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Examining Market Quality on the Egyptian Exchange (EGX): An Intraday Liquidity Analysis

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Abstract: This study examines the intraday dynamics of liquidity and trading activity on the Egyptian Exchange (EGX) to assess its market quality. Using reconstructed five-minute limit order book data, this study measures liquidity dimensions and explores anomalies through interval-of-day and day-of-week models. Key findings reveal an inverted J-shaped pattern in spreads due to information asymmetry, a U-shaped pattern in total depth, and a J-shaped market depth pattern. Additionally, significant day-of-week effects are observed, with Sundays showing the lowest liquidity and Thursdays the highest trading activity. These patterns highlight the impact of the EGX's unique microstructure, including tick sizes and a preference for limit orders. This study underscores the influence of market structure on liquidity, trading efficiency, and cost, emphasizing the need for tailored regulatory and trading strategies. It provides valuable insights for investors optimizing trading strategies and policymakers seeking to enhance market integrity. Concluding, this research offers a foundation for understanding intraday liquidity patterns in emerging markets like the EGX and proposes future exploration of how information flows and trading mechanisms affect price discovery and market efficiency.

Keywords: market microstructure; liquidity; intraday patterns; limit order book; spreads; depth; immediacy

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1. Introduction

Market quality is a pivotal concept in market microstructure research that encapsulates a market's capacity to provide liquidity and ensure efficient pricing. As highlighted by O'Hara and Ye (2011), markets characterized by lower transaction costs and greater price efficiency are deemed higher in quality. This directly benefits investors by facilitating smoother trading processes and ensuring that prices more accurately reflect underlying values. Consequently, high market quality is essential for a robust and efficient financial system, attracting investment by reducing transaction costs, maintaining price stability, and bolstering investor confidence. These factors collectively stimulate economic growth by efficiently channeling capital to its most productive uses. In addition, high market quality mitigates investor risk by reducing volatility and enhancing price discovery and transparency.

This study investigates intraday liquidity patterns to assess market quality on the Egyptian Exchange (EGX). As a prominent emerging market, EGX employs an order-driven system facilitated by the NASDAQ OMX X-Stream Trading Platform. While intraday liquidity in developed markets has been extensively studied, a comprehensive analysis within EGX context remains limited.

Prior research on EGX has predominantly focused on market performance at daily, weekly, and monthly levels, overlooking the microstructure and intraday dynamics. For instance, studies such as those by El-Ansary and Atuea (2013) used daily data from July 2001 to March 2010 to examine the relationship between stock return and trading volume in the Egyptian stock market. The authors focused on 26 companies listed on the EGX 30 Index to understand the market's structure, information arrival process, and investor behavior. Their findings demonstrated a weak contemporaneous relationship between trading volume and stock return, suggesting noise trading and informational inefficiency in the Egyptian stock market. In another study, Otaify (2016) used descriptive statistics to analyze the performance and activity of the Egyptian Exchange (EGX) from 2002 to 2015. Key indicators such as market capitalization, trading volume, and the number transactions were examined to assess the market's growth and development. The study used annual data to track trends and changes in these indicators over the specified period.

This study advances a unique methodological approach by reconstructing the EGX limit order book using transaction and order file data, enabling a granular analysis of its microstructure. This reconstruction facilitates the identification of distinctive intraday patterns within the EGX and allows for comparative analysis with established trends in global markets.

Furthermore, this study contributes to a comprehensive assessment of EGX liquidity by employing a diverse set of market microstructure variables. It presents robust visual and quantitative evidence on key metrics, including bid–ask spread, depth, immediacy, and tick size. Uniquely, this research explores intraday liquidity patterns through the lens of interval-of-day and day-of-week effects, utilizing a variety of market microstructure measures.

These findings offer valuable insights for investors seeking to optimize trading strategies on the EGX and for policymakers aiming to foster a more efficient and robust regulatory framework.

The remainder of this paper is structured as follows: Section 2 reviews the related literature and empirical studies on liquidity provision and intraday patterns. Section 3 details the market structure of EGX, and the databases and analytical framework. Section 4 provides an analysis of market liquidity using market microstructure variables. Section 5 analyzes intraday liquidity patterns and examines the interval-of-day and day-of-week effects on order books and trading activities, concluding with a discussion of the results and findings.

Our goal is to identify the level of market quality in terms of intraday patterns specific to EGX and compare them with established patterns in both developed and emerging markets. By analyzing liquidity measures derived from the order book, we seek to understand how market participants interact during the different phases of the trading day.

2. Literature and Empirical Review

Market quality is a multifaceted construct that encompasses several critical elements. Liquidity, the ease with which assets can be traded without significantly impacting prices, is of paramount importance. It is measured by factors such as the bid–ask spread (where narrower spreads indicate greater liquidity), market depth (the volume of available buy and sell orders), and overall transaction costs (which should be minimized). Additionally, efficient price discovery, the process by which prices quickly incorporate new information, is crucial. Markets should exhibit appropriate levels of volatility while demonstrating resilience by recovering rapidly from disruptions.

In the microstructure context, equity market liquidity can be defined as the ability to execute an order within a short period at a price close to the stock's consensus value (Foucault et al. (2013)). According to Kyle (1985) and O'Hara (1995), market liquidity can be assessed through five distinct dimensions: (1) *Tightness*, which refers to the cost of turning a position around quickly and is commonly measured by the bid–ask spread (Huang & Stoll, 1997). A lower spread signifies higher liquidity, implying that transactions can occur close to the advertised prices without a substantial price concession; (2) *immediacy*, which describes the speed with which trades can be executed without impacting the price significantly, reflecting the market's ability to absorb new orders swiftly (Hasbrouck & Saar, 2013); (3) *depth*, which is indicated by the volume of orders available at different price levels beyond the best available prices, with deeper markets able to handle larger orders without material impacts on price stability (Madhavan, 2000); (4) *breadth*, which pertains to the distribution of orders around the current price and is a measure of the market's ability to manage large orders without significant price changes, indicating a robust order book structure (Brunnermeier & Pedersen, 2009); and (5) *Resiliency*, which relates to the market's capacity to recover to its former price levels following a substantial trade or market move (Foucault et al., 2013). This dimension is crucial for maintaining confidence in market fairness and efficiency.

While high-frequency data provide a granular view of these liquidity dimensions, enabling the detection of rapid changes in market conditions, they also introduce challenges. The benefits of high-frequency liquidity measurements include the ability to monitor liquidity in real-time, providing insights into market behavior under various conditions (Goyenko et al., 2009). However, such datasets require complex data handling and processing capabilities and may introduce noise that complicates the interpretation of market dynamics (Hagströmer & Norden, 2013).

Olbrys et al. (2021) highlighted the significance of high-frequency transaction data in offering granular insights into the microstructure of financial markets. The key strength of these data lies in their ability to capture trade at irregular intervals, as observations can occur at varying time intervals, a property emphasized by Goodhart and O'Hara (1997). Consequently, high-frequency data allow for the identification of potential intraday "seasonal" patterns in various aspects of stock market activity. Employing empirical analysis and visualization techniques to explore these patterns can be a valuable tool. For investors, such insights can inform decision making by revealing how specific market characteristics fluctuate throughout a trading session.

Analyzing intraday variations in market quality is crucial for investors and analysts to inform strategic decision making. By identifying periods of peak liquidity, characterized by tight bid–ask spreads and robust market depth, they can optimize the execution of large orders with minimal price impact. A careful analysis of intraday fluctuations in price, volume, and spreads explains the process of price discovery, revealing how new information is integrated into asset valuations. Additionally, for exchanges and regulators, the detection of anomalous intraday patterns can expose potential market inefficiencies, manipulative practices, and informational asymmetries, prompting further investigation and ensuring market integrity.

The existence of intraday seasonality or anomalies may challenge this efficient market hypothesis. The intraday patterns of liquidity and volatility were first documented by Wood et al. (1985), and Jain and Joh (1988). These patterns reflect how trading behavior incorporates information into prices within an exchange's institutional framework. Seminal studies documented U-shaped intraday patterns for liquidity, including McInish and Wood (1992) and Lee et al. (1993), while NASDAQ stocks experience a narrowing spread towards the close (Chan et al. (1995)).

Admati and Pfleiderer (1988)'s model posits that uninformed traders (liquidity traders) cluster trade at the open and close to minimize the adverse selection costs against informed traders. Brock and Kleidon (1992)'s market closure model suggests that transaction demand is higher and less elastic at market opening, as accumulated information changes investors' optimal portfolio, and at market close, as traders strategically attempt to close their positions before the end of the trading session because of the risks associated with open positions.

Charoenwong et al. (2003) observed an inverted J-shaped pattern for the bid–ask spread (BAS) exhibits, while the depth exhibited a J-shaped market (displayed), and total depths were at the minimum during the first half hour of the trading, but they increased to reach a higher level by the end of the session, confirming maximum liquidity at the market close. They also argued that limit order traders submit quotes away from the best bid–ask at market close, as the length of the order book is highest at the close compared with the length at market open. Madhavan (1992) attributes the inverted J-shape of BAS to higher asymmetric information costs at the open, which diminish over the day. Wood et al. (1985) and Foster and Viswanathan (1993) showed that volatility exhibits a U-shaped pattern. In addition, Ahn et al. (2002) reported a U-shaped pattern for volatility on the Hong Kong Stock Exchange, whereas depth follows a reverse U-shaped pattern consistent with the documented pattern in the NYSE (C. M. Lee et al. (1993)) and the Paris Bourse (documented by Biais et al. (1995)).

A substantial body of research has documented that market characteristics, such as trading volume, bid–ask spreads, order book depth, price returns, market resiliency, order flows, and transaction costs, all exhibit distinct intraday patterns. However, empirical findings on the specific nature of these intraday patterns across global stock exchanges remain somewhat diverse. For instance, Vo (2007) examined the Canadian Stock Exchange in Toronto and found that bid–ask spreads form a U-shaped pattern, while market depth exhibits an inverted U-shape. Similarly, trading volume is lower in the open condition, remains stable throughout the day, and experiences an increase near the close.

Similar findings have also been observed in other markets. Hamao and Hasbrouck (1995)'s analysis of individual stocks on the Tokyo Stock Exchange indicates that similar to U.S. data, key market statistics display distinct intraday patterns. They further emphasize the tendency for an elevated trading volume at the beginning and end of the trading sessions.

Research on the London Stock Exchange (LSE), a dealership market, reveals distinctive intraday patterns compared with order-driven exchanges. Abhyankar et al. (1997) demonstrate that, while average bid/ask spreads exhibit a common U-shape, trading volume notably deviates, displaying a double-humped pattern. This finding contrasts with U-shaped volume patterns frequently observed in other markets.

Cai et al. (2004) corroborated these findings. Their analysis of high-frequency LSE data confirms the double-humped volume pattern and highlights a distinctive inverted J-shaped pattern in bid/ask spreads.

Studies examining order-driven exchanges reveal diverse intraday patterns in liquidity and trading volume, highlighting the impact of market structure and regional factors. Ahn and Cheung (1999)'s investigation of the Hong Kong Stock Exchange, a pure electronic order-driven market, found U-shaped patterns in spread and trading volume. However, the market depth exhibits an inverse U-shaped pattern.

Y. T. Lee et al. (2001), analyzing the most active stocks on the Taiwan Stock Exchange, observed a departure from the commonly found U-shaped volume pattern. Their results indicate a J-shaped pattern, suggesting that trading volume at the open interval is not significantly different from other intraday intervals, except for a surge near the close interval.

