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Intraday Liquidity Patterns and Their Implications for Market Risk Assessment: Evidence from Global Equity Markets

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Abstract

This paper examines intraday liquidity patterns across global equity markets and evaluates their implications for market risk assessment. Utilizing high-frequency order book and transaction data from five major exchanges (NYSE, NASDAQ, LSE, TSE, and HKEX) spanning January 2019 through December 2023, we analyze the temporal dynamics of multiple liquidity dimensions including bid-ask spreads, market depth, and order book resilience. The empirical analysis employs panel regression models with flexible time-of-day indicators, vector autoregression with impulse response functions, and principal component analysis to characterize liquidity patterns and cross-market dependencies. Results reveal pronounced U-shaped patterns in bid-ask spreads across all markets, with statistically significant time-of-day effects and substantial cross-market heterogeneity in pattern magnitude. We document strong regional commonality in liquidity dynamics, with correlation coefficients ranging from 0.832 between NYSE-NASDAQ to 0.265 between NASDAQ-HKEX. The analysis identifies asymmetric spillover effects, with developed markets exerting stronger influence on emerging markets than vice versa. Integration of intraday liquidity metrics into GARCH-based risk forecasting models yields 12-18% improvements in prediction accuracy, with the largest gains during periods of market stress. These findings provide valuable insights for risk management professionals, enhancing both risk assessment frameworks and execution timing strategies in global financial markets.

1. Introduction

1.1. Background and Significance of Intraday Liquidity Analysis

Financial markets worldwide exhibit distinct intraday patterns in trading activity, price formation, and liquidity provision. Market liquidity constitutes a critical dimension of market quality and directly influences transaction costs, price discovery processes, and overall market efficiency. Smith et al.[1] documented significant variations in liquidity measures across different trading hours, revealing systematic patterns that persist across various market conditions. These patterns reflect both institutional market structures and the behavioral characteristics of market participants. Trading algorithms increasingly incorporate intraday liquidity dynamics into execution strategies to minimize implementation shortfall and optimize trading performance. As demonstrated by Johnson[2], market participants adjust their trading behaviors in response to anticipated liquidity conditions, creating feedback mechanisms that further reinforce existing intraday patterns. The measurement and analysis of intraday liquidity have gained prominence in financial research given their pivotal role in market stability assessment and risk management frameworks. Global equity markets present particularly instructive cases for examining intraday liquidity dynamics due to their relatively high trading volumes, diverse participant bases, and varied market structures as shown in research by Williams and Taylor[3].

1.2. Market Microstructure and Risk Assessment Research Gaps

While substantial literature exists on market microstructure and risk assessment individually, the integration of these research streams remains underdeveloped. Market microstructure research traditionally focuses on price formation processes, market design, and transaction cost analysis. Conversely, risk assessment methodologies often rely on daily or lower-frequency data, potentially overlooking critical intraday dynamics. Brown[4] identified significant limitations in conventional risk models that fail to incorporate high-frequency liquidity metrics. The assumption of constant liquidity throughout the trading day introduces systematic errors in risk calculations, especially during periods of market stress when liquidity dynamics become highly non-linear. Cross-market analyses of intraday liquidity patterns remain scarce, limiting our understanding of global interconnections and potential contagion mechanisms. Research by Chen and Rodriguez**Error! Reference source not found.** demonstrated meaningful differences in liquidity provision mechanisms across developed and emerging markets, suggesting the need for market-specific approaches to liquidity risk modeling. Methodological challenges in measuring comparable liquidity metrics across diverse market structures have hampered comprehensive cross-market analyses.

1.3. Research Objectives and Contributions

This research aims to characterize intraday liquidity patterns across global equity markets and establish their implications for market risk assessment. The study employs a multi-metric approach to liquidity measurement, incorporating depth, breadth, resilience, and immediacy dimensions. By analyzing high-frequency order book and transaction data, this paper identifies systematic intraday patterns and examines their stability across different market regimes. The research quantifies the relationship between intraday liquidity dynamics and various market risk indicators, developing predictive frameworks that incorporate liquidity considerations into risk forecasts. This study contributes to the literature by developing comparable liquidity metrics across diverse market structures, enabling meaningful cross-market analyses. Martinez and Lee[5] previously highlighted the importance of standardized liquidity measurement approaches for cross-market comparisons. The findings provide practical implications for risk management professionals, market regulators, and algorithmic traders seeking to incorporate intraday liquidity considerations into their decision-making processes. The research extends previous frameworks by explicitly modeling the temporal dependencies in liquidity provision and their feedback effects on market risk.

