirit to ours, Li et al. (2017) develop a methodology to classify all NASDAQ trade orders as either HFT or LFT limit orders, offering a complementary perspective on the segmentation of trading activity.

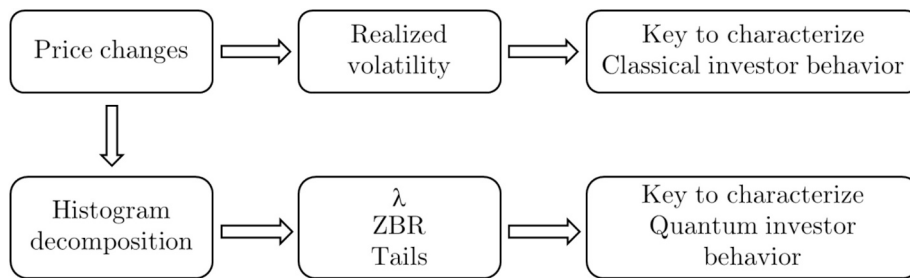


Fig. 1. Classical and Quantum metrics.

them according to classical or quantum behavior and identifying the structural features that drive this classification.

To explore the behavioral drivers of stock price formation, we examine twelve firms from the Nasdaq-100, selected for their representativeness, trading intensity, and structural diversity. Our sample is organized into three analytical groups. First, we consider Advanced Micro Devices, Inc. (AMD), Booking Holdings Inc. (BKNG), and Mercado Libre, Inc. (MELI)—firms that illustrate distinct microstructural patterns and serve as a reference point for classifying investor behavior into classical and quantum regimes. Second, we analyze companies that underwent significant stock splits during the sample period: Broadcom Inc. (AVGO), NVIDIA Corporation (NVDA), and O'Reilly Automotive Inc. (ORLY). These firms offer compelling empirical cases of behavioral transition, displaying classical features in the pre-split period and quantum characteristics post-split. Finally, we turn to the remaining major U.S. technology firms commonly referred to as the “Magnificent Seven” (M7): Alphabet Inc. (GOOG, GOOGL), Amazon.com Inc. (AMZN), Apple Inc. (AAPL), Meta Platforms Inc. (META), Microsoft Corporation (MSFT), and Tesla, Inc. (TSLA). While AVGO replaced TSLA in the 2025 Nasdaq-100 rankings, we retain both in our analysis given their relevance to the broader behavioral landscape.

Our empirical classification reveals consistent and meaningful variation across these firms. AMD displays pronounced quantum characteristics, while BKNG and MELI align with classical investor behavior. The post-split dynamics of AVGO, NVDA, and ORLY signal a clear shift toward quantum features, contrasting with their classical pre-split profiles. Among the M7, AMZN, AAPL, GOOGL, and TSLA exhibit strong quantum signatures; META adheres more closely to classical dynamics; and MSFT occupies an intermediate position. These distinctions have important implications for understanding liquidity formation and investor strategy in modern markets. To support this classification, we analyze millions of nanosecond-level observations—representing over half of Nasdaq-100 trading activity between July 1, 2024, and June 30, 2025. Visual insights are drawn from the full-resolution data, while our econometric analysis relies on 10-minute interval aggregation to ensure robustness and tractability. Together, this multi-tiered approach offers a novel empirical lens on the evolving structure of price formation in the algorithmic trading era.

The remainder of the paper is structured as follows. Section 2 develops the theoretical intuition drawn from physics that underpins the quantum analogy. Section 3 introduces the data and key variables, which in Section 4 are employed to characterize stock investment dynamics across firms from both classical and quantum perspectives. Sections 5 and 6 present the empirical models and the core quantitative results. Finally, Section 7 concludes with a discussion of the main findings and their broader implications.

2. Underpinning the quantum analogy

The key concept of this work is the accumulation of trades in the zero-bin, which arises from both the quantized nature of price variations and the limited risk tolerance of market participants. We refer to this phenomenon as ‘quantum’ because of its analogy with quantum condensation in ultralow-temperature physical gases. We argue that this analogy is particularly insightful: it introduces a thermodynamic perspective that generates testable, structural predictions about the joint behavior of the ZBR and algorithmic variance, predictions that go beyond what a purely statistical description of the histogram would yield.

To gain an intuitive understanding of this phenomenon, we describe the two essential conditions for Bose–Einstein condensation to occur (Pathria and Beale, 2011). First, particles can only occupy quantized energy states, meaning that the energy levels available to them are discrete. Second, the total thermal energy available in the system is limited, preventing all particles from being excited to higher energy levels. When both conditions hold, the histogram of particle occupancy across energy levels exhibits a pronounced spike at the ground state (zero energy). This is the quantum condensed state — by analogy with the condensation of water vapor into liquid, a macroscopic fraction of particles accumulates at the lowest available energy level.

A direct parallel operates in financial markets. First, price movements occur in discrete units — steps of one cent — so the energy-level quantization of the physical system maps onto the tick structure of equity prices. Second, market participants face binding constraints on the risk they are willing to accept, which limits their ability to take on large price-variation positions. The consequence is a disproportionately high number of transactions executed at zero price change: investors — and in particular HFTs competing for the spread within infinitesimally narrow margins — are pushed toward placing orders at the same price as the previous trade. This clustering of activity at a single price level mirrors the overpopulation of the ground state in Bose–Einstein condensation and motivates the thermodynamic interpretation of microstructure dynamics we develop in this paper.

The analogy, however, extends well beyond this observation. In physical condensed systems there is a direct and theoretically grounded relationship between two quantities: the fraction of particles at the ground state (zero energy), and the dispersion of the distribution across non-zero energy levels. Both are governed by a common variable — temperature — which measures the total

thermal energy available to the system. When temperature is low, particles lack the energy to occupy excited states: the ground state fills up and the dispersion of the non-zero distribution narrows. When temperature is high, particles spread across many energy levels: ground-state occupancy falls and dispersion rises. The two quantities move in opposite directions, governed by a single latent variable.

We observe a structurally identical pattern in financial markets. There is no a priori statistical reason why the frequency of zero-price-change transactions should be linked to the variance of the non-zero price changes in the central body of the distribution. Yet our findings show that precisely such a relationship emerges: firms and intervals with a high ZBR systematically exhibit a low algorithmic variance λ , and vice versa. We interpret this co-movement as evidence that both quantities are governed by a common latent variable — the intensity of HFT competition for the spread — which plays the role of temperature in the physical system. When HFT competition is intense, traders are forced toward zero-variation strategies, the ZBR rises, and λ contracts. When competition is less intense, a broader range of algorithmic strategies is viable, the ZBR falls, and λ expands. This inverse relationship is the communicating vessels property of our framework, and it constitutes the primary empirical signature of the quantum condensation mechanism.

One of the main differences between physical systems and financial markets lies in the nature of their constituents. In physical systems, particles are identical and indistinguishable, which limits complexity. In financial markets, investors differ substantially in their strategies, risk preferences, and technological capabilities. This heterogeneity generally increases the complexity of market dynamics. Despite this, we show that the complexity of financial strategies can be reduced to two dominant types — those operating with limited price variation (HFTs) and those engaging in transactions with larger price changes (LFTs) — sufficiently to make the thermodynamic analogy operational (see also Alvarez and Sala, 2026). The histogram of price changes is the key diagnostic tool: in several of the firms we study, the two strategy types can be sharply differentiated in the cross-section of the distribution, with the central Gaussian body mainly attributable to HFTs and the tails attributable to LFTs.

In summary, the quantum analogy is not merely illustrative. It delivers three concrete payoffs. First, it motivates the three-part decomposition of the return histogram as a structural feature of the price process rather than an arbitrary statistical partition. Second, it predicts the inverse relationship between ZBR and λ as a necessary consequence of a common latent variable, rather than as a coincidence. Third, it suggests the existence of regime transitions — from classical to quantum behavior — driven by changes in the relative proportions of HFTs and LFTs, for instance following stock splits that alter the absolute price level and with it the profitability of HFT strategies. All three predictions are confirmed by the empirical evidence presented in Sections 4 to 6.

3. Data

The characteristics described in the previous section are statistical in nature. This implies that, to observe them it is necessary to perform averaging. In our analysis, we have employed 10-minute intervals to compute the relevant magnitudes. In this section, we present the data utilized and the averaging procedures applied.

3.1. Database

Our dataset spans the 12-month period from July 1, 2024, to June 30, 2025, for most selected companies. In all cases, we source high-frequency trading data —comprising bid-ask spreads, transaction prices, and traded volumes with nanosecond-resolution timestamps— from Polygon.io. These data, obtained at nanosecond frequency, underpin the construction of the statistical magnitudes from which we derive our two key distributional metrics: the algorithmic variance and the ZBR. In addition, they support the computation of bid-ask spreads at the transaction level. All observations are then aggregated into 10-minute intervals, which constitute the primary unit of analysis for our econometric estimations. Our sample is restricted to regular trading hours on Nasdaq-100-listed stocks, excluding weekends and official U.S. market holidays observed between New Year's Day and Christmas.