Tissaoui (2012) found that trading activity, liquidity, and return volatility in the Tunisian stock market exhibit a U-shaped intraday pattern and justifies this behavior by the role of adverse selection, especially among the spread and depth at the best bid–ask price. In addition, Koksal (2012) reported that returns, trading volume, and number of trades follow a U-shaped pattern, while spreads follow an inverted J-shape on the Istanbul Stock Exchange due to the asymmetric information problem at the market open.

Giudici (2019) investigated intraday patterns in the trading volume of the SPY ETF, finding that trading volumes tend to be higher at the open and close of the market. The study suggests that this pattern may be due to information-based trading and portfolio rebalancing activities. These findings have implications for high-frequency traders and large investors seeking to optimize the timing of large orders to minimize their impact on ETF prices.

Olbrys et al. (2021) highlight that some intraday patterns in the stock market are possible, but it is not surprising that perfectly shaped visual patterns rarely appear as shown in Table 1. There are several attributes that help differentiate the most important shapes, such as U-shaped, inverted-U, W-similar, M-similar, J-similar, and inverted J-similar patterns.

Table 1. The most frequent intraday patterns of stock market characteristics.

Pattern	Characteristics	Causes
M-Shaped Pattern	Exhibits lower values at the beginning and end of a trading session, with peak values occurring shortly after the open and just before the close. Additionally, values tend to be lower and more stable during the middle of the session. **The opposite is W-Shaped Pattern**	**Profit Taking:** some traders might sell positions for profit after the initial price increase at the open or right before the close. **Strategic Timing:** Traders may avoid the volatility of the opening and closing periods, opting for more stable conditions in the middle of the session. This could contribute to the dips in the pattern.
U-Shaped Pattern	This pattern features elevated values at the beginning and end of a trading session with a period of lower more stable values during the middle of the session. **The opposite is Inverted-U Shaped Pattern**	**Informational Asymmetry:** The beginning and end of the day might experience heightened informational asymmetry, with some traders possessing more up-to-date information. This can lead to increased trading volumes and wider spreads. Thus, some traders may avoid the high volatility of the opening and closing periods, opting for more stable conditions in the middle of the session (strategic trading).
J-Shaped Pattern	This pattern resembles a U-shaped pattern, with elevated values at the end of the trading session. However, it differs by exhibiting lower values at the beginning of the session. **The opposite is Reverse-J Shaped Pattern**	**End-of-Day Adjustments:** traders may strategically adjust positions or make last-minute trades as the market approaches the close, leading to a spike in activity. **Accumulated Information:** As the trading day progresses, more information becomes publicly available. Increased activity towards the end of the session might reflect traders acting upon this accumulated information.

Source: Researchers researchers' elaboration using Olbrys et al. (2021).

In addition, recent research has explored intraday liquidity patterns in diverse emerging markets, highlighting regional variations and market structure influences. Balasubramanian et al. (2020) examined the Indian stock market, finding time-of-day and day-of-week effects on liquidity, with lower liquidity at the open, close, and on Mondays. These patterns were attributed to information asymmetry and investor behavior.

Nguyen and Vuong (2021) investigated the Vietnamese stock market, observing a U-shaped intraday liquidity pattern and an inverted U-shaped volatility pattern. Their findings revealed a negative correlation between liquidity and volatility.

Miranda and Gomes (2022) analyzed the impact of market fragmentation on liquidity in the Brazilian stock market, discovering a negative effect, especially during high-stress periods. They found that a centralized limit order book improved liquidity. Mudzingiri et al. (2023) investigated intraday liquidity and order book resilience in the South African equity market, finding lower liquidity at the open and close and highlighting the impact of large trades on liquidity.

Ozkan and Cakici (2023) examined the Turkish stock market, demonstrating the influence of information arrival on intraday liquidity, with informed traders' actions contributing to the observed patterns.

This study addresses several gaps in the existing literature on market liquidity, particularly within the context of emerging markets like the Egyptian Exchange (EGX). Previous research has often focused on developed markets and has not fully explored the implications of technological advancements on market liquidity in emerging market contexts. Our study contributes to this area by analyzing the impacts of recent technological upgrades at EGX on its liquidity profile across the liquidity dimensions.

Additionally, prior studies examining market liquidity on the Egyptian Exchange (EGX) have primarily concentrated on lower frequency datasets, predominantly using daily, weekly, or even monthly time intervals to draw conclusions about market behavior and liquidity. These approaches, while valuable for understanding broader market trends, fail to capture the microstructural changes that occur within the trading day, which are essential for detailed liquidity analysis. By focusing on higher frequency intraday data, our study aims to fill this gap by providing a more granular view of liquidity fluctuations and trading patterns throughout the trading session on EGX.

3. Methodology

This study aims to analyze the intraday dynamics of liquidity and trading activity on the Egyptian Exchange (EGX) using high-frequency data. To achieve this, we employ a comprehensive methodology involving limit order book reconstruction, calculation of liquidity measures, analysis of intraday patterns, and estimation of realized volatility, and we employ regression analysis to investigate the relationships between liquidity measures and market variables, such as time-of-day and day-of-the-week effects.

We reconstruct the limit order book (LOB) from the EGX's order and transaction data, following the methodology outlined in Schroeter et al. (2014). In the process of reconstructing the limit order book (LOB) from the raw data, we employ a series of meticulous filters and checks to enhance the data integrity and ensure accuracy. Firstly, we address missing data by implementing interpolation methods for timestamps missing entries, while ensuring alignment with known market events to prevent data distortion. Secondly, to handle canceled orders, a verification process is established to identify and exclude these from the final dataset, ensuring that only active orders influence the reconstructed LOB. These measures ensure that the reconstructed LOB represents the market dynamics, providing a reliable basis for further analysis of market microstructure.

We employ several market microstructure variables to assess the liquidity of the EGX. These variables are calculated as follows:

- **Quoted Bid–Ask Spread (QBAS):** This is the difference between the best ask price (the lowest price at which a seller is willing to sell) and the best bid price (the highest price at which a buyer is willing to buy) at any given time. A narrower QBAS indicates higher liquidity.
- **Relative Bid–Ask Spread (RBAS):** This is the QBAS normalized by the midpoint price (the average of the best ask and best bid prices). It provides a measure of transaction costs as a percentage of the stock price.

- **Market Depth:** This represents the number of shares available for trading at the best bid and ask prices. It indicates the market's ability to absorb buy or sell orders without causing significant price fluctuations.
- **Immediacy:** This is the probability of executing a market order (an order to buy or sell at the best available price) at any given time. It is calculated as the proportion of time when limit orders are available at the best bid and ask prices.

These measures help quantify the tightness and immediacy of the market, directly relating to our research problem of exploring how microstructural elements influence liquidity.

Intraday Patterns Analysis: To examine the intraday patterns in liquidity and trading activity, we employ two regression models: one for the interval-of-day effect and the other for the day-of-week effect. These models allow us to identify any systematic variations in our chosen variables throughout the trading day and across different days of the week. This methodological approach allows us to systematically identify and analyze patterns that previous studies, relying on less frequent data, may have overlooked. This is crucial for developing a deeper understanding of market behaviors in response to specific microstructural changes.

By employing these methods, we aim to address the research problem of understanding the intraday dynamics of liquidity and trading activity on the EGX. The reconstructed LOB allows us to analyze high-frequency data and identify patterns that would not be visible at lower frequencies. The liquidity measures provide insights into the efficiency and cost of trading on the EGX. Finally, the intraday pattern analysis helps us understand how market participants behave during different phases of the trading day and across different days of the week.

4. Market Structure and Data

The Egyptian Exchange (EGX) is an order-driven market, where the trading mechanism shifted from an outcry system to an automated order-driven system in 1994. In 2008, EGX introduced the current NASDAQ OMX "*X-Stream Trading*" Platform. The main trading session functions as a continuous auction market, operating on Sundays through Thursdays from 10:00 a.m. to 2:30 p.m. This session is preceded by a pre-open phase (8:30 a.m. to 10:00 a.m.), where limit orders (excluding those with hidden quantities) are accepted. Within this pre-open phase, a price discovery session occurs randomly between 9:50 a.m. and 10:00 a.m.

To mitigate adverse selection issues arising from large-value trades, the EGX introduced a designated mechanism for "block trading". Block trade is defined as transactions that exceed either of the following:

- The average daily trading value of the stock over the preceding six-month review period and not less than 1% of the issuer's total voting rights.
- EGP 10 million (Egyptian Pounds).

To ensure market transparency and stability, block trades require pre-market approval from EGX. The exchange facilitates these trades as "put-through" transactions that are processed before the continuous trading session commences. This pre-arranged execution window occurs between 9:15 and 9:45.

EGX prioritizes orders based on a price-then-time priority rule. Established orders are eligible for execution during the pre-session and trading session, the priority then goes to regular limit orders without special terms, and the lowest priority is given to crossing/matching an order from the same buyer and seller brokerage firm. Traders can adjust limit order prices or volumes; however, in this case, the limit order loses its time priority.

In September 2018, EGX implemented a two-tiered tick-size system. Stocks priced below EGP 2 or USD 2 have a tick size of 0.001, while all other securities have an EGP 0.01

or a USD 0.01 tick size. However, during the sample period, the minimum price variation for all traded stocks is unified and equal to an EGP 0.01 tick size.

To maintain price stability, EGX has set price limits for firm orders within ±10% of the opening price, the price range for the opening price must lie within ±10% of the previous closing price, and if the price change exceeds ±5%, trading is halted for 10 min. The Exchange service fee is 0.012% (EGP 12/EGP 100 thousand) of the trading value of each party in the transaction, up to a maximum of EGP 5000.

This study utilizes three datasets provided by the EGX Information Center during the study period (trade, transaction, and order files). These datasets cover a 123-day period from August 2017 to January 2018 for the constituents of the EGX 30 benchmark index. Although the selected stocks are from 30 out of 248 listed companies, they represent 50% of market capitalization, and 84% and 86% of traded value and traded volume, respectively, also representing 67% of total number of transactions during the study period Thus, it offers a representative sample consistent with prior research.

- **Trade File:** daily trading statistics for each stock (value, volume, number of transactions, closing price), totaling 18,324 observations.
- **Transaction File:** records 1.74 million transactions, including ticket number, ISIN, trade execution timestamp, details on volume and value, and cancellation information (if applicable).
- **Order File:** The most extensive dataset, with 9.46 million observations and 2.8 million orders. It details order characteristics (ID, ISIN, timestamp, direction, limit price, volume, execution status, time-in-force, and X-stream action) to the millisecond level.
- **Limit Order Book Reconstruction (Quote File):** Using the order file and applying appropriate filters (Schroeter et al., 2014), we reconstructed the EGX limit order book (LOB). The resulting quote dataset contains five-minute interval best bid–ask quotes and associated depths for 199,260 observations.

The Order File dataset can be divided into three subsets:

- **Resting Orders:** non-executed, non-canceled, and non-expired limit orders with time in force.
- **Pre-Session Orders:** limit orders placed between 8:30 and 9:59 am.
- **Session Orders:** orders placed during the primary trading session.

Table 2 reveals several insights into session order patterns. On average, 22,723 orders are placed daily, with a mean size of 805 million shares and a mean value of EGP 2.1 billion. Importantly, only 63.9% of these orders see execution. Buy orders comprise a slightly smaller proportion of the total orders (45.9%).

Market orders represent only 2% of total orders, indicating a strong preference for liquidity provision via limit orders, compared with the Saudi Stock Exchange (29%) (Al-Suhaibani & Kryzanowski, 2000) and the Thailand Stock Exchange (26%) (Charoenwong et al., 2003).