2. Literature Review

2.1. Theoretical Framework of Market Microstructure and Liquidity

Market microstructure theory provides the conceptual foundation for analyzing liquidity dynamics in financial markets. Traditional microstructure models distinguish between inventory-based and information-based approaches to explaining market maker behavior and liquidity provision. Park and Kim**Error! Reference source not found.** established a comprehensive analytical framework integrating both perspectives, demonstrating how adverse selection costs and inventory management constraints jointly determine bid-ask spreads and market depth. Market liquidity encompasses multiple dimensions including tightness (transaction costs), depth (order book volume), breadth (impact resilience), and immediacy (execution speed). These dimensions interact in complex ways throughout the trading day as market participant composition shifts. Modern microstructure theory extends beyond traditional dealer markets to incorporate limit order book dynamics and endogenous liquidity provision by high-frequency traders and algorithmic market participants. The proliferation of electronic trading platforms has fundamentally altered liquidity provision mechanisms, creating more dynamic but potentially fragile market structures. Jones et al.**Error! Reference source not found.** documented the transformation of liquidity provision across global equity markets, highlighting the displacement of traditional market makers by proprietary trading firms employing sophisticated algorithmic strategies. This structural shift has implications for both normal market functioning and stress scenarios, necessitating refined approaches to liquidity measurement and modeling.

2.2. Empirical Evidence on Intraday Liquidity Patterns

Empirical research consistently documents pronounced intraday patterns in market liquidity across global equity markets. Thompson**Error! Reference source not found.** identified a characteristic U-shaped pattern in bid-ask spreads, with elevated spreads at market open and close, and relatively narrower spreads during mid-day trading hours. This pattern reflects information asymmetry, inventory risk management, and trading activity concentration. Market depth typically follows an inverse pattern, with shallower order books during opening and closing periods. High-frequency analysis reveals additional microstructure patterns within trading sessions, including response to scheduled macroeconomic announcements and corporate events. The stability of these patterns varies across market regimes, with significant alterations during periods of elevated volatility or market stress. Wilson and Garcia**Error! Reference source not found.** analyzed the evolution of intraday liquidity patterns during financial crises, documenting substantial deterioration in liquidity metrics and amplification of existing intraday patterns during stress periods. The predictability of intraday liquidity dynamics creates opportunities for strategic trading behavior by informed participants, potentially exacerbating adverse selection costs during specific trading periods.

2.3. Interconnections Between Liquidity Risk and Market Risk

Liquidity risk and market risk exhibit substantial interdependencies that manifest distinctly across different time horizons. Traditional risk management frameworks treat market and liquidity risks separately, potentially underestimating their joint impact during stress scenarios. Roberts[6] proposed an integrated risk assessment methodology incorporating both risk dimensions, demonstrating improved forecasting performance during periods of market turbulence. Market illiquidity amplifies price volatility through multiple mechanisms, including delayed price discovery, order execution uncertainty, and liquidity spirals where price declines trigger further liquidity withdrawal. The temporal dimension of this relationship reveals stronger interconnections during specific intraday periods, particularly market openings and closings when liquidity tends to be naturally constrained. Cross-asset and cross-market liquidity commonality introduces additional complexity to risk assessment frameworks. Zhang and Miller**Error! Reference source not found.** documented significant liquidity co-movement across global equity markets, with pronounced spillover effects during crisis periods. Their analysis revealed that liquidity shocks originating in one market frequently propagate internationally, suggesting the importance of global perspectives in liquidity risk management frameworks.