Table 1 provides an overview of the data set used in our analysis. Between July 1, 2024, and June 30, 2025, Nasdaq-100 stocks recorded approximately 3.04 billion transactions involving 241.84 billion traded shares. The twelve companies selected for this study account for approximately 50% of the total trading activity in the index, with NVDA and TSLA alone contributing around half of that volume.

For the three firms that underwent stock splits during this period (AVGO, NVDA and ORLY), later we extend coverage to include both pre- and post-split wider intervals.

Table 1
Nasdaq-100 trade activity. July 1, 2024 – June 30, 2025. Data in millions*.

	N_{ij}	%	Q_{ij}	%		N_{ij}	%	Q_{ij}	%
NVDA	451.750	14.8%	57,645.087	23.8%	GOOGL	102.355	3.4%	6,032.747	2.5%
MSFT	87.556	2.9%	3,722.071	1.5%	TSLA	315.275	10.4%	22,775.737	9.4%
AAPL	150.108	4.9%	9,958.462	4.1%	AMD	102.538	3.4%	9,260.857	3.8%
AMZN	120.796	4.0%	8,344.155	3.5%	BKNG	4.840	0.2%	46.985	0.02%
META	69.629	2.3%	2,971.560	1.2%	MELI	5.932	0.2%	80.406	0.03%
AVGO	76.121	2.5%	5,088.415	2.1%	ORLY	5.124	0.2%	109.997	0.05%
Total	1,492.025	49.0%	126,036.480	52.1%					
Nasdaq-100	3,042.874	100.0%	241,840,699	100.0%					

Note: N_{ij} denotes the number of transactions per firm at nano-frequency j , Q_{ij} the number of traded shares.

* For AVGO, NVDA and ORLY we later extend the sample period of analysis.

Note also that our analysis spans the complete set of regular trading hours of the NASDAQ exchange (09:30–16:00 EST), thereby excluding pre-market and after-hours trading sessions. In the empirical market microstructure literature, some studies also exclude the first and last 30 min of each trading day to mitigate biases associated with microstructure noise (Amihud and Mendelson, 1987; Stoll, 2000; Comerton-Forde and Putniņš, 2014). At the market open, bid-ask spreads tend to widen due to elevated uncertainty and limited liquidity. The opening auction aggregates overnight orders, often inducing excess volatility that reflects temporary order imbalances rather than shifts in fundamental value. Similarly, the market close is characterized by spikes in trading volume—primarily driven by institutional rebalancing—which may lead to short-term price dislocations. In contrast to these studies, we do not exclude such periods. We view the volatility arising at the open and close as an integral component of market dynamics, reflective of genuine trading behavior, and therefore treat it as analytically relevant rather than as noise to be filtered out. We therefore work with 39 intervals per day per company (6.5 trading hours $\times$ 10-minute intervals), each summarizing millions of nanosecond-level transactions, as shown in Table 1.

3.2. Variable definitions

Our main variables of interest are the following:

1. **Stock Price** (P_{ij}): Is the stock price of company i for each nanosecond transaction j . P_{ik} denotes the average of the price of stock i at 10-minute interval k , which is given by

$$\bar{P}_{ik} = \frac{1}{N_{ik}} \sum_{j=1}^{N_{ik}} P_{ij} \quad (1)$$

where N_{ik} represents the number of transactions observed in interval k .

2. **Price Variance** (σ_{ik}^2): Measures the variance of absolute price changes (rather than log returns) for stock i during interval k :

$$\sigma_{ik}^2 = \frac{1}{N_{ik}} \sum_{j=1}^{N_{ik}} (P_{ij} - \bar{P}_{ik})^2 \quad (2)$$

Like standard realized volatility, this measure reflects the extent of intra-period price variation but focuses on levels rather than proportional changes. It is particularly useful in disclosing abrupt shifts in price regardless of scale normalization.

3. **Bid Price** (B_{ij}): Is the highest price at which a buyer is willing to purchase one share of stock i at nanosecond transaction j . At the 10-minute interval level, B_{ik} denotes the highest price at which a buyer is willing to purchase one share of stock i during interval k , reflecting the demand side of the market.
4. **Ask Price** (A_{ij}): Also referred to as the offer price, this is the lowest price at which a seller is willing to sell one share of stock i at nanosecond transaction j . At the k interval level, A_{ik} denotes the lowest ask price observed during interval k , representing the supply side of the market.
5. **Bid-Ask Spread** (S_{ij}): Defined as $S_{ij} = A_{ij} - B_{ij}$, the spread captures transaction costs, market liquidity, and information asymmetry at the nanosecond level. The average spread over each 10-minute interval is computed as the average of the difference in the k interval.

$$\bar{S}_{ik} = \frac{1}{N_{ik}} \sum_{j=1}^{N_{ik}} S_{ij} \quad (3)$$

Narrower spreads indicate higher liquidity and lower trading costs, while wider spreads suggest elevated uncertainty, lower liquidity, or heightened risk of adverse selection.

6. **Trading Volume** (Q_{ij}): The total number of shares of stock i traded in nanosecond transaction j . Q_{ik} represents the total trading volume for stock i during interval k . It provides a measure of trading activity and market depth.

We also consider the key distributional metrics that will be thoroughly discussed in Section 4: the algorithmic variance (λ_{ik}), as opposed to the standard volatility measure, and the Zero Bin Ratio ($\mathcal{Z}_{ik}$).

7. **Algorithmic Variance** (λ_{ik}): This metric captures the price variation generated by high-frequency traders operating in the central body of the return distribution. Its construction follows three steps:

Step 1: Histogram of price changes. For each 10-minute interval k and stock i , we collect all nanosecond-level transaction prices and compute the consecutive price change $\Delta P_{ij} = P_{ij} - P_{ij-1}$ for every transaction pair j within the interval. These price changes are binned into a histogram with bin width equal to the minimum tick size (\$0.01), yielding a discrete frequency distribution over integer-cent increments.

Step 2: Three-part decomposition. The histogram is partitioned into three analytically distinct components. Part 1 is the zero bin ($\Delta P = 0$), containing all transactions executed at no price change; the count of such transactions defines the ZBR numerator. Part 3 consists of the tails — extreme bins associated with large, infrequent price movements driven by low-frequency trading — which are captured by standard realized volatility σ_{ik}^2 . Part 2 is the central body: the intermediate bins surrounding the zero bin but excluding the tails, which follow an approximately Gaussian shape and constitute the domain from which λ_{ik} is estimated.

Step 3: Gaussian fit and extraction of λ . Having excluded the zero bin (Part 1) and the tails (Part 3), we fit the functional form: $A \cdot e^{-\Delta P^2/2\lambda}$ to the remaining central-body observations within the interval $[-0.05, 0.05]$, using the *curve_fit* function from the *scipy.optimize* library in Python. Parameter A is the amplitude of the fitted Gaussian and λ is the variance of the distribution. Algorithmic variance λ_{ik} is therefore the variance of the best-fitting normal distribution to the central body of the return histogram, after excluding both the zero-change bin and the tails.

As an illustration, consider the AAPL histogram shown in Fig. 2. The red arch is precisely this fitted Gaussian. The reported value $\lambda = 0.00028953$ is the estimated width parameter, and $A = 2,917$ is the fitted amplitude — that is, the number of Part 2 transactions entering the fit after excluding Parts 1 and 3.

8. **Zero Bin Ratio** ($\mathcal{Z}_{ik}$): Also discussed in Section 4, this measure reflects the proportion of transactions occurring without a price change. Formally,

$$\mathcal{Z}_{ik} = \frac{N_{Zero,k}}{N_{Zero,k} + N_{Exc,k}} \quad (4)$$

where N_{Zero} denotes the number of transactions that generate no price change (i.e., trades within the zero-return bin), and N_{Exc} denotes transactions associated with price movement. Together, they allow us to describe the degree of price “condensation” or trading centralization, a hallmark of the quantum framework. Also, note that $N_k = N_{Zero,k} + N_{Exc,k}$ accounts for the total number of transactions.

3.3. Descriptive analysis

Table 2 reports summary statistics at the 10-minute frequency. The number of observations differs from Table 1 in the three cases affected by stock splits, reflecting the extension of the sample windows pre- and post-split required for the econometric analysis.

We also note that the mean and median stock prices are closely aligned across firms, indicating limited skewness in the distributions. While not definitive, this pattern is broadly consistent with the Normality assumption that underpins our analytical framework.