Table 3 reports the cross-sectional summary statistic for the quote dataset, comprising 1,348,169 quotes across 187,674 intervals (representing an average of 6256 intervals per stock). Panel (A) provides key insights into liquidity measures, the mean (median) quoted bid–ask spread-QBAS is EGP 0.63 (0.07), and relative bid–ask spread-RBAS is 1.22% (0.95%), and the mid-point price mean (median) is EGP 17.3 (EGP 9.17).

Panel B shows the structure of the EGX order book. The average order book depth is 7.2 quotes, with greater concentration on the ask side. This finding suggests that ask orders tend to be more dispersed than bid orders are. Additionally, the panel reveals that, on average, public traders contribute to market immediacy for 84.2% of the trading period.

Table 2. Descriptive statistics of the session data subset. This table shows the descriptive statistics of the main trading session orders, which are stacked by stocks and dates for 123 trading days in the sample.

	All Obs.	Mean	Stdev	Min	Median	Max
Total Orders	2,794,899	22,723	5541	11,595	22,660	33,527
Panel A. Order Direction and Type						
Sell	1,517,619	12,338	3273	5952	12,307	19,096
Buy (%)	45.7	45.9	2.7	40.4	45.5	52.8
Limit (%)	98.30	98.31	0.23	97.72	98.31	98.75
Market Sell	27,723	225	60	114	222	389
Market Buy (% of MO)	41.6	40.4	9.2	20.6	40.4	60.6
Limit Sell	1,489,896	12,113	3236	5826	12,093	18,724
Limit Buy (% of LO)	45.7	46.0	2.8	40.2	45.5	53.3
Panel B. Value, Size, and Execution						
Order Value (EGP million)	256,129	2082	649	727	2077	3559
Order Size (million shares)	98,987	805	323	259	748	1809
Executed (%)	63.9%	63.5%	3.3%	54.6%	63.5%	70.2%
Canceled (%)	3.5%	3.5%	0.3%	3.0%	3.4%	4.4%

Table 3. Descriptive statistics of the quote dataset. This table shows the cross-sectional descriptive statistics of the reconstructed quote dataset for the limit order book.

	All Obs.	Mean	Stdev	Min	Median	Max
Number of Observations	187,674	6256	687.5	2980	6473	6627
Panel A. Spreads						
QBAS (EGP)	0.630	0.630	2.680	0.01	0.0659	14.8
RBAS ($\times$100)	1.226	1.226	0.949	0.380	0.953	3.994
Midpoint (EGP)	-	17.33	32.50	0.28	9.17	480.00
Panel B. Length and Immediacy						
Bid	-	3.0	2.5	0.0	2.0	38.0
Ask	-	4.2	3.7	0.0	3.0	44.0
Total	-	7.2	5.5	1.0	6.0	69.0
Immediacy (%)	84.2%	82.6%	16.7%	19.4%	86.0%	97.6%
Panel C. Depth (1000 shares)						
Best Bid (B1)	22,266,993	131.0	748.8	0.001	4.9	100,316
Best Ask (A1)	18,579,092	105.7	477.4	0.001	4.4	23,943
Market Depth	40,846,086	217.6	954.2	0.001	9.0	101,558
Bid	37,769,850	222.2	975.1	0.001	18.8	103,932
Ask	39,179,668	222.9	825.4	0.001	22.2	91,018
Total Depth	76,949,518	410.0	1462.8	0.001	40.4	128,661

Panel C delves into the relative depths of the best bid and asks for quotes. The results indicate that the mean depth of the best bid is greater than that of the best ask. This pattern implies a preference among traders to supply liquidity by placing ask orders away from the best ask price, while concentrating bid orders at the best bid price.

5. Analysis of Market Liquidity

5.1. Distribution of Liquidity and Equality Test

Using the five quotes' levels on both sides, these five price levels refer to the five best available bid and ask prices at any given five-minute interval. Each level represents a distinct price point at which traders are willing to buy (bid) or sell (ask) shares. Level 1 includes the immediate best bid and ask, reflecting the most competitive market prices, while Levels 2 through 5 provide deeper insights into the order book.

Table 4 presents cross-sectional summary statistics for the time-series averages of adjacent quoted bid–ask spreads (QBASs), relative bid–asset spreads (RBASs), and market depths. For the spread measures, the mean QBAS is EGP 0.63 (median EGP 0.07) and the inside QBAS is approximately double the adjacent QBAS on both sides of the book, while the mean RBAS is 1.23% (median 0.95%). Thus, compared with other exchanges, EGX exhibits a lower RBAS than the Stockholm, Saudi, and Thailand exchanges (Niemeyer & Sandas, 1995; Al-Suhaibani & Kryzanowski, 2000; Charoenwong et al., 2003). However, the median RBAS remains higher than the median of 0.65% across 15 major indices (Angel, 1997).

Table 4. Successive spreads and depths. This table shows the cross-sectional summary of adjacent spreads and depths.

Panel A. Spreads between adjacent quotes									
	B4–B5	**B3–B4**	**B2–B3**	**B1–B2**	**BAS**	**A2–A1**	**A3–A2**	**A4–A3**	**A5–A4**
					QBAS (EGP)				
Mean	0.16	0.25	0.20	0.23	0.63	0.28	0.27	0.26	0.18
Median	0.08	0.07	0.06	0.05	0.07	0.07	0.08	0.09	0.10
Stdev	0.27	0.85	0.62	0.80	2.68	0.94	0.80	0.67	0.25
Max	1.40	4.69	3.47	4.42	14.77	5.19	4.42	3.65	1.02
RBAS ($\times$100)									
Mean	0.94	1.04	0.98	0.90	1.23	1.02	1.08	1.11	1.12
Median	0.76	0.73	0.67	0.59	0.95	0.79	0.88	0.92	0.95
Stdev	0.54	0.75	0.78	0.79	0.95	0.73	0.63	0.54	0.47
Min	0.36	0.35	0.26	0.21	0.38	0.40	0.57	0.67	0.75
Max	2.67	3.45	3.65	3.67	4.00	3.58	3.16	2.81	2.55

Panel B. Depth (1000 shares)										
	B5	**B4**	**B3**	**B2**	**B1**	**A1**	**A2**	**A3**	**A4**	**A5**
Mean	28.9	60.2	122.1	272.2	742.2	619.3	284.9	168.6	91.4	49.3
Median	10.2	19.4	27.1	39.2	35.8	34.4	33.9	27.2	22.9	14.1
Stdev	60.0	115.2	221.6	529.0	1747	1449	584.0	318.1	156.3	88.2
Max	324.4	602.0	974.6	1920	6962	5556	2065	1056	622.1	410.3

For the ask asymmetry, on average, both adjacent QBAS and RBAS exhibit lower values on the bid side than on the ask side

Our calculated relative bid–ask spread (RBAS) aligns with the calculated median simple spread (MSS)[1] by the World Federation of Exchanges (WFE) from August 2017 to January

2018. For large capitalization companies in EGX, the MSS is 60.8 bps compared with 70.6 bps for 22 exchanges in the EMEA region (WFE, 2019).

Analysis of the EGX order book reveals a total depth of 76.9 billion shares, with an approximately equal distribution between the bid and ask sides (49% and 51%, respectively). Notably, 53% of the total depth is concentrated in the market (the best bid–ask price). Furthermore, 60% of the bid-side depth is concentrated at the B1 level, with 742.2 thousand shares. This suggests that limit-order buyers tend to place more aggressive orders than limit-order sellers. Figure 1 illustrates the distribution of depth across the order book levels.

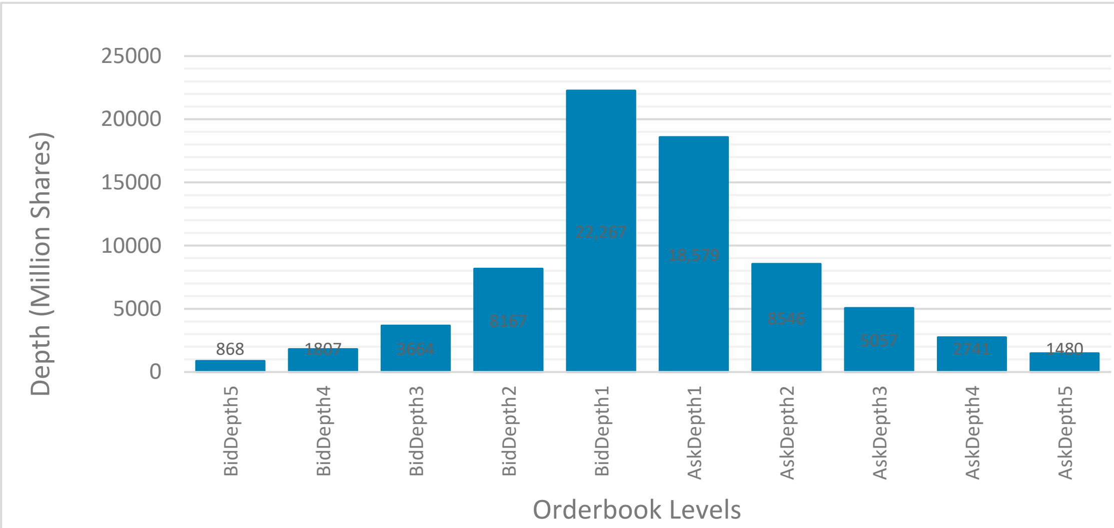

Figure 1. Distribution of the depth at order book levels.

To examine the equality of adjacent spreads and depths, we regressed the time-series average value of the spreads and depth on a set of dummy variables representing the five price levels on each side as follows:

$$Spread_i = \beta_{B4-B5}D_{B4-B5} + \beta_{B3-B4}D_{B3-B4} + \beta_{B2-B3}D_{B2-B3} + \beta_{B1-B2}D_{B1-B2} + \beta_{A1-B1}D_{A1-B1} + \beta_{A2-A1}D_{A2-A1} + \beta_{A3-A2}D_{A3-A2} + \beta_{A4-A3}D_{A4-A3} + \beta_{A5-A4}D_{A5-A4} + \varepsilon_i \quad (1)$$

$$Depth_j = \beta_{B5}D_{B5} + \beta_{B4}D_{B4} + \beta_{B3}D_{B3} + \beta_{B2}D_{B2} + \beta_{B1}D_{B1} + \beta_{A1}D_{A1} + \beta_{A2}D_{A2} + \beta_{A3}D_{A3} + \beta_{A4}D_{A4} + \beta_{A5}D_{A5} + \varepsilon_j \quad (2)$$

where $Spread_i$ is the time series average adjacent spreads, $Depth_j$ is the total number of shares at each quote on both sides of the order book, and the explanatory variables are dummy variables that are equal to one if the observation of the dependent variable belongs to the quote's level.

We employed the Wald test of equality to examine variations across bid–ask spreads and market depths, both including and excluding the best bid–ask (BAS). Null hypotheses of equality were tested independently for the bid and ask sides (results not reported). Panels A and B of Table 5 demonstrate a rejection of the null hypotheses in both the inclusion and exclusion scenarios for the QBAS and RBAS.

- **Non-Constant Spreads:** adjacent spreads across the order book are not constant, with the QBAS being approximately double the adjacent quoted spread on both the bid and ask sides.
- **Bid/Ask Asymmetry:** statistically significant differences exist between spreads on the bid and ask sides.

Furthermore, to thoroughly check for any multicollinearity among the explanatory variables, we also conducted a variance inflation factor (VIF) analysis. The VIF values obtained were all less than 2, indicating a clear absence of multicollinearity among the variables used in our models. This additional test further supports the statistical independence of our explanatory variables, reinforcing the validity of our regression analysis results.