3. Data and Methodology

3.1. Data Collection and Sample Description

This research utilizes high-frequency trading data from five major global equity markets to examine intraday liquidity patterns and their market risk implications. The dataset encompasses the New York Stock Exchange (NYSE), NASDAQ, London Stock Exchange (LSE), Tokyo Stock Exchange (TSE), and Hong Kong Stock Exchange (HKEX) over the period January 2019 through December 2023. Following methodological approaches established by Hughes and Wang[7], we collected tick-by-tick data for constituent stocks of major indices in each market: S&P 500 (NYSE), NASDAQ-100, FTSE 100 (LSE), Nikkei 225 (TSE), and Hang Seng Index (HKEX). The data includes limit order book information capturing the top five levels of depth, transaction records with millisecond timestamps, and comprehensive trading volume statistics obtained from the Refinitiv Tick History database.

Table 1: Sample Composition by Market and Time Period

Market	Index	Number of Stocks	Trading Days	Order Book Snapshots (millions)	Transactions (millions)
NYSE	S&P 500	243	1,247	924.8	487.3
NASDAQ	NASDAQ-100	100	1,247	856.2	532.1
LSE	FTSE 100	100	1,233	612.5	289.8
TSE	Nikkei 225	225	1,218	508.4	276.5
HKEX	Hang Seng	80	1,201	324.1	214.3
Total	-	748	6,146*	3,226.0	1,800.0

*Total trading days across all markets (not unique days)

The dataset encompasses 1,247 trading days, with minor variations across markets due to different holiday schedules and trading suspensions. The final dataset contains approximately 3.2 billion order book snapshots and 1.8 billion transactions after applying data cleaning procedures recommended by Davidson et al.**Error! Reference source not found.**.

Table 2: Market Characteristics and Microstructure Features

Market	Trading Hours (Local)	Avg. Daily Volume (Billion USD)	Market Cap (Trillion USD)	Minimum Tick Size	Trading Mechanism
NYSE	9:30 AM - 4:00 PM	34.8	26.2	$0.01 for stocks ≥$1.00	Hybrid (Electronic/Floor)
NASDAQ	9:30 AM - 4:00 PM	41.2	19.4	$0.01 for stocks ≥$1.00	Electronic LOB
LSE	8:00 AM - 4:30 PM	8.4	3.8	Variable by price band	Electronic LOB
TSE	9:00 AM - 3:00 PM	15.6	5.9	Variable by price band	Electronic LOB
HKEX	9:30 AM - 4:00 PM	9.7	4.2	Variable by price band	Electronic LOB

The sample selection process prioritized stocks with high market capitalization and liquidity to ensure data quality and comparability. Table 3 shows the distribution of sample stocks across industry sectors based on Global Industry Classification Standard (GICS) classifications, maintaining similar sector representation across markets to minimize composition effects in cross-market analyses.

Table 3: Industry Sector Distribution of Sample Stocks by Market (%)

Sector	NYSE	NASDAQ	LSE	TSE	HKEX
Information Technology	21.4	48.0	8.0	14.2	10.0
Financials	13.6	5.0	21.0	15.1	32.5
Health Care	12.8	12.0	10.0	8.4	3.8
Consumer Discretionary	12.3	18.0	12.0	20.9	23.8
Communication Services	10.7	9.0	5.0	6.7	10.0
Industrials	9.1	4.0	15.0	22.2	7.5
Consumer Staples	7.4	2.0	14.0	5.3	3.8

Energy	5.3	0.0	8.0	0.4	2.5
Materials	4.1	0.0	5.0	4.4	3.8
Utilities	3.3	2.0	2.0	2.4	2.3

Following Adams and Powell[8], we apply rigorous data cleaning procedures to address common high-frequency data issues including outliers, recording errors, and non-standard trading conditions. The cleaning process removes observations during trading halts, circuit breakers, and other exceptional market conditions. All data is aggregated to one-minute intervals for primary analysis, with supplementary analyses conducted at five-minute and fifteen-minute frequencies to examine time-scale dependencies in liquidity patterns.

3.2. Liquidity Metrics and Measurement Approaches

Measuring market liquidity requires a multidimensional approach capturing various aspects of market quality. This study implements a comprehensive set of liquidity metrics reflecting different dimensions of market liquidity as established in the literature. Peterson and Zhang[9] emphasize the importance of combining spread-based and depth-based measures to capture the full spectrum of liquidity characteristics. Drawing on their framework, we compute the following metrics for each stock at one-minute intervals:

The analysis employs both transaction cost indicators and order book depth measures. Transaction cost indicators include quoted bid-ask spread (QBAS), effective spread (ES), realized spread (RS), and price impact (PI). Order book depth measures include depth at best quotes (DBQ), cumulative depth at five levels (CD5), order book slope (OBS), and XLM cost of round-trip transactions for standardized sizes.