4. Fitting stock investment dynamics

4.1. Tails, lambda and the zero bins

Figs. 2 and 3 plot the price of AAPL and BKNG stocks at nanosecond transactions within a 10-minute interval, together with the histogram of the price change. The choice of February 3, 2025, is arbitrary, but of course common to all companies (see the Online

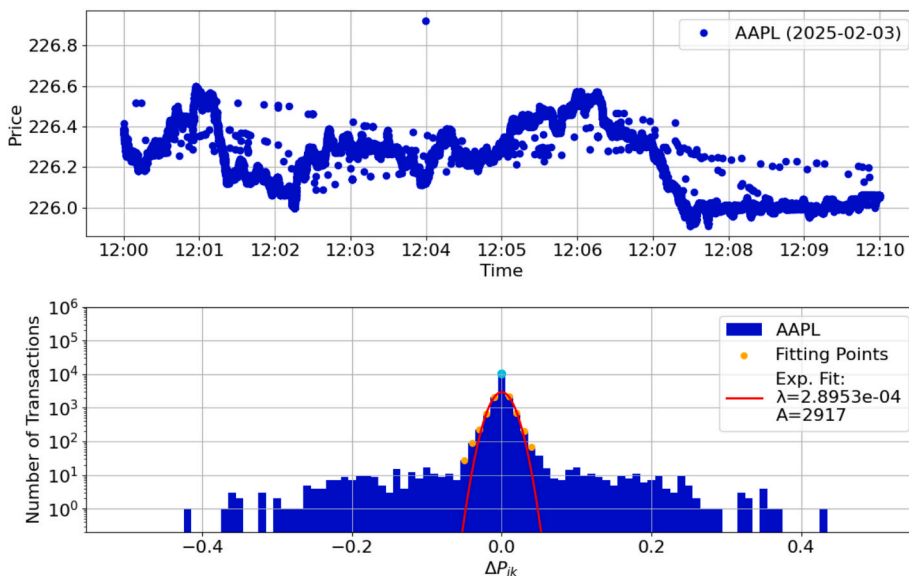


Fig. 2. AAPL. Price evolution, histogram and fit in a selected 10-minute interval.

Table 2

Descriptive analysis. July 1, 2024 – June 30, 2025*.

	$\bar{P}_{ik}$					Q_{ik}					$\bar{S}_{ik}$					Obvs.
	Mean	Median	Max	Min	St. dv.	Mean	Median	Max	Min	St. dv.	Mean	Median	Max	Min	St. dv.	
AMD	129.4	127.7	186.7	77.0	23.5	953,646	695,620	13,433,350	1,414	846,164	0.02	0.02	0.13	0.01	0.01	102,538,203
AMZN	200.1	198.1	242.4	155.5	19.0	859,248	589,090	16,997,254	1,296	956,273	0.03	0.02	0.14	0.01	0.01	120,796,196
AAPL	223.2	224.9	259.4	170.1	15.8	1,026,857	704,503	24,758,721	666	1186,026	0.02	0.02	0.29	0.01	0.01	150,108,120
AVGO																
Pre-split	1,345.0	1,316.2	1,839.1	1,042.6	168.0	64,003	41,789	1,793,560	671	80,827	1.46	1.39	6.68	0.45	0.51	14,492,662
Post-split	193.6	181.3	271.4	132.9	33.8	547,148	356,130	16,087,767	107	667,810	0.09	0.08	0.39	0.01	0.04	74,564,963
BKNG	4,618.6	4,731.2	5,705.1	3,206.9	578.9	5,018	3,289	102,310	5	6,251	15.65	13.07	125	2.95	9,394	4,840,130
GOOGL	171.9	168.9	206.6	141.7	13.3	621,228	409,500	20,975,621	313	745,142	0.02	0.02	0.31	0.00	0.01	102,355,112
MELI	2,040.1	2016.5	2,630.0	1,568.5	243.1	8,584	5,542	299,915	8	11,183	6.68	5.85	41.73	0.94	3.37	5,932,225
META	589.5	586.9	740.1	446.0	66.3	306,031	213,317	5,214,804	184	317,035	0.26	0.24	1.59	0.08	0.10	69,629,473
MSFT	423.4	422.1	499.1	346.8	27.6	395,250	264,524	12,555,764	278	507,820	0.09	0.08	0.63	0.02	0.04	87,555,505
NVDA																
Pre-split	816.1	864.8	1,245.8	474.4	166.1	1,169,646	914,622	12,396,111	230,524	862,683	0.28	0.27	1.00	0.05	0.12	97,790,327
Post-split	127.0	128.2	158.5	87.8	13.4	6,031,489	4,597,734	81,749,682	24,918	4,859,772	0.01	0.01	0.06	0.01	0.00	482,897,499
ORLY																
Pre-split	1,245.4	1,238.7	1,449.5	1,010.5	106.6	7,084	4,622	181,166	118	9367	2.67	2.30	37.00	0.70	1.67	4,236,145
Post-split	89.6	89.5	92.0	87.1	1.1	95,051	68,516	2,447,724	25	141,561	0.06	0.05	0.80	0.01	0.06	1,086,896
TSLA	295.7	274.8	486.5	187.0	69.7	2,351,165	1,814,622	26,114,834	15,042	1,861,087	0.08	0.07	0.33	0.02	0.04	315,274,819

* Note that for AVGO, NVDA and ORLY we extend the sample period of analysis to increase the number of observations. ORLY (15-for-1), AVGO (10-for-1), and NVDA (10-for-1) underwent significant stock splits. Accordingly, two sample periods are defined for each company: ORLY: Jan 2, 2024 – Jun 9, 2025 (Pre), Jun 10 – Jul 22, 2025 (Post); AVGO: Jan 2 – Jul 12, 2024 (Pre), Jul 15, 2024 – Jun 30, 2025 (Post); NVDA: Jan 2 – Jun 7, 2024 (Pre), Jun 10, 2024 – Jun 30, 2025 (Post).

Appendix for the figures corresponding to the rest of companies we consider).

The histograms in Figs. 2 and 3 (and Figs. A1–A3 in the Online Appendix) reveal a distribution with three distinct components. The first one, probably the most striking feature of this analysis, is a sharp spike at the zero-return bin. Its visibility, even on a logarithmic scale, underscores the magnitude of this concentration. Surrounding this spike, the distribution follows an approximately Gaussian shape over small price variations. This is the second component. Beyond the central region of the histogram made of the first two components, a broader third component emerges, characterized by larger price changes that do not align with a clear statistical distribution.

In quantum condensed systems, lowering the temperature increases the occupation of the ground state: as thermal energy decreases, particles lack the energy to move into excited states, leading to accumulation at the lowest level. A similar dynamic can be observed in financial markets: when high-frequency investors reduce the risk they are prepared to take, more of them concentrate their activity at the most secure outcome — the zero-return bin.

To characterize the tails of the distribution, we rely on the traditional measure of volatility. By its very nature, this metric is only weakly influenced by the dynamics of small price variations and is instead driven primarily by the occurrence and magnitude of large price changes.

4.2. Market dynamics and investor behavior

The central part of the distribution can be attributed to HFTs who adjust positions almost instantaneously, leading to an excess of intervals with no net price change. The wider component reflects the behavior of slower, long-term investors, whose trades are less dependent on immediate past prices and instead generate comparatively larger shifts.

As discussed previously, we interpret the spike at the zero-return bin as the combined result of two factors: the quantized nature of price changes (with a minimum tick size of one cent) and the very low variability that exists immediately after the last price change. For very high-frequency investors, the range of plausible prices becomes extremely narrow. Within this group, those with greater risk aversion tend to converge on zero variation as the preferred outcome, producing the sharp excess at the zero bin.

This behavior bears resemblance to the quantum statistics of gases, in which the total level of risk in the market can be seen as analogous to the thermal energy, and the zero bin corresponds to the ground energy state, where risk-averse “particles” condense.

In the lower plot corresponding to BKNG, the central region seems to vanish within the broader variability of returns. However, its presence is still revealed by the excess at the zero-return bin. This indicates that HFTs remain active, though their relative weight is clearly diminished. A plausible explanation is the high absolute price of the stock, which reduces the profitability of high-frequency strategies in this market.

4.3. Illustration: classical vs. quantum behavior

Table 3 presents the correlation coefficients between the bid-ask spread ($\bar{S}_{ik}$) and key explanatory variables. Three distinct groups emerge from the data.