Our findings differ from those of Al-Suhaibani and Kryzanowski (2000) and Charoenwong et al. (2003). While both prior studies rejected the null hypothesis of equality for the RBAS when including the best limit, they could not reject it when excluding the best limit. This pattern highlights that the RBAS is greater at the best limit than the adjacent spreads. Furthermore, their findings indicate no statistically significant bid–ask spread asymmetry.

Panel C of Table 5 demonstrates that we reject the null hypothesis of equal successive market depths regardless of whether the best bid–ask prices are included. This indicates a statistically significant difference between the depths on the bid and ask sides.

These findings show that larger QBAS and RBAS on the ask side indicate higher costs to mitigate the higher asymmetric information at the seller side compared with the buyer side, with a larger depth away from the best ask side compared with the bid side.

Table 5. Equality tests of spreads and depths. This Table presents an equality test of price spreads and depths using the Wald linear restriction test.

Panel A: Equality of QBASs	**DF**	**Wald Statistic**	***p*-Value**
QBASs including BAS : $\beta_{B4-B5} = \beta_{B3-B4} = \beta_{B2-B3} = \beta_{B1-B2} = \beta_{A1-B1} = \beta_{A2-A1} = \beta_{A3-A2} = \beta_{A4-A3} = \beta_{A5-A4}$	9	46.9	<0.001 ***
QBASs excluding BAS : $\beta_{B4-B5} = \beta_{B3-B4} = \beta_{B2-B3} = \beta_{B1-B2} = \beta_{A2-A1} = \beta_{A3-A2} = \beta_{A4-A3} = \beta_{A5-A4}$	8	42.2	<0.001 ***
Panel B: Equality of RBASs	**DF**	**Wald Statistic**	***p*-value**
RBASs including BAS : $\beta_{B4-B5} = \beta_{B3-B4} = \beta_{B2-B3} = \beta_{B1-B2} = \beta_{A1-B1} = \beta_{A2-A1} = \beta_{A3-A2} = \beta_{A4-A3} = \beta_{A5-A4}$	9	696.7	<0.001 ***
RBASs excluding BAS : $\beta_{B4-B5} = \beta_{B3-B4} = \beta_{B2-B3} = \beta_{B1-B2} = \beta_{A2-A1} = \beta_{A3-A2} = \beta_{A4-A3} = \beta_{A5-A4}$	8	648.3	<0.001 ***
Panel C: Equality of Depth	**DF**	**Wald Statistic**	***p*-value**
Depth including market depth (B1 + A1) : $\beta_{B5} = \beta_{B4} = \beta_{B3} = \beta_{B2} = \beta_{B1} = \beta_{A1} = \beta_{A2} = \beta_{A3} = \beta_{A4} = \beta_{A5}$	10	56.8	<0.001 ***
Depth excluding market depth (B1 + A1) : $\beta_{B5} = \beta_{B4} = \beta_{B3} = \beta_{B2} = \beta_{A2} = \beta_{A3} = \beta_{A4} = \beta_{A5}$	8	46.4	<0.001 ***

Significant codes: 0 '***' 0.001.

5.2. Tick Size

Tick size defines the lower bound or constraint on the spread, which imposes price discreteness in the trading process, thus influencing liquidity dynamics. Large tick sizes incentivize investors to submit limit orders providing liquidity by enforcing minimum compensation and imposing a high cost of transactions on market order traders.

The stock prices in our sample exhibit a wide range (EGP 0.29 to 462.77), resulting in relative tick sizes (tick size/price) between 0.002% and 3.45%. The median relative tick size of 0.06% is lower than the median of 0.38% reported for 2517 stocks by Angel (1997).

Table 6 presents summary statistics on tick size for full sample and price-based subsamples. In the full sample, the tick size is binding for 29.2% of inside QBAS (the inside quoted spread equals one tick), 11.6% of the inside QBAS equal two ticks, 8.2% of the inside QBAS equal three ticks, and more than 50% of the inside spread is greater than three ticks. Meanwhile, 80.3% of the inside spreads in the lowest price range (less than EGP 2) is bound by the tick size, and none of the highest price level (more than EGP 100).

The findings also show that the mean market depth is negatively correlated with price levels, as shown in Table 6, and the market depth is the largest in the lowest price level subsample of 1.3 million shares, compared with only 0.0045 million shares in the highest price level subsample.

Table 6. Summary statistics for tick size according to the price level subsamples.

	Full Sample	Price Level Subsamples				
		1	2	3	4	5
Price range (EGP)	0.29:462.7	<2	2:10	10:20	20:100	>100
Number of stocks	30	5	12	8	4	1
Quote midpoint (EGP)	17.33	0.84	7.80	15.85	61.07	356.19
Quote midpoint range	0.28:480	0.28:1.675	2.41:17.62	9.20:29.20	19.38:170.25	273.5:480.0
IQBAS * = 1 tick (%)	29.2	80.3	29.1	6.0	2.8	0.0
IQBAS = 2 ticks (%)	11.6	11.5	17.1	6.9	3.6	0.0
IQBAS = 3 ticks (%)	8.2	4.3	11.9	7.2	4.6	0.0
IQBAS > 3 ticks (%)	50.9	3.9	41.9	79.8	89.0	100.0
IQBAS (ticks)	18.38	1.37	6.05	17.14	43.9	1521
Relative tick size/lowest RBAS- (%)	0.06	1.2	0.13	0.06	0.01	0.002
Range of relative tick size (%)	3.57:0.002	3.57:0.59	0.41:0.06	0.12:0.03	0.05:0.006	0.004:0.002
Mean market depth (shares)	246,659	1,229,509	34,294	8173	6305	4482

* IQBAS is the inside QBAS.

5.3. Availability of Immediacy

Immediacy is the probability of executing market orders and is calculated as the time at which traders find quotes at the best bid and ask price levels. In order-driven markets, immediacy depends on the availability of limit orders.

Table 7 reveals that immediacy is unavailable at the best request for 6.3% of the trading time compared with 9.4% at the best bid. Price-level subsample analysis highlights price sensitivity in terms of immediacy availability. The highest price level exhibits the greatest lack of immediacy (40.6% bid, 40% ask), whereas the lowest price level shows the least (6.9% bid, 3.6% ask).

Table 7. Immediacy analysis according to the price level subsamples.

	Full Sample	Price Level Subsamples				
		1 (Lowest)	2	3	4	5 (Highest)
Immediacy is unavailable (%)						
B5	79.2	92.9	72.3	83.3	71.5	99.4
B4	68.20	84.0	59.6	73.8	59.1	98.6
B3	52	65.1	43.4	58.4	43.0	95.4
B2	30.7	34.4	24.7	37.5	24.7	83.0
B1	9.4	6.9	7.5	13.2	7.3	40.6
A1	6.3	3.6	4.7	9.1	5.4	40.0
A2	21.6	18.7	16.2	29.2	18.9	84.7
A3	38.3	41.6	29.6	47.4	35.5	96.1
A4	53.7	63.9	43.2	61.9	50.8	99.2
A5	65.7	78.3	54.9	72.7	64.0	100

Figure 2 shows that the unavailability of immediacy on the bid side is larger than that on the ask side, which means that going further away from the market (Bid 1), the limit orders are unavailable for 79.2% at Bid 5 and 68.2% at Bid 4 compared with 65.7% and 53.7% at Ask 5 and Ask 4 levels.

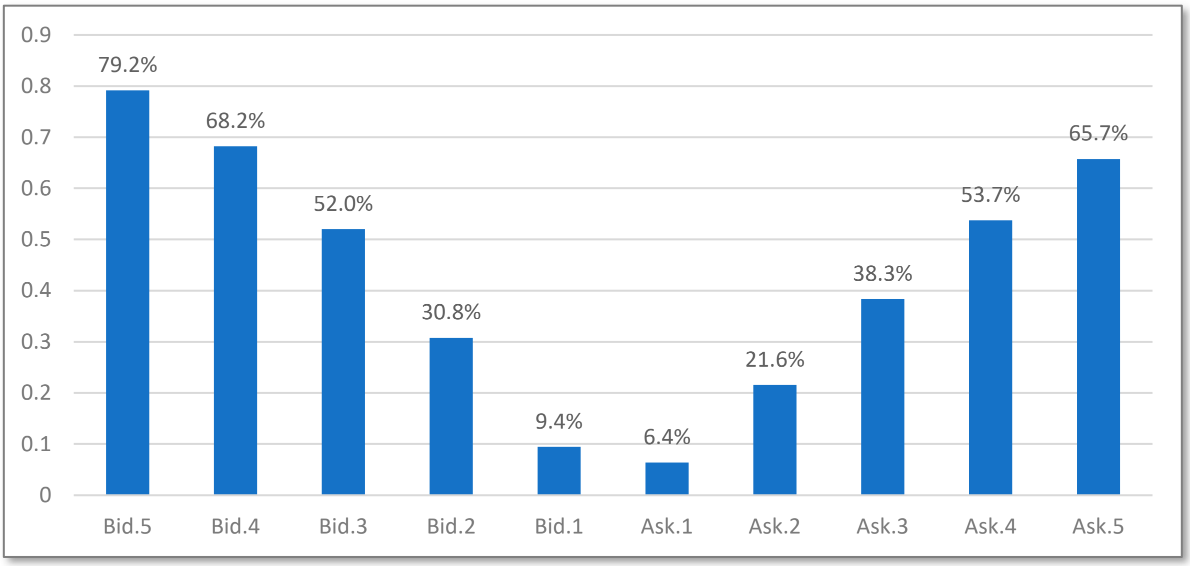

Figure 2. Unavailability of immediacy (%) full sample.

These findings suggest that liquidity, as measured by immediacy, varies across the EGX order books. The reasons for these disparities, particularly the influence of the price level on liquidity, warrant further investigation.

6. Analysis of Intraday Patterns

Stock markets frequently exhibit characteristic intraday patterns in activity measures such as volume, returns, and spreads. Common shapes include M-similar, U-similar, W-similar, inverted-U, J-similar, and reverse J-similar.

Analyzing these intraday patterns hinges on the availability of high-frequency transaction data (e.g., tick-by-tick or second-by-second). Much of the existing research focuses on American capital markets, particularly the NYSE and AMEX. Seminal studies in this area include those of Wood et al. (1985), who examine high-frequency NYSE data, revealing intraday patterns in returns and trade characteristics, and Foster and Viswanathan (1990), who observe a U-shaped pattern in hourly trade volumes across NYSE stocks. Research on other exchanges has also demonstrated intraday patterns. For instance, McInish and Wood (1992) document a U-shaped pattern in the number of shares traded for stocks on the Toronto Stock Exchange.

- The intraday pattern of RBAS

While many studies document a U-shaped intraday spread pattern, several exchanges exhibit patterns similar to those of EGX. Al-Suhaibani and Kryzanowski (2000), Chan et al. (1995), and Niemeyer and Sandas (1995) observe spreads peaking at the start of trading sessions, followed by progressive narrowing. This pattern aligns with the findings of the Stockholm, Saudi, and NASDAQ exchanges.

Intraday behavior of mean RBAS using 5 min interval.

Interestingly, EGX displays a partial return to higher spreads in the final trading interval, as shown in Figure 3. This behavior, despite the absence of market makers in pure order-driven EGX, suggests a potential monopolistic power.