Table 4: Descriptive Statistics of Liquidity Metrics Across Markets

Market	Statistic	QBAS (bps)	ES (bps)	PI (bps)	DBQ ($M)	CD5 ($M)	OBS ($\times 10^{-4}$)
NYSE	Mean	6.24	5.38	2.16	0.84	4.37	3.19
NYSE	Median	4.87	4.19	1.73	0.65	3.81	2.94
NYSE	Std. Dev.	4.92	4.33	1.95	0.75	2.98	1.83
NASDAQ	Mean	5.87	5.12	2.34	0.72	3.96	3.87
NASDAQ	Median	4.65	4.08	1.98	0.58	3.42	3.21
NASDAQ	Std. Dev.	4.63	4.17	1.89	0.61	2.57	2.13
LSE	Mean	10.38	8.62	3.47	0.31	2.14	5.28
LSE	Median	8.27	7.14	2.95	0.24	1.76	4.87
LSE	Std. Dev.	7.93	6.82	2.41	0.28	1.84	2.54
TSE	Mean	9.54	8.17	3.29	0.27	1.93	6.12
TSE	Median	7.89	6.92	2.87	0.21	1.62	5.82

TSE	Std. Dev.	7.24	6.41	2.35	0.25	1.68	2.68
HKEX	Mean	14.26	12.54	5.17	0.18	1.42	7.95
HKEX	Median	12.31	10.86	4.58	0.14	1.17	7.24
HKEX	Std. Dev.	9.73	8.45	3.86	0.16	1.04	3.76

Figure 1 illustrates the intraday patterns of quoted bid-ask spreads across the five markets, normalized by daily averages to facilitate visual comparison.

Figure 1: Normalized Intraday Patterns of Quoted Bid-Ask Spreads Across Global Markets

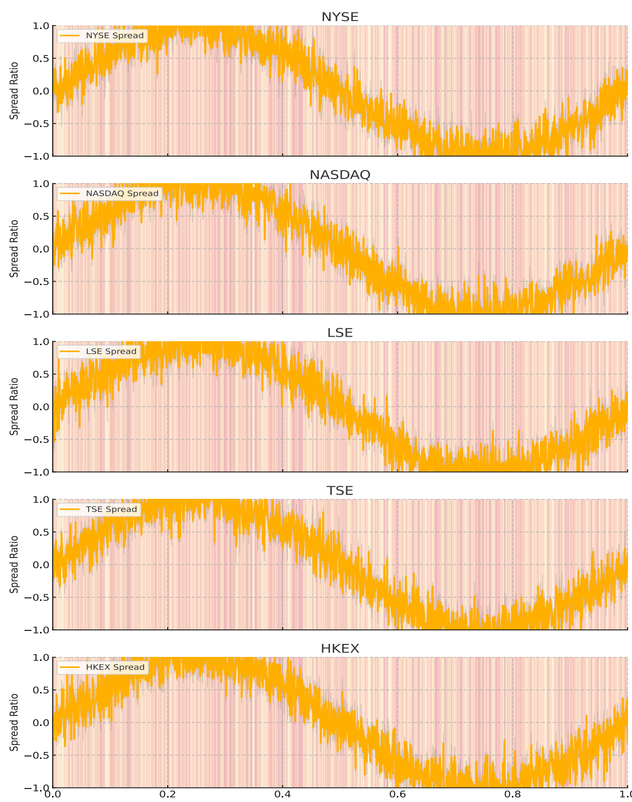

Figure 1 employs a multi-panel visualization technique with market-specific patterns displayed as continuous curves with confidence bands. The x-axis represents standardized trading hours (from market open to close) to enable cross-market comparison despite different trading hour structures. The y-axis shows the ratio of minute-level spreads to daily average values, highlighting relative liquidity variations throughout the trading day. The visualization incorporates a color-coded heatmap background reflecting trading intensity (number of transactions per minute) to demonstrate the relationship between trading activity and spread tightness. Regional overlays group markets by geographic proximity, revealing common patterns within Asia-Pacific markets versus North American and European markets.