The first group includes AVGO (pre-split), BKNG, MELI, NVDA (pre-split), and ORLY (pre-split). These firms are characterized by: (i) high correlations with price variance (σ_{ik}^2), ranging from 0.67 to 0.82, with NVDA pre-split exhibiting a moderate 0.48; (ii) negative

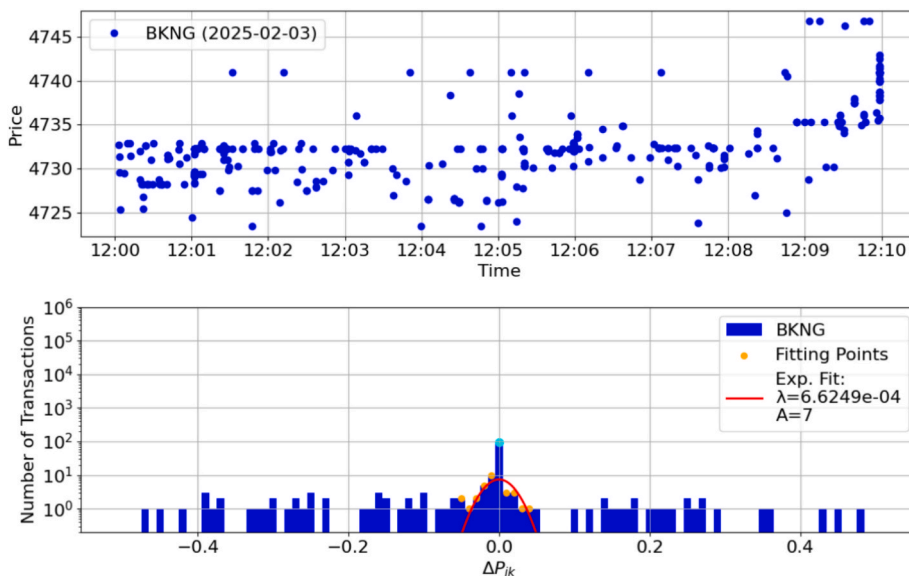


Fig. 3. Booking. Price evolution, histogram and fit in a selected 10-minute interval.

or near-zero correlations with algorithmic variance (λ_{ik}); and (iii) low correlations with the zero-bin ratio metric ($\mathcal{Z}_{ik}$). In addition, the ZBR levels are modest, with average values below 35%. Taken together, these features are consistent with a classical behavioral profile.

The second group includes AMD, AMZN, AAPL, GOOGL, NVDA and ORLY (post-split), and TSLA. This cohort is characterized by: (i) relatively low correlations with price variance (σ_{ik}^2), generally between 0.25 and 0.52; (ii) strong positive correlations with algorithmic variance (λ_{ik}), ranging from 0.70 to 0.96 (except GOOGL at 0.54); and (iii) significant correlations with $\mathcal{Z}_{ik}$, spanning from -0.58 to 0.75 , with AAPL and ORLY post-split at -0.39 and -0.46 , respectively. These firms also exhibit elevated ZBR values—centered around 55%, with AMZN at 48% and peaks reaching up to 70%—highlighting a clear quantum behavioral pattern.

Intermediate cases include AVGO (post-split), MSFT, and META. AVGO post-split shows a high correlation with σ_{ik}^2 (0.33), but an even stronger inverse correlation with $\mathcal{Z}_{ik}$ (-0.75), and an average ZBR of 43%, making it the most “Quantic” among the three. MSFT displays moderate correlations with both σ_{ik}^2 and λ_{ik} (around 0.5), a weaker link with $\mathcal{Z}_{ik}$ (-0.32), and a ZBR average of 41%, positioning it between the two regimes. META presents a stronger correlation with σ_{ik}^2 (0.52), negligible association with λ_{ik} , a modest correlation with $\mathcal{Z}_{ik}$ (-0.38), and a relatively low ZBR of 34%, thus aligning more closely with classical behavior.

Taken together, these findings support the empirical characterization of a quantum investor regime, where the central mass of the price change distribution seems to play a dominant informational role relative to the tails (queues). In such setting, the algorithmic variance (λ_{ik}) demonstrates stronger alignment with liquidity-related costs than standard realized variance/volatility, with the ZBR serving as a second key metric capturing market condensation within the zero-change bin. The regression analysis we conduct in Section 6 will help us to fine tune the characterization of these companies according to the following empirical models.

4.4. Why is volatility not enough?

Wrapping-up, quantum-like behavior in markets is fundamentally determined by the relationship between price variance and the minimum trading increment (the price step). When these two magnitudes are comparable, changes in price have a disproportionately large impact relative to the existing amplitude of fluctuations — a dynamic that strongly characterizes HFTs. By contrast, when price variance is sufficiently large, as is typically the case for Low-Frequency Traders, this impact becomes much less significant. This effect naturally correlates with the absolute price level of the asset, since market fluctuations themselves are closely linked to price.

The visibility of this impact is largely lost when fluctuations are normalized through the use of volatility. Volatility was designed to allow comparison between assets with very different price levels, but by definition it masks the influence of the minimum trading unit on market fluctuations. For this reason, volatility alone is not sufficient to interpret the behavior of HFT strategies, which appear to follow dynamics driven by extremely small price variations — producing patterns that resemble those observed in quantum-like systems.

We recognize that a strictly orthodox quantum interpretation — for example, invoking a wave function governing HFT behavior — has no realistic place within financial theory. Nevertheless, we argue that the influence of the minimum trading increment in fast, highly automated, and high-volume markets dominated by HFT activity may justify viewing this similarity with low-energy thermal systems as genuinely meaningful rather than merely metaphorical.

Table 3
Quantum behavior indicators. Jan 1, 2024 – June 30, 2025*.

	Correlation of $\bar{S}_{ik}$ versus:					$\mathcal{Z}_{ik}$					Obsvs.
	σ_{ik}^2	λ_{ik}	$\mathcal{Z}$	N_{Zero}	N_{Exc}	Mean	Median	Max	Min	Std.v.	
AMD	0.25	0.83	-0.71	0.09	0.37	0.51	0.50	0.73	0.19	0.06	9,750
AMZN	0.45	0.71	-0.59	0.16	0.41	0.48	0.48	0.70	0.22	0.06	9,750
AAPL	0.49	0.89	-0.39	0.20	0.44	0.53	0.51	0.86	0.15	0.08	9,750
AVGO											
Sample 1	0.67	-0.45	-0.23	0.05	0.13	0.31	0.31	0.50	0.18	0.04	4,563
Sample 2	0.33	0.24	-0.75	-0.19	0.09	0.43	0.43	0.67	0.16	0.06	9,902
BKNG	0.82	0.04	-0.18	0.06	0.20						
GOOGL	0.38	0.54	-0.59	0.04	0.27	0.55	0.55	0.74	0.17	0.06	9,750
MELI	0.82	-0.01	-0.13	0.03	0.12	0.25	0.24	0.52	0.02	0.06	9,406
META	0.52	-0.04	-0.38	0.18	0.30	0.34	0.34	0.55	0.17	0.04	9,749
MSFT	0.50	0.52	-0.32	0.04	0.23	0.41	0.39	0.79	0.19	0.08	9,456
NVDA											
Sample 1	0.48	-0.18	-0.13	0.41	0.53	0.33	0.31	0.62	0.21	0.07	4,290
Sample 2	0.30	0.96	-0.32	0.38	0.51	0.55	0.55	0.77	0.31	0.05	10,296
ORLY											
Sample 1	0.82	0.02	0.04	0.05	0.04	0.30	0.30	0.58	0.05	0.06	8,760
Sample 2	0.67	0.70	-0.46	-0.10	0.09	0.53	0.53	0.79	0.27	0.06	647
TSLA	0.51	0.82	-0.58	0.21	0.52	0.40	0.39	0.81	0.26	0.09	9,726

* ORLY (15-for-1), AVGO (10-for-1), and NVDA (10-for-1) underwent significant stock splits. Accordingly, two sample periods are defined for each: ORLY: Jan 2, 2024 – Jun 9, 2025 (Pre), Jun 10 – Jul 22, 2025 (Post); AVGO: Jan 2 – Jul 12, 2024 (Pre), Jul 15, 2024 – Jun 30, 2025 (Post); NVDA: Jan 2 – Jun 7, 2024 (Pre), Jun 10, 2024 – Jun 30, 2025 (Post). Note that we have extended the sample periods of analysis to increase the number of observations in these three cases.

5. Empirical models

In terms of data construction, we utilize nanosecond-resolution timestamp data, which we aggregate into 10-minute intervals. Theoretically, our quantum framework offers a structural characterization of investor behavior that emphasizes cross-sectional microstructure features observed within each interval, rather than dynamic or intertemporal dependencies. Our focus is thus more aligned with capturing the state of the market at discrete moments in time than with modeling the propagation of shocks or persistence effects across time. Accordingly, our benchmark model draws from the foundational frameworks explained in [Madhavan \(2000\)](#) and [Stoll \(2000\)](#), which were originally developed for static cross-sectional analysis and remain influential in the empirical market microstructure literature ([Pan and Misra, 2021](#); [Guloglu and Ekinci, 2022](#)). While our empirical context fits naturally with the static nature of these models, we also estimate autoregressive specifications as a robustness exercise. These dynamic models, while methodologically valid, consistently underperform relative to our static models in both statistical fit and economic interpretability. This comparison endorses the empirical adequacy and theoretical relevance of the static specification for our specific research focus.