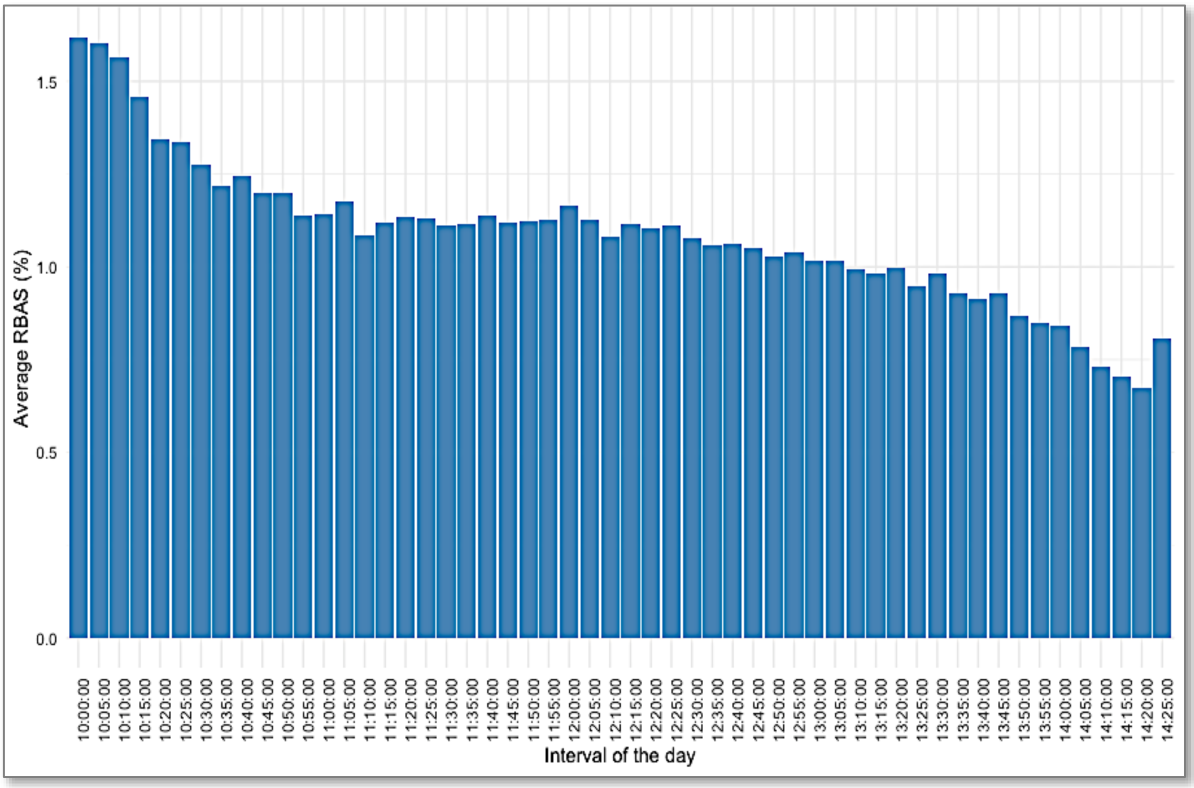

Figure 3. Intraday pattern of mean RBAS.

- Total Depth and Market Depth

The behavior of total depth (U-shape) indicates trading clustering at the market opening and closing, with a peak of 26.1 million shares at the opening, then declines to a minimum of 7.8 million shares, after which it increases throughout the rest of the trading session to reach its second peak at the last interval with 20.3 million shares, as shown in Figure 4. While the behavior of market depth follows a partially J-shaped pattern, it decreases slowly after the first interval to reach a minimum of 4.5 million shares, but, as the level of asymmetric information alleviates during the trading process, the market depth increases and reaches a peak of 12.8 million shares in the last interval, as shown in Panel B Figure 4.

- Intraday Length of the Orderbook

The average total length of the order book exhibits a U-shaped pattern. It peaks at 12 levels when the market opens, declines to a midday minimum of 5.74 levels, then increases to 9.1 and 8.0 levels in the final two intervals. This pattern suggests that limit order traders providing liquidity at the open and close place quotes further from the best bid/ask. These findings align with the observed patterns in the total depth and market depth. Figure 5 reveals a greater length on the ask side of the order book, implying that limit order traders place ask quotes further from the best ask price compared with bid quotes.

This figure shows the intraday patterns of the average total length, bid side, and ask side.

- Intraday Variation of Trading Activity

Analysis of transaction data reveals a J-shaped pattern for the average trading volume, value, and number of transactions, as shown in Figure 6. This confirms the concentrated trading activity at the beginning and end of the trading sessions.

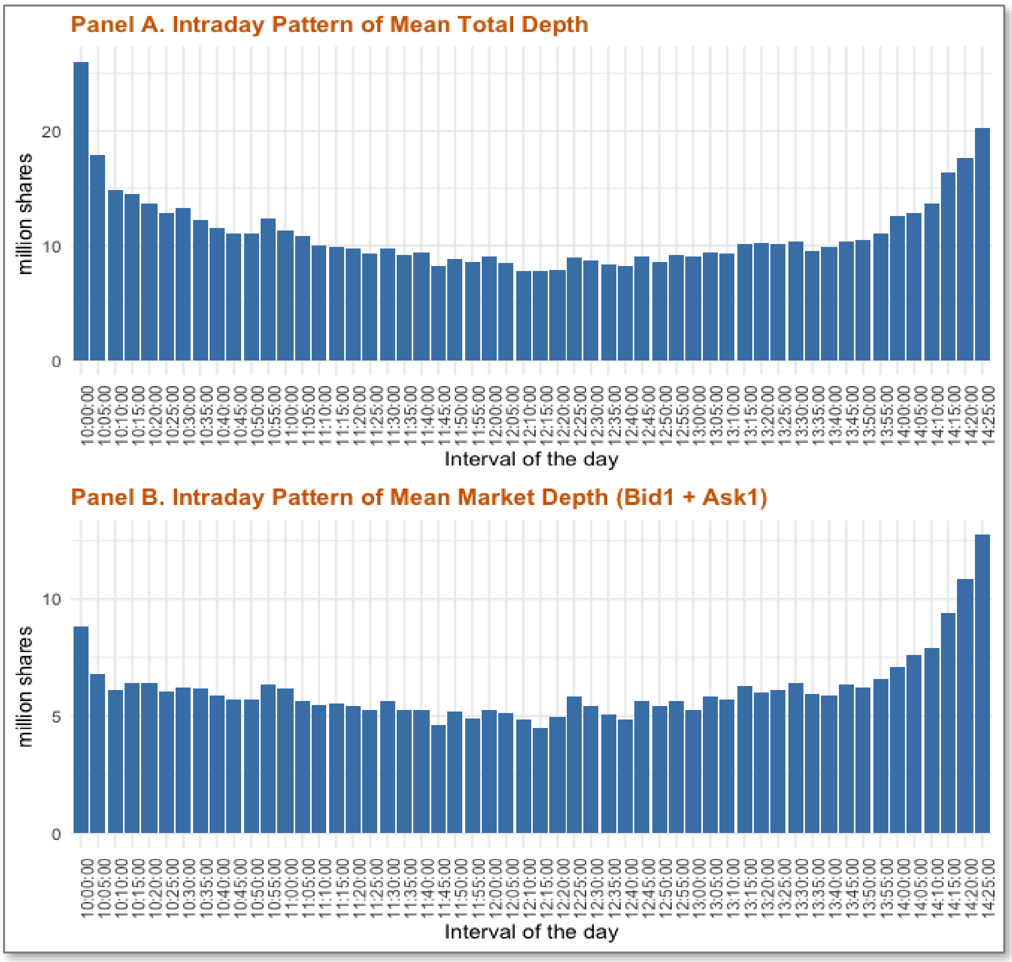

Figure 4. Intraday patterns of total depth and market depth.

Also, the intraday patterns of trading activities show that, despite the relatively constant average value per trade during the market open and close EGP 48,376 and EGP 50,340, respectively, the average volume per trade is higher at the market open 30,267 shares compared with the market close 17,159 shares, confirming that low-priced stocks are traded more than higher priced stocks in the market open, while the high-priced stocks are traded actively at the market close.

- Intraday Variation of Return and Volatility

Chordia et al. (2008) investigated intraday data and found that a market that is efficient during the day is not inherently efficient at a certain time of day. We document the intraday patterns of return and volatility for the transaction price and quote mid-point price (QMP), which suggest potential profit opportunities and warrant consideration when developing intraday trading strategies. As shown in Figure 7, log returns on intraday QMP exceed those of transaction prices. The QMP return exhibits an inverted J-shape, peaking at 0.3% during the initial trading session and becoming negative throughout most final trading hours (except for a 0.07% return at the close). This pattern aligns with observations by Abhyankar et al. (1997) regarding absolute QMP returns on the London Stock Exchange.

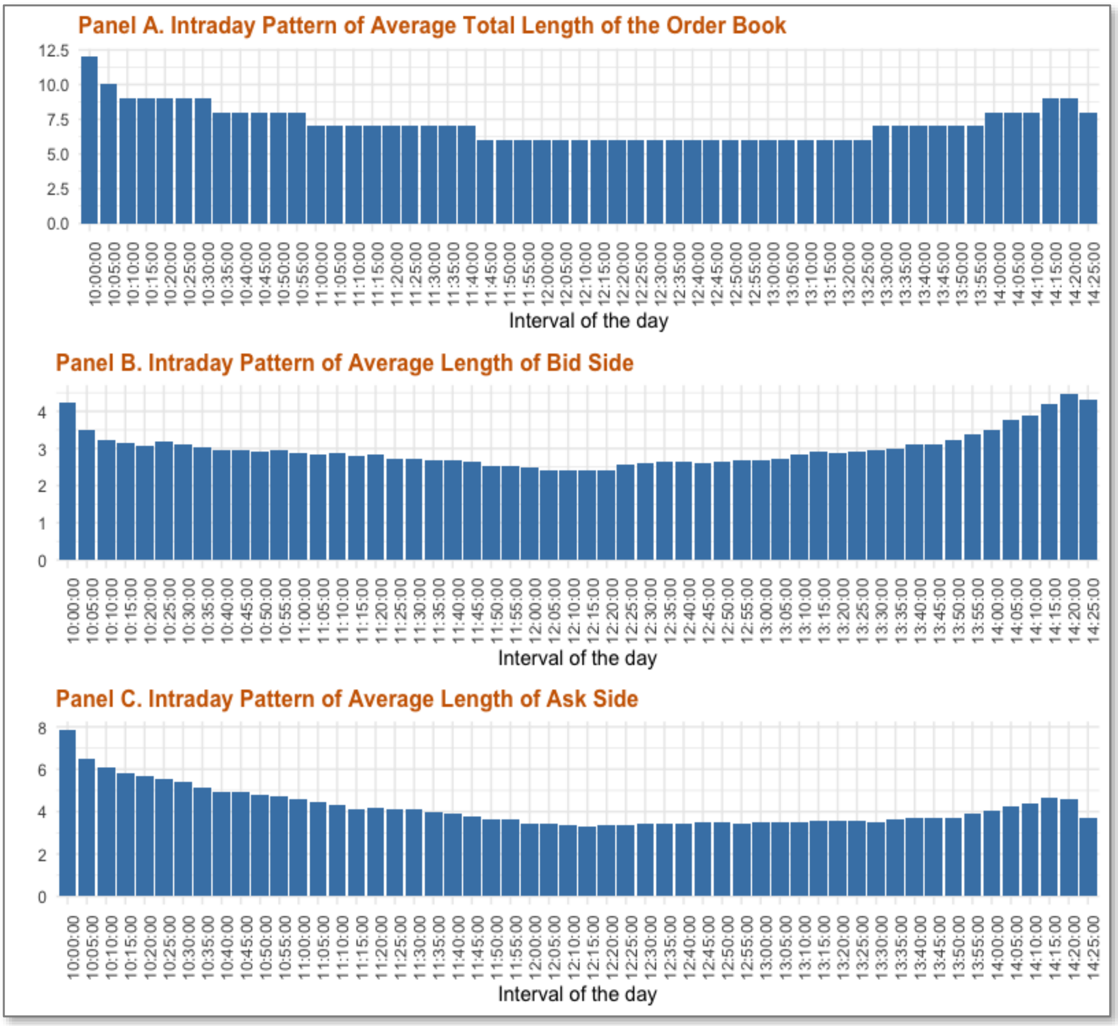

Figure 5. Intraday pattern of length of EGX order book.