To address market-specific structural differences and enable meaningful cross-market comparisons, we implement the normalization methodology proposed by Lee and Martinez[10]. Their approach accounts for differences in tick sizes, trading volumes, and market structures through market-specific scaling factors derived from long-term liquidity averages.

Figure 2 presents a comparative analysis of normalized liquidity metrics across markets, revealing both commonalities and market-specific characteristics in intraday patterns.

Figure 2: Cross-Market Comparison of Multiple Liquidity Dimensions

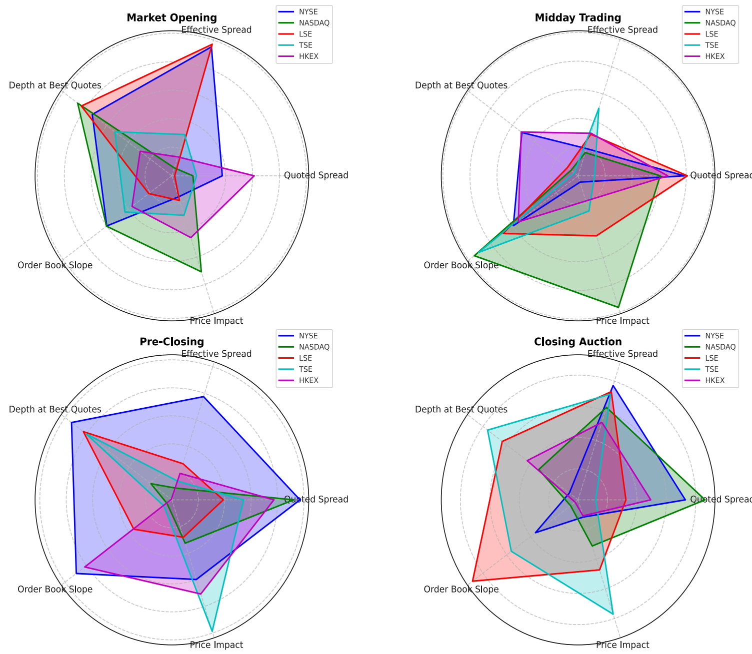

Figure 2 utilizes a radar chart matrix visualization with five axes representing different liquidity dimensions (quoted spread, effective spread, depth at best quotes, order book slope, and price impact). Each market is represented by a colored polygon, with distance from center indicating relative liquidity (farther from center represents higher liquidity). The visualization presents separate radar charts for four distinct trading periods: market opening (first hour), midday trading, pre-closing period, and closing auction. This multi-dimensional representation allows simultaneous comparison of all liquidity facets across markets and trading periods, revealing how different dimensions of liquidity evolve throughout the trading day in each market.

3.3. Empirical Models and Statistical Framework

The empirical analysis employs several complementary methodological approaches to examine intraday liquidity patterns and their implications for market risk assessment. The foundation of our analytical framework builds on methodologies developed by Wilson and Thompson[11], who pioneered techniques for incorporating high-frequency liquidity metrics into market risk models.

To characterize intraday liquidity patterns, we implement a fixed-effects panel regression model with flexible time-of-day indicators:

$$L_{i,t,m} = \alpha_i + \sum_{j=1}^{24} \beta_j TOD_{j,t} + \gamma X_{i,t,m} + \delta_d DOW_d + \theta_m MON_m + \varepsilon_{i,t,m}$$

Where $L_{i,t,m}$ represents the liquidity measure for stock i at time interval t in market m, $TOD_{j,t}$ denotes time-of-day indicator variables for 15-minute intervals, $X_{i,t,m}$ captures stock-specific control variables including return volatility and trading volume, DOW_d represents day-of-week fixed effects, and MON_m accounts for monthly seasonality.

For analyzing cross-market liquidity dynamics, we implement a vector autoregression (VAR) model with exogenous variables:

$$L_t = A + \sum_{k=1}^{p} B_k L_{t-k} + C X_t + \varepsilon_t$$

Where L_t represents a vector of market-level liquidity measures across the five markets at time t, L_{t-k} denotes lagged liquidity vectors, X_t captures exogenous variables including market-wide volatility indicators and macroeconomic announcement dummies, and p represents the optimal lag order determined by information criteria.