Accordingly, maintaining the notation introduced in [Section 3](#), our baseline specification for any firm i is given by:

$$S_k = \beta_0 + \beta_1 \sigma_{ik}^2 + \beta_2 MV_k + \beta_3 Q_k + \beta_4 P_{ik} + \varepsilon_k \quad (5)$$

where the β 's are parameters to be estimated, ε is the error term, and MV denotes the firm's market capitalization. In our setting, the role of MV is largely redundant: the number of outstanding shares remains constant within each 10-minute interval, and the stock price (P_k) is already included as a regressor. Instead, we follow [Pan and Misra \(2021\)](#) and incorporate the absolute number of transactions (N_k). This yields an updated specification for intraday high-frequency data:

$$S_k = \beta_0 + \beta_1 \sigma_{ik}^2 + \beta_2 N_k + \beta_3 Q_k + \beta_4 P_{ik} + \varepsilon_k \quad (6)$$

To test the empirical relevance of the quantum approach, we introduce two changes. First, we substitute overall price variance σ_{ik}^2 , the key parameter in the classical framework, with λ , the central parameter in the quantum approach. Second, we substitute N_k by the ZBR ($\mathcal{Z}_k$). Following standard practice for bounded regressors ([Papke and Wooldridge, 1996](#)), we replace N_k with the logit transformation of the $\mathcal{Z}_k$, defined as: $L\mathcal{Z}_k = \log(\mathcal{Z}_k/(1 - \mathcal{Z}_k))$, which maps the bounded $[0,1]$ interval to the full real line, allowing the marginal effect of trade concentration to vary non-linearly with the level of condensation. This yields the quantum specification:

$$S_k = \beta_0 + \beta_1 \lambda_k + \beta_2 L\mathcal{Z}_k + \beta_3 Q_k + \beta_4 P_{ik} + \varepsilon_k \quad (7)$$

In the two specifications we use, [\(6\)](#) and [\(7\)](#), we expect $\beta_1 > 0$. In the classical model, a positive coefficient on σ_{ik}^2 reflects the intuitive notion that the bid-ask spread incorporates compensation for heightened price risk, particularly as order book depth becomes more relevant. In the quantum specification, a positive coefficient on λ_k captures the contribution of investors positioned away from the ZBR, yet not contributing to the distribution's tails—those trading in the intermediate region of the order flow spectrum. In addition, as established in [Section 3](#), λ and the ZBR are functionally linked. Given the observed positive relationship between S_k and λ_k , we expect the spread to be inversely related to the ZBR so that $\beta_2 < 0$.

A similar consideration applies to the inclusion of Q_k . While the core of our analysis—aside from the role of β_1 —centers on the estimation of β_2 in [Eq. \(7\)](#), which captures the composition of trades via N_{Zero} and N_{Exc} , it is essential to control for overall trading volume. Including Q_k ensures that the estimated effects of order type are not conflated with shifts in aggregate market activity. This allows for a more precise interpretation of how the components of the ZBR influence the bid-ask spread. Indeed, a higher proportion of zero-return trades (i.e., an increase in N_{Zero}) holding N_{Exc} raises the ZBR, which in turn implies a reduction in the bid-ask spread. Conversely, an increase in N_{Exc} , holding N_{Zero} constant, lowers the ZBR and increases the spread.

Following [Madhavan \(2000\)](#), inverse price is often used as a regressor, given that minimum tick sizes induce convexity in spreads—implying that lower-priced stocks tend to exhibit larger percentage spreads. In contrast, our specification includes the stock price directly, consistent with the approach of [Stoll \(2000\)](#), who argues that the price level itself “controls for the effect of discreteness” ([Stoll, 2000](#), p. 1480). Moreover, price serves as an additional proxy for risk, as lower-priced stocks are generally more volatile. Accordingly, we expect $\beta_4 > 0$, and we emphasize that our analysis of classical and quantum investor behavior is conducted with this control for price discreteness in place.

6. Quantum portfolios and the limits of volatility

6.1. Characterizing classical and quantum behavior in selected Nasdaq-100 companies

In this Section, we work with a selection of three Nasdaq-100 companies on account of their diverse investor behavior, representative of classical and quantum characteristics. Advanced Micro Devices, Inc. (AMD) is a prominent semiconductor company known for its high-performance computing and graphics technologies, ranking within the top 15 Nasdaq-100 firms by market capitalization. Booking Holdings Inc. (BKNG), a global leader in online travel and related services, is consistently positioned among the top 25 companies in the index. Mercado Libre, Inc. (MELI), the largest e-commerce and fintech platform in Latin America, holds a mid-range position in the Nasdaq-100 by market value as of July 2025.

As shown in the right-hand side (RHS) panel of [Fig. 4](#), MELI exhibits a near one-to-one relationship between the bid-ask spread and overall price variance (or realized volatility). In contrast, both the algorithmic variance and the ZBR show no apparent association with the spread, as indicated by the lack of correlation in the corresponding panels. According to the theoretical framework outlined in

Section 3, this pattern is indicative of strong classical behavior. Conversely, AMD displays a clear one-to-one relationship between the bid-ask spread and algorithmic variance (LHS panel), alongside a lack of correlation with price variance (RHS panel). In addition, the spread exhibits a negative relationship with the ZBR, which is the second key defining feature of quantum behavior as characterized in our framework. BKNG is not pictured because it behaves qualitatively as MELI.

Table 4 provides the formal regression analysis corresponding to the qualitative distinctions observed in **Fig. 4**. The specifications applied are grounded in the modeling framework developed through Eqs. (6) and (7), which separately capture classical and quantum microstructural dynamics. By mapping the relationships discussed visually between the bid-ask spread and the different measures of variance (volatility) and trade concentration onto a quantitative structure, the table serves to formalize the behavioral classification and deepen the interpretation of investor activity across the three firms.

Specification (6) yields a poor fit for AMD, with an R^2 of only 0.24, but performs strongly for BKNG and MELI, where the values reach 0.81 and 0.79, respectively. In contrast, specification (7) provides a substantially better explanation of AMD's bid-ask spread dynamics ($R^2 = 0.78$), while its performance deteriorates sharply for BKNG and MELI, falling to 0.26 and 0.15. These contrasting outcomes support a clear behavioral distinction: BKNG and MELI align closely with classical market behavior, whereas AMD exhibits features characteristic of quantum behavior.

This classification is grounded in the differential performance of the explanatory variables across models. As anticipated from the visual evidence in **Fig. 4**, price variance plays a dominant role in BKNG and MELI, with estimated coefficients of around 0.40, but is largely uninformative in the case of AMD. Conversely, algorithmic variance assumes a central role in AMD, with a coefficient of 0.783 — statistically significant at the 1% level — consistent with the defining features of quantum behavior. In BKNG and MELI, the λ coefficient is statistically indistinguishable from zero, or negative in the case of MELI, further confirming that algorithmic dynamics in the central body of the distribution play no role in explaining the spread for these classical firms. The ZBR reinforces this characterization: its coefficient in AMD is -0.500 , approximately twice as large in absolute value as in BKNG (-0.262) and two and a half times as large as in MELI (-0.201). The ZBR is statistically significant across all three firms, suggesting that trade concentration at the zero bin carries some informational content even in the classical regime — though this alone is insufficient to generate quantum behavior in the absence of a significant λ contribution.

Volume, included as a control in both specifications, is statistically significant only in specification (7), where it consistently displays a positive association with the spread, with coefficients around 0.10. The price control exhibits varying effects, likely reflecting differences in nominal price levels: BKNG and MELI trade at several thousand U.S. dollars per share, while AMD's stock price is below \$150 (see **Table 2**). These pricing differences may influence the relative salience of price-based frictions and investor segmentation.

6.2. From classical to quantum behavior: significant splits matter

Broadcom Inc. (AVGO) is a global technology company specializing in semiconductor and infrastructure software solutions, consistently ranked among the top 5 Nasdaq-100 firms by market capitalization. NVIDIA Corporation (NVDA), a market leader in graphics processing units and AI computing, holds one of the top three positions in the Nasdaq-100 by market value. O'Reilly Automotive (ORLY) is a leading firm in the automotive replacement parts industry, ranked approximately 50th by market capitalization within the Nasdaq-100 as of July 2025. Of particular interest for our analysis is these companies' implementation of stock splits: a 10-for-1 split by AVGO and NVDA, and a 15-for-1 split by ORLY, which became effective in July 2024, June 2024, and June 10, 2025, respectively. While stock splits are not uncommon, the unusually large split ratios adopted by these companies offer a distinctive setting to examine behavioral responses in equity markets. As we demonstrate below, these events provide a natural experiment to study how a firm's capital market policy —absent fundamental changes— can trigger significant shifts in investor and market participant behavior.