- Intraday Realized Volatility (RV)

We employ realized volatility (RV), a non-parametric measure derived from observed quote mid-point prices, to examine intraday volatility patterns. Following Degiannakis and Floros (2015), we define realized volatility for the time interval $[a,b]$, which is partitioned in τ equidistant points as

$$RV_{[a,b]} = \sum_{j=1}^{\tau} \left(logM_{tj} - logM_{tj-1} \right)^2 \tag{3}$$

Andersen et al. (2003) proposed realized volatility as an alternative measure of daily volatility in financial markets, with their modeling based on the use of the sum of squared intraday returns to generate more accurate daily volatility measures.

We use quote mid-point returns to reduce the spurious volatility in transaction returns due to the bid/ask bounce reflected in the transaction prices. Figure 8 shows that intraday realized volatility is higher at the beginning of the trading session, with a peak of 0.25%, but throughout the trading day, volatility decreases, especially in the last hour before the closing of the session. The volatility measured in standard deviation, not reported, indicates the same inverted J-shaped pattern.

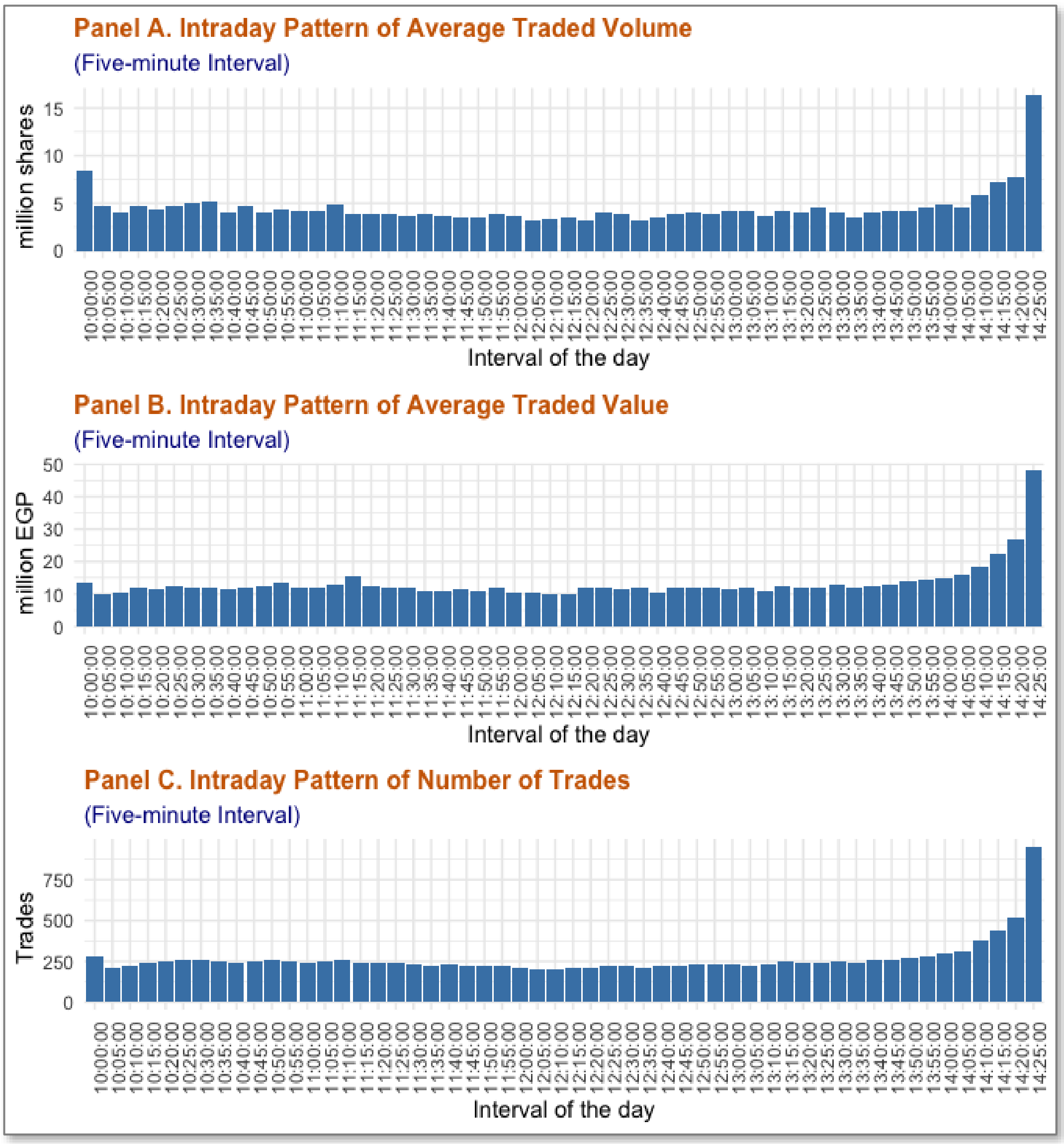

Figure 6. Intraday pattern of trading activities.

- Interval-of-Day and Day-of-Week Effects

In this section, we investigate the intraday patterns of order books and the trading activity variables. For each variable, we fit two distinct regression models: one for the time-of-day effect and the other for the day-of-the-week effect.

The regression models are constructed based on theoretical predictions about the behavior of these variables at market opening, mid-session, and market close, and based on the prior graphical analysis; the number of intervals to be used in the model is 18. Specifically, we include intervals 10:00–10:05/10:25–10:30 for the market open, 12:00–12:05/12:25–12:30 for the mid-session, and 14:00–14:05/14:25–14:30 for the market close.

Our regression model follows the approach of Al-Suhaibani and Kryzanowski (2000). We construct a regression model so that the constant represents the coefficient of the variable of interest during the omitted intervals, and the slopes represent the difference between each of the included intervals and the omitted intervals. In this model, the *t-statistics* are based on white covariance matrix estimation and offer a straightforward measure of whether there are any intraday differences between the excluded intervals and other intervals, whereas the *F-statistics* display overall significance. For the day-of-week model, to avoid linear dependency among the explanatory variables, the dummy variable belonging to the day with the lowest mean is dropped, and we use the other four dummy variables.

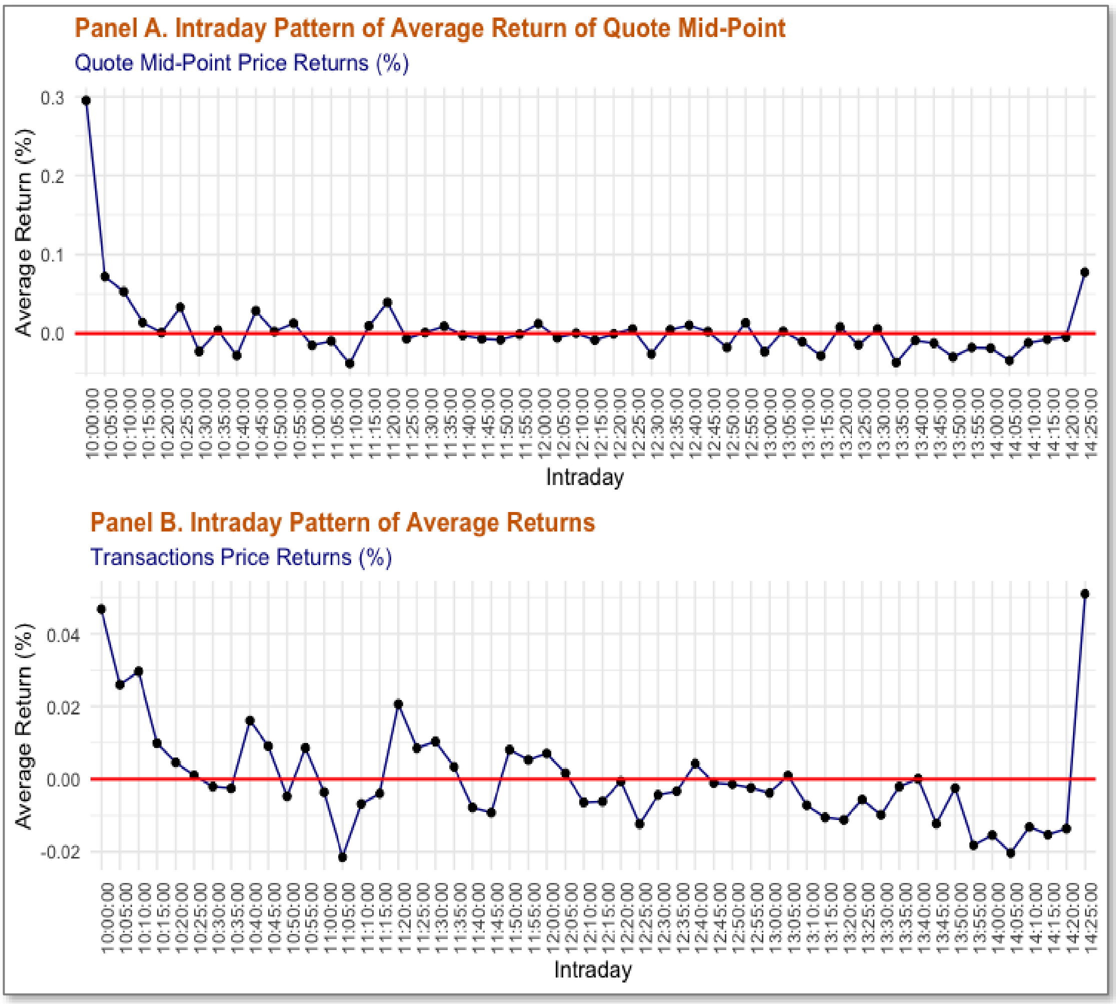

Figure 7. Intraday pattern of average return and average quote mid-point.

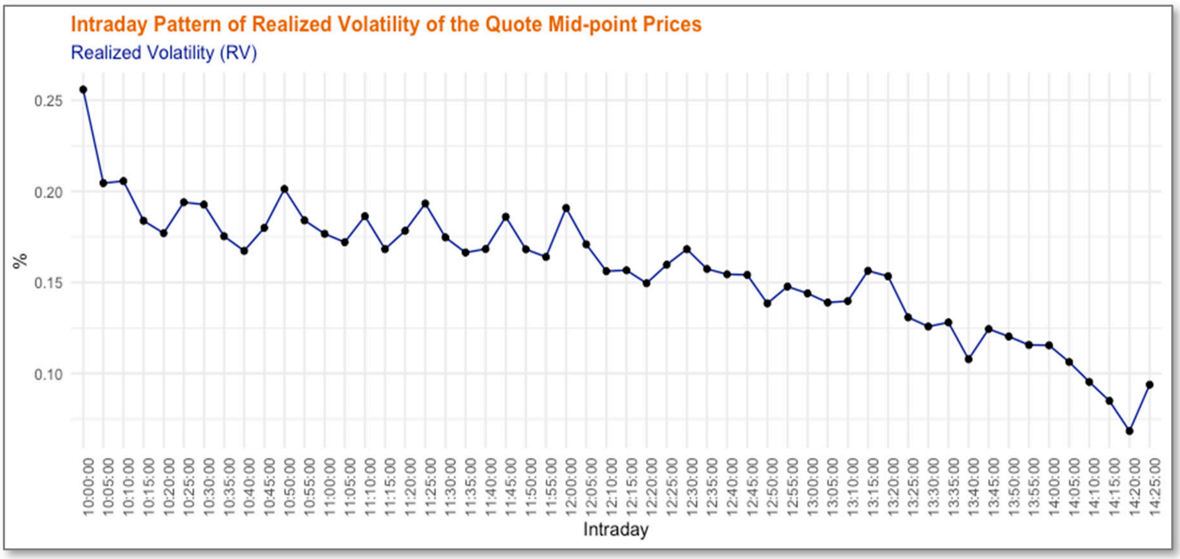

Figure 8. Intraday pattern of realized volatility (RV) of the mid-point returns.