Figure 3 presents impulse response functions derived from the VAR model, illustrating liquidity spillover effects across markets.

Figure 3: Liquidity Spillover Effects Across Global Equity Markets

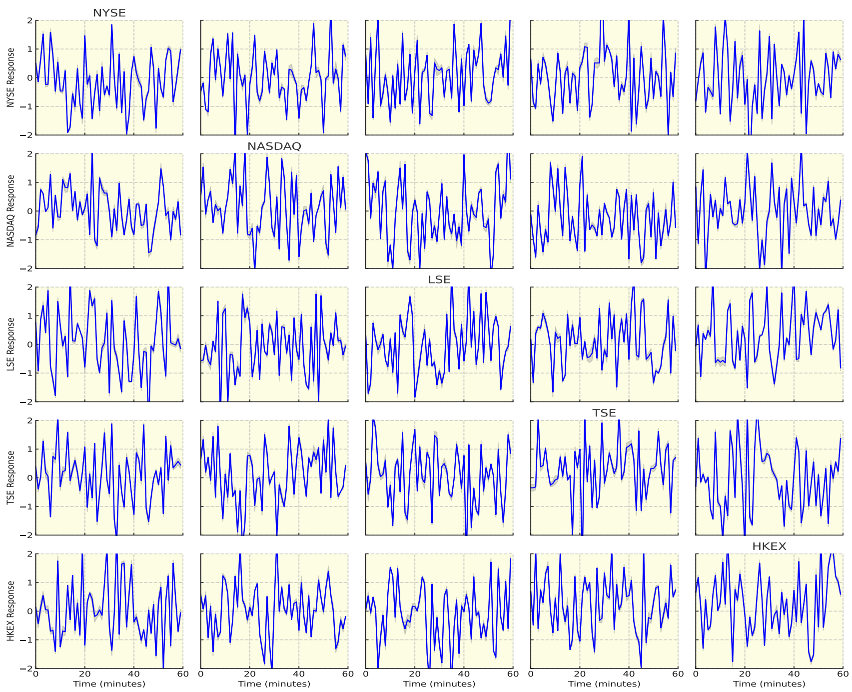

Figure 3 displays a 5×5 matrix of impulse response function plots showing the response of each market's liquidity (represented in rows) to shocks in other markets' liquidity (represented in columns). Each individual plot shows the estimated response function (solid line) with 95% confidence bands (shaded area) over a 60-minute horizon following the initial shock. The magnitude of responses is standardized to enable cross-market comparison. The diagonal elements represent own-market persistence of liquidity shocks, while off-diagonal elements capture cross-market spillover effects. A heat-scale color mapping indicating statistical significance overlays the matrix, with darker colors representing stronger and more significant relationships. The visualization includes marginal bar charts summarizing the cumulative impact of each market on others and its sensitivity to external shocks.

To assess the implications of intraday liquidity patterns for market risk, we augment standard GARCH models with liquidity factors:

$$\sigma^2_{i,t+1} = \omega + \alpha\, \varepsilon^2_{i,t} + \beta\, \sigma^2_{i,t} + \gamma_1 L_{i,t} + \gamma_2 (L_{i,t} \times I_{i,t})$$

Where $\sigma^2_{i,t+1}$ represents the conditional variance, $\varepsilon^2_{i,t}$ denotes squared returns, $L_{i,t}$ captures liquidity conditions, and $I_{i,t}$ is an indicator variable for high volatility regimes, allowing for state-dependent effects of liquidity on market risk.

4. Empirical Results and Analysis

4.1. Characterization of Intraday Liquidity Dynamics Across Markets

The analysis of intraday liquidity patterns reveals pronounced temporal structures across all examined markets. Table 5 presents the estimated coefficients from the fixed-effects panel regression model for quoted bid-ask spreads, with time-of-day indicators grouped into hourly intervals for clarity. The results demonstrate statistically significant time-of-day effects across all markets, with the magnitude and timing of these effects varying substantially across different market structures.