Table 3 reports correlation coefficients that reveal consistent post-split patterns across firms, despite their sectoral and structural differences. Notably, the correlation between the bid-ask spread and the standard price variance declines in all three companies following their respective stock splits: from 0.67 to 0.33 in AVGO, 0.48 to 0.30 in NVDA, and 0.82 to 0.67 in ORLY. In contrast, the correlation with algorithmic variance increases significantly shifting from negative to 0.24 in AVGO, reaching 0.96 in NVDA, and rising from near zero to 0.70 in ORLY. A similar trend is observed for the correlation with the zero-bin ratio, with average ZBR levels increasing by 12, 9, and 23 percentage points, respectively.

These shifts indicate that the splits induce substantial and broad-based changes in investor behavior, reflected across all key microstructural indicators. **Fig. 5** offers a visual synthesis of these dynamics, with the three panels mirroring the structure of **Fig. 4**. Collectively, the evidence points to a systematic reconfiguration in the microstructural determinants of liquidity, highlighting the rising importance of algorithmic variance (LHS panel) and the ZBR (central panel), alongside the declining influence of price variance (RHS panel) in the post-split trading environment.

To formalize the descriptive patterns observed in the correlation structure and visual diagnostics, **Table 5** presents regression estimates quantifying the influence of key explanatory variables on the bid-ask spread across pre- and post-split periods. The odd-numbered columns report results from Equation (6), which includes the standard price variance and the total number of transactions. The even-numbered columns present results from Equation (7), which incorporates the algorithmic variance and the ZBR.

The most general result emerging from the regression analysis is a clear shift in explanatory power — reflected in the adjusted R^2 statistics — between the pre- and post-split periods. Characteristics associated with quantum investor behavior become more prominent after the stock splits, leading to substantial gains in model fit for the quantum specification: the adjusted R^2 increases from 0.365 to 0.859 in AVGO, from 0.696 to 0.925 in NVDA, and from 0.107 to 0.590 in ORLY. Conversely, classical microstructural drivers

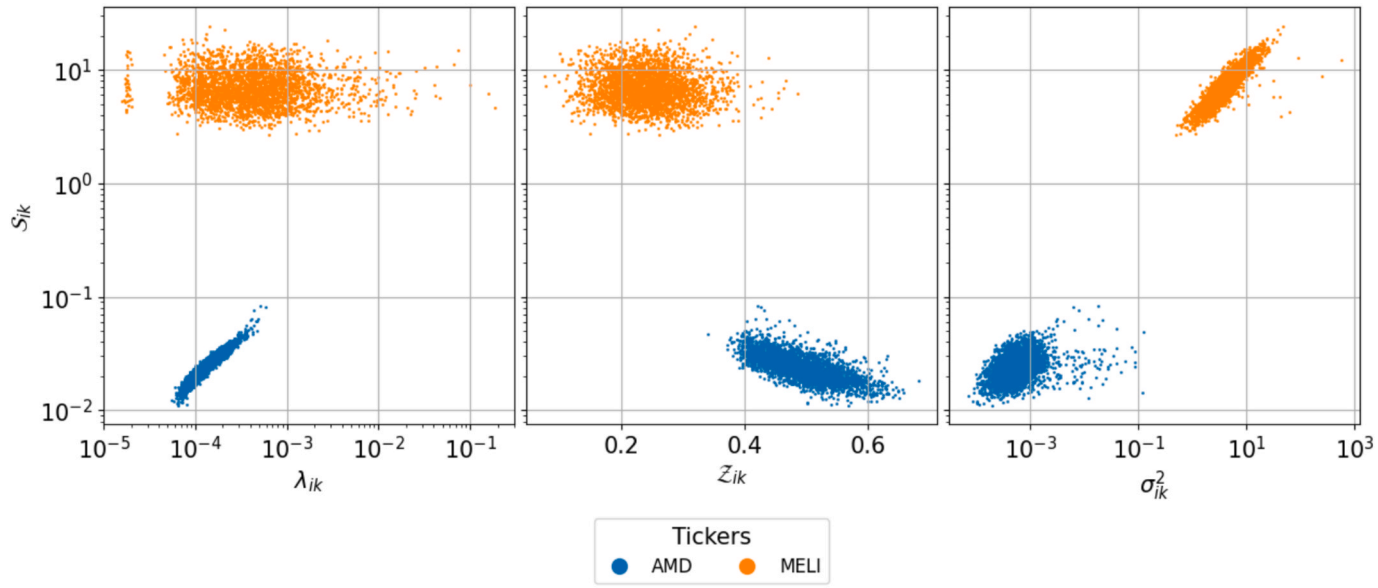


Fig. 4. Bid-Ask spread correlations. AMD and MELI.

Table 4

Regression Analysis of AMD, BKNG and MELI. July 1, 2024 – June 30, 2025.

Dependent variable: Bid-Ask Spread ($\bar{S}_{ik}$).						
	AMD		BKNG		MELI	
	(1)	(2)	(3)	(4)	(5)	(6)
C_i	−6.29*** [0.0000]	−1.556 [0.1790]	−4.08*** [0.0000]	−13.26*** [0.0000]	−2.50*** [0.0000]	−8.306*** [0.0000]
σ_{ik}^2	0.113*** [0.0000]		0.373*** [0.0000]		0.389*** [0.0000]	
N_{Zik}	0.025 [0.5115]		0.117*** [0.0000]		0.045** [0.0150]	
λ_{ik}		0.783*** [0.0003]		−0.003 [0.4562]		−0.012*** [0.0000]
$L \cdot \bar{Z}_{ik}$		−0.500*** [0.0004]		−0.262*** [0.0000]		−0.201*** [0.0000]
Q_{ik}	0.058 [0.1651]	0.097*** [0.0000]	−0.004 [0.6850]	0.135*** [0.0000]	0.015 [0.1616]	0.082*** [0.0000]
$\bar{P}_{ik}$	0.482*** [0.0000]	−0.002 [0.9542]	0.609*** [0.0000]	1.716*** [0.0000]	0.460*** [0.0000]	1.198*** [0.0000]
Adj. R^2	0.2363	0.7822	0.8071	0.2633	0.7942	0.1488
Obs.	9,750	9,750	9,392	9,389	9,400	9,400

Note: Newey-West (HAC) standard errors & covariance computed to account for potential autocorrelation. Probability in brackets; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

diminish in explanatory relevance post-split, with a notable drop in the classical R^2 for NVDA (from 0.735 to 0.219) and ORLY (from 0.750 to 0.526). In AVGO, the classical model retains substantial explanatory power in the post-split period (0.825), as the emerging significance of N_{ik} and Q_{ik} under that specification provides additional explanatory content.

The declining role of overall price variance is underscored by the consistently lower post-split coefficients on σ_{ik}^2 across all three firms. At the same time, algorithmic variance (λ_{ik}) takes on a positive and statistically significant coefficient in the post-split period across all three firms — 0.295 in AVGO, 0.815 in NVDA, and 0.615 in ORLY — confirming the growing relevance of algorithmic dynamics in shaping liquidity costs under the quantum regime. Notably, in the pre-split period, the λ_{ik} coefficients are negative and significant in AVGO (−0.542) and NVDA (−0.119), and statistically indistinguishable from zero in ORLY, which further corroborates the classical profile of all three firms before the splits.

In AVGO and ORLY, the transition to quantum behavior is further supported by an increased sensitivity of the bid-ask spread to ZBR: post-split, the estimated coefficients on $L \cdot \bar{Z}_{ik}$ become strongly negative, reaching −0.943 in AVGO and −1.17 in ORLY, both statistically significant. In NVDA, the ZBR coefficient is also negative and significant post-split (−0.136), but considerably smaller in magnitude. This suggests that NVDA's behavioral shift is primarily driven by the surge in algorithmic variance — whose coefficient of 0.815 is the largest among the three — while the ZBR plays a secondary role, pointing to a different pathway to quantum behavior relative to AVGO and ORLY. In the pre-split period, the ZBR is significant for AVGO (−0.409) and NVDA (−0.102) but not for ORLY (−0.025), consistent with a partial quantum signal already present in the pre-split AVGO and NVDA data, though insufficient to dominate the classical drivers.