For each variable and stock, the data are standardized by subtracting the mean and dividing by the standard deviation prior to regression against the interval-of-day and day-of-week dummies.

- Intraday Variables of Interest

This study tests intraday anomalies and variations for both the limit order book and trading activity data, including the following list of variables of interest:

- Relative BAS (RBAS): RBAS is defined as the difference between the best ask and best bid (QBAS) divided by the mid-quote price (m) at interval t.

$$RBAS_t = (A - B)/m \tag{4}$$

$$m = (A + B)/2 \tag{5}$$

- Total Depth: indicates all outstanding shares available for buying and selling in the limit order book for stock i in interval t.
- Market Depth: the sum of shares at the best bid and best ask limits for stock i in interval t.
- Depth Bid: sum of shares available on the bid side for stock i in interval t.
- Depth Ask: sum of shares available on the ask side for stock i in interval t.
- Length of Order Book: indicates the total number of limit price levels in the limit order book for stock i in interval t.
- Traded Volume.
- Traded Value.
- Number of Transactions.

Using 18 intervals only (6 intervals for market opening, midday, and market closing), we construct the following regression model for the interval-of-day effect:

$$Y_i = \hat{\alpha} + \sum_{h=1}^{18} \hat{\beta}_h \, Dinterval_{h,\, i} + \hat{\varepsilon}_i \tag{6}$$

where Y_i denotes the variables of interest, $Dinterval_{h,\, i}$ is a dummy variable that equals one if the observation of Y_i belongs to interval h, and zero otherwise.

For the day-of-week effect, we construct the following regression model:

$$Y_i = \hat{\alpha} + \sum_{k=1}^{5} \hat{\beta}_k \, Dweek_{k,\, i} + \hat{\varepsilon}_i \tag{7}$$

where $Dweek_{k,\, i}$ is a dummy variable that equals one if the observation of the variable of interest belongs to the day of week k, and zero otherwise.

For the order book data, Table 8 (Panels A and B) presents the results of the interval-of-day and day-of-week regressions.

Panel A reveals a dynamic pattern in relative bid–ask spreads (RBASs) throughout the trading day. The widest RBAS occurs in the first interval (coefficient of 0.384), indicating greater uncertainty and potentially higher compensation sought by liquidity providers at the market open. As the trading day progresses, spreads narrow towards midday, suggesting reduced information asymmetry. However, this trend reverses, with spread widening near the market close, possibly due to increased trading activity or strategic behavior by traders.

Table 8. Tests for time variation in the order book data.

Panel A. Tests for intraday patterns (interval-of-day effect) in the order book for the EGX						
	Relative BAS	**Total Depth**	**Market Depth**	**Depth (Bid Side)**	**Depth (Ask Side)**	**Length of Order Book**
N	157,988	187,674	187,674	187,674	187,674	187,674
(Intercept)	−0.005. (−1.8570)	−0.071 *** (−26.5938)	−0.035 *** (−13.1344)	−0.062 *** (−23.9100)	−0.057 *** (−21.4139)	−0.083 *** (−31.0491)
Dinterval.1	0.384 *** (21.7149)	0.669 *** (31.7034)	0.027 * (2.0365)	0.343 *** (19.4953)	0.766 *** (31.3499)	1.162 *** (53.2482)
Dinterval.2	0.383 *** (17.8700)	0.321 *** (17.9435)	−0.032 * ((−2.3149)	0.127 *** (8.3939)	0.400 *** (19.9811)	0.710 *** (34.6338)
Dinterval.3	0.359 *** (15.9424)	0.212 *** (11.6049)	−0.069 *** (−5.2358)	0.066 *** (4.1744)	0.287 *** (14.4545)	0.568 *** (27.4460)
Dinterval.4	0.262 *** (12.9018)	0.199 *** (9.1111)	−0.064 *** (−5.2806)	0.032 (1.4987)	0.278 *** (12.9002)	0.486 *** (23.9391)
Dinterval.5	0.188 *** (9.3185)	0.168 *** (8.9350)	−0.045 *** (−3.6305)	0.049** (2.7000)	0.214 *** (11.2963)	0.444 *** (22.5563)
Dinterval.6	0.170 *** (8.5311)	0.152 ** (9.0168)	−0.050 *** (−3.8183)	0.038 ** (2.5920)	0.206 *** (11.3267)	0.427 *** (21.6080)
Dinterval.25	0.085 *** (3.7965)	−0.091 *** (−4.9847)	−0.039 ** (−2.5823)	−0.077 *** (−4.8967)	−0.081 *** (−4.0277)	−0.184 *** (−12.2651)
Dinterval.26	0.065 ** (2.8108)	−0.115 *** (−8.4379)	−0.056 *** (−3.8008)	−0.089 *** (−6.8606)	−0.090 *** (−6.3714)	−0.198 *** (−12.9482)
Dinterval.27	0.036. (1.7833)	−0.135 *** (−10.4323)	−0.077 *** (−5.7744)	−0.114 *** (−8.8537)	−0.108 *** (−8.0254)	−0.225 *** (−14.9314)
Dinterval.28	0.062 ** (2.8024)	−0.105 *** (−6.5525)	−0.034. (−1.7082)	−0.074 *** (−4.6417)	−0.090 *** (−5.3757)	−0.228 *** (−14.7909)
Dinterval.29	0.050 * (2.3022)	−0.110 *** (−7.8080)	−0.035 * (−2.5039)	−0.084 *** (−6.2246)	−0.096 *** (−6.7429)	−0.220 *** (−14.5410)
Dinterval.30	0.053 * (2.3768)	−0.072 *** (−4.3324)	−0.032. (−1.8724)	−0.032. (−1.8011)	−0.089 *** (−6.0683)	−0.191 *** (−12.0691)
Dinterval.49	−0.196 *** (−14.9005)	0.206 *** (12.7041)	0.178 *** (9.5708)	0.217 *** (12.0229)	0.129 *** (8.4883)	0.140 *** (9.2996)
Dinterval.50	−0.250 *** (−21.3400)	0.260 *** (15.8121)	0.211 *** (9.9124)	0.292 *** (15.5954)	0.153 *** (9.6310)	0.232 *** (15.0795)
Dinterval.51	−0.295 *** (−32.4211)	0.351 *** (21.7257)	0.283 *** (15.5573)	0.368 *** (19.8124)	0.232 *** (14.2858)	0.304 *** (19.9756)
Dinterval.52	−0.322 *** (−36.3104)	0.527 *** (26.2495)	0.405 *** (17.5921)	0.541 *** (26.0629)	0.346 *** (17.7491)	0.415 *** (26.4921)
Dinterval.53	−0.349 *** (−47.2830)	0.671 *** (30.9158)	0.517 *** (23.1411)	0.746 *** (31.9492)	0.390 *** (18.4696)	0.474 *** (30.3244)
Dinterval.54	−0.248 *** (−23.9135)	0.661 *** (31.3612)	0.760 *** (21.3251)	0.971 *** (33.2495)	0.198 *** (11.8702)	0.305 *** (21.7266)
F-statistic	F (18, 157,969) 188.5	F (18, 187,655) 384.3	F (18, 187,655) 227.1	F (18, 187,655) 416	F (18, 187,655) 256.9	F (18, 187,655) 696.6
p-value	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$

Table 8. *Cont.*

Panel B. Tests for the day-of-week effect in the order book for the EGX						
	Relative BAS	**Total Depth**	**Market Depth**	**Depth (Bid Side)**	**Depth (Ask Side)**	**Length of Order Book**
N	157,988	187,674	187,674	187,674	187,674	187,674
(Intercept)	−0.026 *** (−4.8431)	−0.086 *** (−16.436)	−0.070 *** (−14.581)	−0.067 *** (−12.4344)	−0.078 *** (−16.524)	−0.080 *** (−15.784)
DSunday	0.092 *** (11.1693)	*Excluded*	*Excluded*	*Excluded*	*Excluded*	*Excluded*
DMonday	*Excluded*	0.099 *** (13.651)	0.088 *** (12.175)	0.085 *** (11.5737)	0.082 *** (11.837)	0.093 *** (12.914)
DTuesday	0.016 * (2.1826)	0.095 *** (13.106)	0.083 *** (11.855)	0.071 *** (9.7457)	0.090 *** (12.925)	0.079 *** (11.173)
DWednesday	0.014. (1.9583)	0.099 *** (13.911)	0.081 *** (11.722)	0.073 *** (10.3382)	0.095 *** (13.637)	0.095 *** (13.343)
DThursday	0.010 (1.3377)	0.141 *** (18.125)	0.099 *** (13.705)	0.107 *** (13.5121)	0.123 *** (16.776)	0.140 *** (18.292)
F-statistic	*F* (4, 157,983) 42.21	*F* (4, 187,669) 96.27	*F* (4, 187,669) 57.91	*F* (4, 187,669) 57.85	*F* (4, 187,669) 76.96	*F* (4, 187,669) 91.87
p-value	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$

Significant codes: 0 '***' 0.001; '**' 0.01; '*' 0.05.

Depth measures, including total depth, depth at the bid and ask sides, and order book length, exhibit a U-shaped pattern, indicating a clustering of trading activity at the beginning and end of the trading day. Market depth, however, follows a J-shaped pattern, with significant increases in the last 30 min of the trading session. The results for the market depth and depth at the bid side suggest that, after a transaction that removes liquidity from the order book, liquidity is not immediately replenished.

Furthermore, Panel A highlights a negative correlation between spreads and market depth, confirming the inverse relationship between transaction costs and liquidity. The market open is characterized by the widest RBAS and significantly lower depth, indicating reduced liquidity at the start of trading.

Panel B reveals significant day-of-week effects on RBAS, where Sundays exhibit the highest average RBAS, likely due to lower liquidity. While Monday's data are excluded as the lowest value, the remaining days show a negative relationship between RBAS and other liquidity measures, as expected [cite: 257, 258, 259].

Our findings support Madhavan (1992)'s argument that wider spreads at the market open reflect higher information asymmetry and the risk of adverse selection, discouraging liquidity provision and leading to a less liquid market opening.

The interval-of-day effect is tested using the following regression model, $Y_i = \hat{\alpha} + \sum_{h=1}^{18} \hat{\beta}_h \, Dinterval_{h,\, i} + \hat{\varepsilon}_i$, where Y_i denotes the variables of interest and $Dinterval_{h,\, i}$ is the dummy variable equal to one if the observation of Y_i belongs to the interval h, or zero otherwise. The t-statistic is based on the White covariance matrix estimation, providing a direct test of whether any intraday differences exist between the omitted intervals and the other intervals.

The day-of-week effect is tested using the following regression model, $Y_i = \hat{\alpha} + \sum_{k=1}^{5} \hat{\beta}_k \, Dweek_{k,\, i} + \hat{\varepsilon}_i$, where Y_i denotes the variables of interest, $Dweek_{k,\, i}$ is a dummy variable equal to one if the observation of the variable of the interest belongs to the day of the week k, or zero otherwise. To avoid linear dependency among the explanatory variables, the dummy variable belonging to the day with the lowest mean is removed for this purpose. The t-statistic is based on the White covariance matrix estimation, providing a direct test of whether any day of the week differences exist between the omitted day and the other days.