Volume (Q_{ik}) is statistically significant in both firms under specification (7), but not under specification (6), except for ORLY pre-split where it enters negatively. Interestingly, traded volume is not statistically significant in NVDA post-split under specification (7). This likely reflects the stock's exceptional liquidity during the sample period, when it ranked among the most actively traded stocks in both the Nasdaq-100 and S&P 500 indices (as shown in Table 1, NVDA accounts for 23.8% of Nasdaq-100 traded shares). Lastly, the inclusion of the stock price as a control — generally displaying a positive and significant relationship with the spread — helps account for potential behavioral adjustments triggered by the split, beyond those captured by other explanatory variables. The only exception is NVDA post-split, where the price coefficient turns negative (−0.053), consistent with the dynamics of a very high-liquidity, high-demand stock during the sample period.

6.3. The remaining Magnificent 7 and Tesla

Table 6 presents regression estimates for the remaining M7 companies plus TSLA, who was replaced by AVGO in 2025. As with Tables 4 and 5, odd-numbered columns report results from Equation (6), which includes standard price variance and the total number of transactions, while even-numbered columns present results from Equation (7), incorporating algorithmic variance and the ZBR.

In the classical specification (Equation (6)), price variance (σ_{ik}^2) consistently exhibits a positive and statistically significant association with the bid-ask spread across all six companies, with estimated coefficients ranging from 0.109 in GOOGL to 0.165 in META. This implies that a 1% increase in price variance corresponds to a 0.109 to 0.165 percentage point increase in the spread. Similarly, the number of transactions shows a positive relationship with the spread—ranging from 0.096 to 0.176 in four of the companies—with MSFT being the exception (not significant) and TSLA displaying the strongest effect. The number of traded shares is generally not significant, except in TSLA, while the price control is statistically significant across all cases. Among the firms, TSLA exhibits the

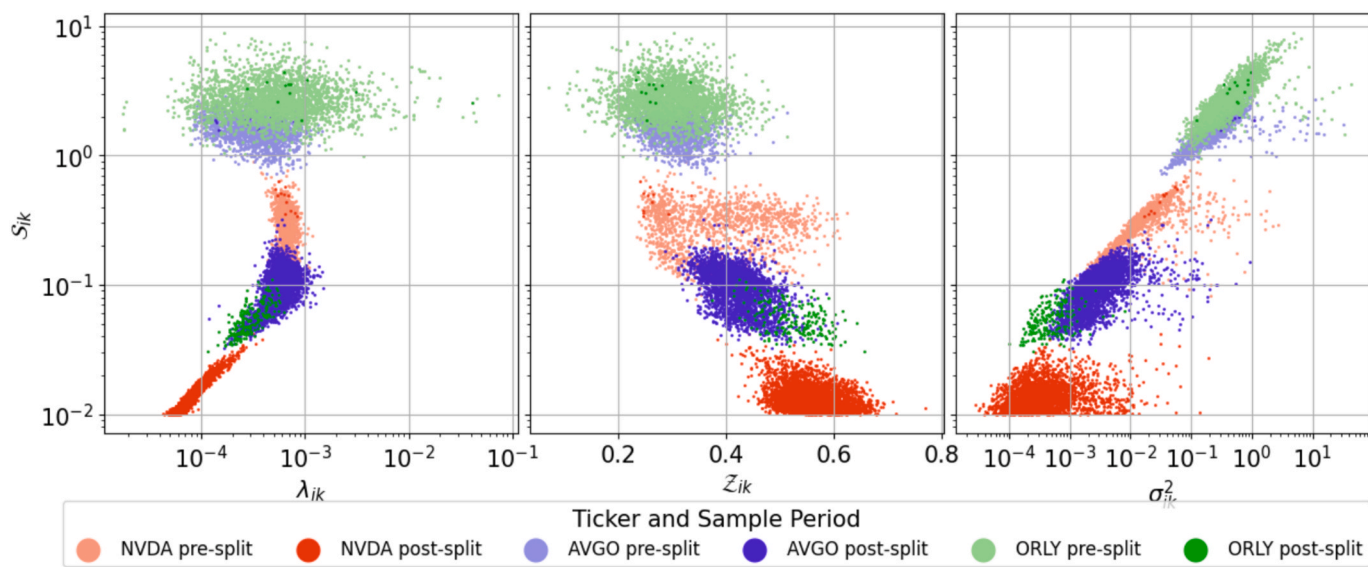


Fig. 5. Bid-Ask spread correlations. AVGO, NVDA and ORLY. Pre- and Post-Split Periods.

Table 5

Regression Analysis of Pre- and Post-split Periods.

Dependent variable: Bid-Ask Spread ($\tilde{S}_{ik}$).												
	AVGO				NVDA				ORLY			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Pre	Pre	Post	Post	Pre	Pre	Post	Post	Pre	Pre	Post	Post
C_i	−1.94** [0.0026]	−8.91*** [0.0000]	−7.02*** [0.0000]	−10.1*** [0.0000]	−10.9*** [0.0000]	−15.8*** [0.000]	−5.91*** [0.0000]	3.60*** [0.0000]	−3.35*** [0.0000]	−10.2*** [0.0000]	−40.6*** [0.0000]	−12.8 [0.1075]
σ_{ik}^2	0.206*** [0.0000]		0.197*** [0.0000]		0.085*** [0.0000]		0.034*** [0.0000]		0.354*** [0.0000]		0.308*** [0.0000]	
N_{zik}	0.005 [0.8218]		0.002 [0.9604]		0.138*** [0.0000]		0.133*** [0.0001]		−0.026* [0.0884]		−0.254*** [0.0000]	
λ_{ik}		−0.542*** [0.0000]		0.295*** [0.0004]		−0.119* [0.0166]		0.815*** [0.0000]		0.002 [0.3006]		0.615*** [0.0001]
$L \tilde{Z}_{ik}$		−0.409*** [0.0000]		−0.943*** [0.0000]		−0.102*** [0.0000]		−0.136*** [0.0000]		−0.025 [0.4098]		−1.17** [0.0207]
Q_{ik}	−0.0002 [0.9909]	0.087*** [0.0000]	0.061** [0.0362]	0.180*** [0.0000]	0.053 [0.1043]	0.237*** [0.0000]	0.013 [0.7620]	−0.001 [0.6934]	0.067*** [0.0000]	0.054*** [0.0000]	0.215*** [0.0000]	0.194*** [0.0000]
$\bar{P}_{ik}$	0.772*** [0.0000]	0.808*** [0.0000]	1.33*** [0.0000]	1.17*** [0.0000]	1.340*** [0.0000]	1.52*** [0.0000]	0.119*** [0.0248]	−0.053*** [0.0001]	1.30*** [0.0000]	1.49*** [0.0000]	9.394*** [0.0000]	2.66* [0.0904]
$Adj R^2$	0.4937	0.3646	0.8253	0.8585	0.7346	0.6955	0.2193	0.9247	0.7498	0.1065	0.5263	0.5903
Obs	4,563	4,563	9,902	9,902	4,290	4,290	10,296	10,296	8,760	8,760	647	647

Note: AVGO: Jan 2 – Jul 12, 2024 (Pre-split), Jul 15, 2024 – Jun 30, 2025 (Post-split); NVDA: Jan 2 – Jun 7, 2024 (Pre), Jun 10, 2024 – Jun 30, 2025 (Post); ORLY: Jul 1, 2024 – Jun 9, 2025 (Pre), Jun 10 – Jul 03, 2025 (Post). Newey-West (HAC) standard errors & covariance computed to account for potential autocorrelation. Probability in brackets; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Regression Analysis of the Rest of the M7 and Tesla. July 1, 2024 – June 30, 2025.

Dependent variable: Bid-Ask Spread ($\bar{S}_{ik}$).												
	AMZN		AAPL		GOOGL		MSFT		META		TSLA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
C_i	−7.81***	−5.28***	−1.83	3.73**	−9.66***	−5.95***	2.41**	0.854	−4.38***	−7.60***	−8.20***	−4.39***
	[0.0000]	[0.0000]	[0.0577]	[0.0019]	[0.0000]	[0.0000]	[0.0047]	[0.3732]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
σ_{ik}^2	0.116***		0.117***		0.109***		0.138***		0.165***		0.153***	
	[0.0000]		[0.0000]		[0.0000]		[0.0000]		[0.0000]		[0.0000]	
N_{zik}	0.176***		0.126***		0.112*		0.020		0.096**		0.275***	
	[0.0028]		[0.0001]		[0.0537]		[0.4738]		[0.0014]		[0.0000]	
λ_{ik}		0.276***		1.31***		0.387**		0.640***		0.070*		1.09***
		[0.0003]		[0.0000]		[0.0030]		[0.0000]		[0.0657]		[0.0000]
$L\mathcal{Z}_{ik}$		−1.22***		−0.136***		−0.633***		−0.306***		−0.834***		−0.162***
		[0.0000]		[0.0018]		[0.0000]		[0.0000]		[0.0000]		[0.0000]
Q_{ik}	−0.055	0.175***	−0.009	0.065**	−0.054	0.140***	0.023	0.147***	−0.034	0.151***	−0.108***	0.167***
	[0.1898]	[0.0000]	[0.7899]	[0.0108]	[0.2072]	[0.0000]	[0.3316]	[0.0000]	[0.1732]	[0.0000]	[0.0000]	[0.0000]
$\bar{P}_{ik}$	0.759***	0.304***	−0.412***	−0.477***	1.20***	0.404***	−0.762***	−0.490**	0.509***	0.632***	0.931***	0.609***
	[0.0000]	[0.0000]	[0.0040]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0052]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$Adj\ R^2$	0.3044	0.7073	0.2886	0.8244	0.2386	0.5382	0.2631	0.4041	0.3640	0.2902	0.6722	0.7723
Obs	9,750	9,750	9,750	9,750	9,682	9,682	9,456	9,456	9,749	9,749	9,726	9,726

Note: Newey-West (HAC) standard errors & covariance computed to account for potential autocorrelation. Probability in brackets; *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

highest explanatory power in the classical model, with an R^2 of 0.67, while the remaining companies display more modest fits, with R^2 values ranging from 0.23 (GOOGL) to 0.36 (META).

A key insight of our analysis is the superior explanatory performance of the quantum specification (Equation (6)) for five of the six firms, supporting the view that most companies in this group display elements of quantum-like behavior. The R^2 increases from 0.29 to 0.82 in AAPL, from 0.30 to 0.71 in AMZN, from 0.24 to 0.54 in GOOGL, and from 0.26 to 0.40 in MSFT — indicating a notable improvement in model fit. These firms are therefore listed in descending order of quantum behavior strength, from most to least pronounced. In AAPL, the algorithmic variance (λ_{ik}) is the dominant factor, with a coefficient of 1.31, the largest among the six firms. TSLA exhibits a similarly strong loading on λ_{ik} (1.09) and displays a meaningful gain in R^2 (from 0.67 to 0.77), confirming its quantum classification. In AMZN, GOOGL, and MSFT, the magnitude of λ_{ik} is smaller (ranging from 0.276 to 0.640), and the ZBR emerges as the key explanatory variable, with coefficients of -1.22 , -0.633 , and -0.306 , respectively, all statistically significant at the 1% level.

META presents a markedly different profile. Although the ZBR coefficient is negative and highly significant (-0.834), and λ_{ik} enters with a positive coefficient (0.070, significant only at 10%), the quantum specification fails to improve on the classical model as the R^2 declines from 0.36 to 0.29. This outcome reflects the fact that, while the ZBR is statistically associated with the spread in META, the overall informational content of the quantum decomposition is insufficient to displace the explanatory power of price variance and volume in this firm. META therefore remains the clearest classical case in this group, consistent with its low average ZBR (0.34, as reported in Table 3) and the strong dependence of its spread on overall price variance documented in the classical specification.

To conclude the empirical analysis, Fig. 6 synthesizes the microstructural behavior of the M7 stocks plus TSLA, incorporating both pre- and post-split data for AVGO and NVDA. The LHS panel reveals a clear positive relationship between the bid-ask spread and the algorithmic variance (λ_{ik}) at lower spread levels. The relationship becomes increasingly diffuse at higher spread values, suggesting heterogeneous dynamics.³ This contrasts with the right-hand panel, where the price variance appears to better explain the spread in higher-volatility regimes. Together, these panels highlight the complementary roles of classical and quantum explanatory mechanisms.

In the central panel, we observe the expected negative association between the bid-ask spread and the ZBR, both across and within firms. Intra-firm variation reflects a clear gradation in spread sensitivity as ZBR increases. Inter-firm differences exhibit a mostly non-overlapping stratification, suggesting varying intensities of quantum behavior across companies. META, for instance, aligns most closely with classical microstructural features, while AMZN and AAPL display the most pronounced quantum characteristics, driven by herding activity. Together with the econometric analysis, these patterns provide a nuanced taxonomy of market behavior and reinforce the structural insights developed throughout the paper.

7. Conclusions

This paper introduces a novel framework to classify investor behavior in equity markets into classical and quantum regimes, supported by two new metrics: algorithmic variance and the ZBR. Drawing on nanosecond-level trading data from twelve Nasdaq-100 firms —accounting for over half of the index's total trading volume— we document systematic shifts in the microstructural drivers of liquidity across firms, time, and corporate events. Our analysis reveals that while classical behavior is characterized by a strong dependence on overall price variance (volatility) and volume, quantum behavior emerges when spreads are more responsive to algorithmic variance and the concentration of zero-price-change trades.

A central empirical contribution of the study lies in uncovering clear regime shifts associated with recent stock splits. Firms such as AVGO, NVDA, and ORLY transition from classical to quantum investor behavior post-split, as evidenced by both visual and econometric analyses. Meanwhile, others like AMD, BKNG, and MELI exhibit stable behavioral patterns, allowing for a classification benchmark. Among the Magnificent Seven, we find heterogeneity: firms like AAPL, AMZN, GOOGL, and TSLA exhibit pronounced quantum characteristics, META remains largely classical, and MSFT occupies a transitional position. These findings highlight the behavioral diversity of modern equity markets and underscore the relevance of firm-specific analysis in understanding liquidity formation.

The evidence of structural behavioral change surrounding corporate actions such as stock splits points to new avenues for research and practical application—including liquidity forecasting, trading strategy design, and market regulation. By offering high-frequency tools to detect latent shifts in investor behavior, this work contributes to the growing literature on market microstructure and algorithmic trading. Future research may expand the framework to other asset classes or refine investor classification further by disentangling behavioral signatures across nanosecond, microsecond, millisecond, and second-level activity—where distinct groups, including ultra-fast liquidity takers, may consistently profit by exploiting fleeting informational asymmetries at the ZBR.

CRedit authorship contribution statement

F.Xavier Alvarez: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Hector Sala:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

³ The dispersed observations above 10° in the two LHS panels correspond to AVGO in July 2024, at the beginning of the sample period (pre-split). We retain them for the sake of transparency.

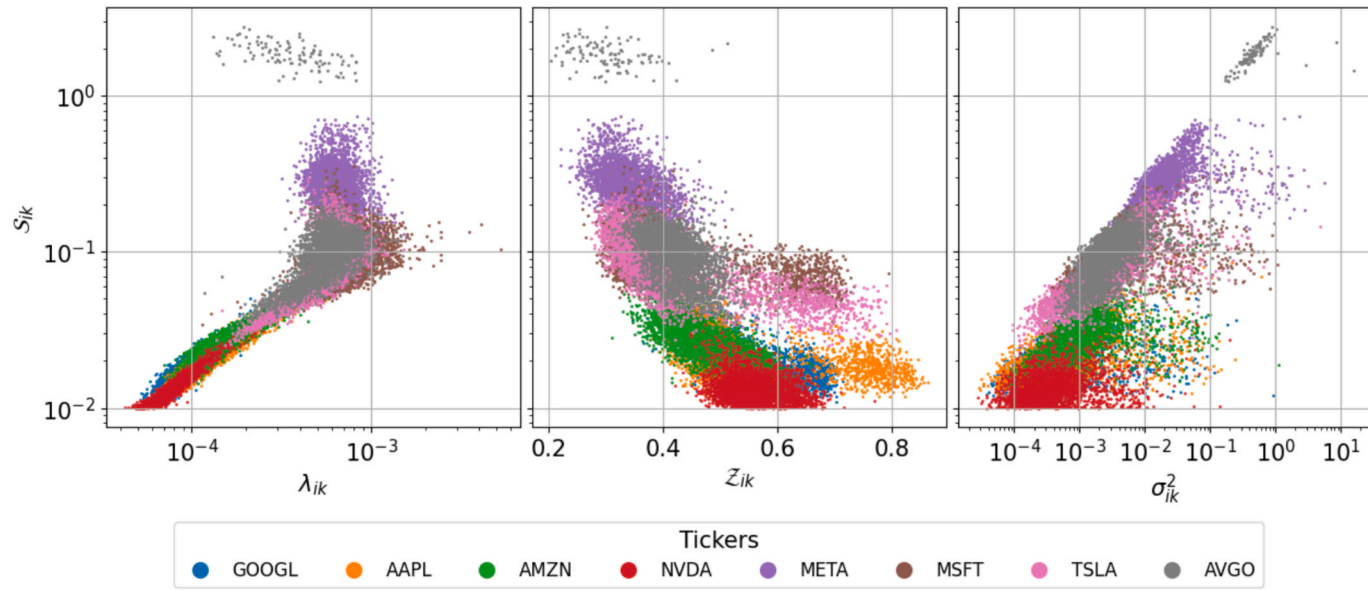


Fig. 6. Bid-Ask spread correlations. M7 and TSLA.

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Declaration of competing interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.najef.2026.102667>.

Data availability

Data will be made available on request.

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