For the trading activity data, an examination of trading activity on the EGX, as presented in Table 9, reveals distinct intraday and day-of-week patterns. Panel A highlights a J-shaped pattern in trading volume, value, and the number of trades, reaching their peak in the final trading intervals (14:00–14:05 and 14:25–14:30). This surge in activity near the market close aligns with observations in other markets, suggesting a concentration of trading decisions towards the end of the trading session. Conversely, midday intervals (12:20–12:25 and 12:25–12:30) frequently exhibit non-significant coefficients, indicating relatively subdued trading activity during the middle of the session.

Table 9. Tests for time variation in the trading activities for the EGX.

Panel A. Tests for interval-of-day effect on trading activities			
	Traded Volume	Traded Value	Number of Trades
N	147,104	147,104	147,104
Intercept	−0.044 *** (−14.5247)	−0.043 *** (−14.4225)	−0.059 *** (−19.7866)
Dinterval.1	0.187 *** (6.2738)	0.192 *** (6.2978)	0.226 *** (6.7938)
Dinterval.2	0.079 *** (3.3518)	0.081 *** (3.4387)	0.079 ** (3.2700)
Dinterval.3	0.068 ** (2.8423)	0.071 ** (2.9420)	0.090 *** (3.3797)
Dinterval.4	0.104 *** (3.7285)	0.108 *** (3.8450)	0.103 *** (3.9685)
Dinterval.5	0.071 *** (3.3893)	0.074 *** (3.4590)	0.092 *** (4.1646)
Dinterval.6	0.070 *** (3.6056)	0.068 *** (3.6026)	0.112 *** (5.0714)
Dinterval.25	−0.039 * (−2.0426)	−0.039 * (−2.0365)	−0.049 * (−2.3713)
Dinterval.26	−0.040 * (−2.2053)	−0.037 * (−2.0967)	−0.068 *** (−4.1808)
Dinterval.27	−0.059 *** (−3.9404)	−0.053 *** (−3.4771)	−0.073 *** (−4.2246)
Dinterval.28	−0.043 * (−2.3821)	−0.042 * (−2.3891)	−0.055 ** (−2.8829)
Dinterval.29	−0.021 (−0.9010)	−0.020 (−0.8740)	−0.057 *** (−3.5347)
Dinterval.30	−0.002 (−0.1119)	−0.002 (−0.1377)	−0.017 (−0.9073)
Dinterval.49	0.046 ** (2.8502)	0.044 ** (2.7533)	0.062 *** (3.5835)
Dinterval.50	0.065 *** (4.5216)	0.061 *** (4.3491)	0.085 *** (5.5234)

Table 9. *Cont.*

Dinterval.51	0.132 *** (8.9357)	0.127 *** (8.7030)	0.203 *** (12.8122)
Dinterval.52	0.200 *** (12.7472)	0.197 *** (12.4691)	0.305 *** (18.9829)
Dinterval.53	0.326 *** (17.1416)	0.320 *** (16.3598)	0.443 *** (26.2224)
Dinterval.54	0.896 *** (33.8096)	0.880 *** (32.1622)	1.229 *** (53.1887)
F-statistic	F (18, 147,085) 189.3	F (18, 147,085) 182.7	F (18, 147,085) 365.6
p-value	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$
Panel B. Tests for the day-of-week effect on trading activities			
	Traded Volume	Traded Value	Number of Trades
N	147,104	147,104	147,104
(Intercept)	−0.066 *** (−11.584)	−0.065 *** (−11.3098)	−0.081 *** (−14.509)
DSunday	*Excluded* *(lowest interval)*	*Excluded* *(lowest interval)*	*Excluded* *(lowest interval)*
DMonday	0.085 *** (10.246)	0.0824 *** (9.8958)	0.103 *** (12.677)
DTuesday	0.063 *** (8.233)	0.061 *** (7.9558)	0.086 *** (10.942)
DWednesday	0.083 *** (10.394)	0.082 *** (10.3053)	0.099 *** (12.450)
DThursday	0.099 *** (11.246)	0.097 *** (10.9950)	0.113 *** (13.322)
F-statistic	F (4, 147,099) 42.37	F (4, 147,099) 40.6	F (4, 147,099) 58.53
p-value	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$	$<2.2 \times 10^{-16}$

Significant codes: 0 '***' 0.001; '**' 0.01; '*' 0.05.

Panel B of Table 9 further reveals significant day-of-week effects on trading activity metrics. Sundays exhibit the lowest average trading activity, reflecting reduced market participation and order flow over the weekend. In contrast, Thursdays, coinciding with the end of the trading week, show the strongest statistically significant coefficients. This heightened activity on Thursdays could be attributed to various factors, such as portfolio rebalancing, the expiration of options contracts, or increased positioning ahead of the weekend.

The consistency between these findings and the results for the limit order data, as shown in Table 8, strengthens the overall analysis. Both datasets reveal non-negligible day-of-week effects, rejecting the null hypothesis of no day-of-week differences in regression coefficients. This suggests that incorporating day-of-week variables into trading models could potentially improve their accuracy and capture recurring weekly patterns in trading activity.

7. Discussion and Policy Implications

This study's findings on the intraday patterns of liquidity and trading activity in the Egyptian Exchange (EGX) are consistent with the earlier literature. First, this study finds that spreads exhibit an inverted J-shaped pattern, with the highest spreads occurring at the market open and then gradually declining throughout the day. This pattern is consistent with the findings of Madhavan (1992) and has been observed in other markets, such as the Stockholm, Saudi, and NASDAQ exchanges (Al-Suhaibani & Kryzanowski, 2000; Chan et al., 1995; Niemeyer & Sandas, 1995).

Second, this study finds that total depth exhibits a U-shaped pattern, with the highest depths occurring at the market open and close and the lowest depths occurring at midday. This pattern is also consistent with the earlier literature and has been attributed to the clustering of trading activity at the beginning and end of the trading day (Brock & Kleidon, 1992). Third, this study finds that market depth exhibits a J-shaped pattern, with depths increasing throughout the day and reaching their peak at the market close. This pattern is consistent with the findings of Y. T. Lee et al. (2001) and Tissaoui (2012) and has been attributed to the gradual accumulation of information throughout the day.

Finally, this study finds that trading activity, as measured by volume, value, and the number of trades, exhibits a J-shaped pattern, with the highest activity occurring at the market close. This pattern is consistent with the findings of earlier studies and has been attributed to a variety of factors, such as portfolio rebalancing, the expiration of options contracts, and increased positioning ahead of the weekend.

These findings offer several policy implications that can enhance market quality and efficiency on the EGX.

1. Tick Size Optimization: This study reveals that the tick size constraint is binding for a significant portion of inside spreads, especially for lower priced stocks. Policymakers should consider a more segmented approach to tick sizes, potentially differentiating tick sizes based on price levels or liquidity tiers. This could improve liquidity and price discovery, particularly for less liquid stocks.
2. Enhancing Immediacy: This study highlights the limited availability of immediacy on the EGX, with the best bid–ask established for only 84.2% of the trading time. Policymakers could explore measures to incentivize liquidity provision and improve order book depth, such as reducing trading fees or implementing market maker schemes. Increasing immediacy would lower transaction costs and improve market efficiency.
3. Mitigating Monopolistic Power: This study finds evidence of monopolistic power in the EGX market structure, as indicated by the partial increase in spreads in the final trading interval. Policymakers should investigate this behavior and consider introducing a closing auction mechanism to enhance price transparency and fairness at the end of the trading day.
4. Addressing Day-of-Week Effects: This study reveals significant day-of-week effects on liquidity and trading activity, with lower liquidity observed on Sundays and Mondays. Policymakers could consider targeted interventions to address these anomalies, such as promoting trading on less active days or adjusting trading schedules to align with global markets. This would improve overall market efficiency and reduce trading costs.
5. Promoting Transparency and Information Dissemination: This study underscores the importance of information in shaping intraday liquidity patterns. Policymakers should prioritize initiatives that promote transparency and efficient information dissemination. This includes ensuring timely disclosure of market data, encouraging investor education, and facilitating access to research and analysis.

By implementing these recommendations, policymakers can foster a more liquid, efficient, and transparent market on EGX, attracting investment, reducing trading costs, and promoting investor confidence.

8. Conclusions

This study examines liquidity dimensions and intraday variations of EGX for EGX30 stocks. While the average relative inside spread is lower than in comparable markets (Saudi, Stockholm, Thailand), wider QBAS persists due to the underlying stock price ranges. This finding aligns with the WFE data. Depth concentrates at the best bid–ask and is distributed equally between the two sides, with the ask side exhibiting a slightly greater average length. Immediacy availability on the EGX is lower than on other exchanges, with the best bid–ask established for only 84.2% of the trading time. The tick size constraint is binding for 29.2% of the inside spreads (full sample), increasing to 80.3% for the lowest-price group. These observations highlight the interplay between the market structure and liquidity dynamics within the EGX.

Our intraday analysis graphically confirms the observed patterns. Despite EGX's unique structure, patterns mirror other markets, e.g., spreads exhibit an inverted J-shape (highest at the open), total depth is U-shaped, and market depth displays a J-shape. These findings align with Madhavan (1992), highlighting information asymmetry risks and reducing liquidity provision in the open market. Trading activity (volume, value, and transactions) is J-shaped, while volatility shows an inverted J-shape.

Our analysis reveals significant day-of-week effects that influence liquidity and trading activities. We observe a relationship between the RBAS and other liquidity metrics. The anomalously low RBAS of Monday warrants further investigation. Conversely, Sunday's significantly higher RBAS aligns with its status as having the lowest liquidity. Furthermore, trading volume, value, and number of transactions display clear day-of-week patterns, with Sundays exhibiting the lowest averages and Thursdays exhibiting the highest.

Our findings underscore the importance of trading structures and institutional settings on EGX liquidity. The dominance of limit orders, with only a small percentage of direct market orders and wider spreads, likely contributes to implicit trading costs. We suggest further segmentation of price levels with differentiated tick sizes, particularly for stocks with higher prices. Additionally, the behavior of trading activity at the open and close, alongside intraday patterns, warrants further investigation in relation to price discovery, information flows, and how EGX incorporates news.

In conclusion, our study provides robust evidence of intraday and day-of-week anomalies in liquidity and trading patterns on the Egyptian Exchange. These findings align with theoretical models, offer practical insights for traders, and highlight avenues for future research on the market structure.

While our study provides valuable insights into the intraday liquidity patterns of the Egyptian Exchange (EGX), it is tailored to the unique market structure of EGX and focuses on a specific high-frequency dataset from a single period. Future research could extend this analysis to compare with other emerging markets or incorporate longer timescales to capture broader economic cycles and their impact on liquidity. Additionally, integrating the analysis of news and public disclosures using market microstructure techniques could offer deeper insights into how information dissemination influences liquidity dynamics and price volatility. Such studies would be instrumental in understanding the immediate effects of news on market behavior, providing a more comprehensive view of market efficiency and information processing in real time, and the future studies could extend this analysis to provide trading strategies based on the intraday patterns and market quality of the Egyptian Exchange.

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Notes

[1] Since January 2015, the World Federation of Exchanges (WFE) collects the data on the MSS form all exchange members. The MSS is defined as a pre-trade indicator reflecting differences in bids and asks over time. Calculated as [(Ask − Bid)/((Ask + Bid)/2)]x × 10,000 and dominated in non-monetary absolute Basis Points (BPS). "Simulation for Median Spread data series Statistics Advisory Group Liquidity indicators—Median Spread WFE".

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