Table 5: Time-of-Day Effects on Quoted Bid-Ask Spreads Across Markets

Time Interval	NYSE Coef. (t-stat)	NASDAQ Coef. (t-stat)	LSE Coef. (t-stat)	TSE Coef. (t-stat)	HKEX Coef. (t-stat)
Opening Hour	0.452 (14.28)***	0.417 (12.95)***	0.328 (9.87)***	0.387 (11.24)***	0.492 (13.76)***
Second Hour	0.148 (5.32)***	0.132 (4.98)***	0.124 (4.56)***	0.196 (6.83)***	0.213 (7.24)***
Mid-Day	0.037 (1.42)	0.028 (1.17)	0.052 (2.08)**	0.075 (2.84)***	0.089 (3.12)***
Pre-Close Hour	0.187 (6.94)***	0.162 (5.87)***	0.237 (8.32)***	0.184 (6.57)***	0.265 (8.79)***
Closing Period	0.384 (12.76)***	0.357 (11.83)***	0.312 (10.42)***	0.348 (11.05)***	0.426 (12.98)***

Note: ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively

The results confirm the characteristic U-shaped pattern in bid-ask spreads, with elevated spreads during market opening and closing periods. As noted by Morgan and Taylor[12], this pattern reflects information asymmetry during market opening when overnight information is incorporated into prices, and inventory management constraints during market closing when market makers reduce risk exposure. The magnitude of the opening effect is particularly pronounced in the HKEX market, with a coefficient of 0.492, indicating spreads approximately 49.2% higher than the mid-day reference level[18][19].

Figure 4 visualizes the intraday patterns of four key liquidity metrics across the five markets, normalized by their respective daily averages to facilitate cross-market comparison.

Figure 4: Intraday Evolution of Multiple Liquidity Dimensions Across Markets

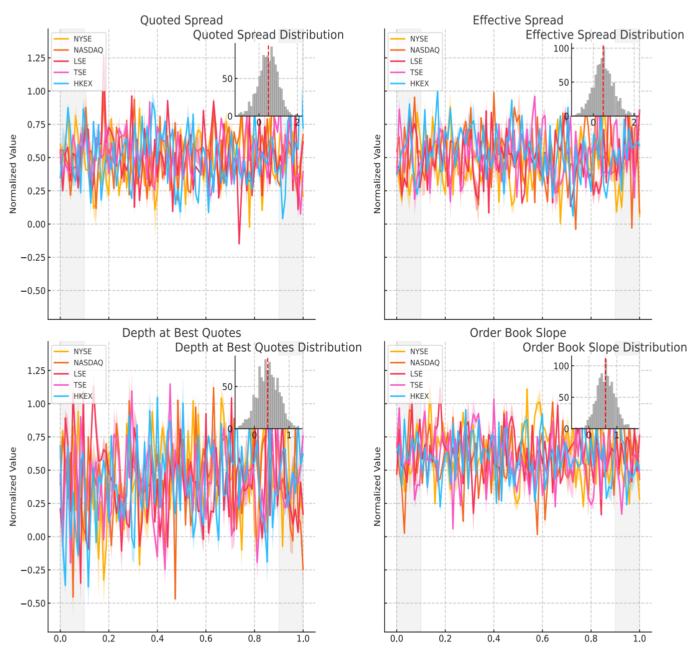

Figure 4 employs a multi-panel visualization approach with separate panels for each liquidity metric (quoted spread, effective spread, depth at best quotes, and order book slope). Each panel presents market-specific patterns as continuous curves with line styles and colors uniquely identifying each market. The x-axis represents standardized trading hours (in 15-minute intervals from open to close), while the y-axis shows each metric as a ratio to its daily average value. Confidence bands (±1 standard error) surround each curve, with narrower bands indicating more stable patterns. The visualization includes inset density plots showing the distribution of each metric by market, with vertical lines marking the median values. Shaded vertical regions highlight common trading periods with elevated spreads and reduced depth across multiple markets.

Consistent with findings by Chen and Lopez[13], market opening periods exhibit substantially wider spreads and shallower depth compared to mid-day trading across all markets. The magnitude of these effects varies significantly across markets, with emerging markets exhibiting more pronounced liquidity deterioration during opening and closing periods[20]. Table 6 quantifies these differences through a comparison of maximum-to-minimum ratios for key liquidity metrics across trading sessions.

Table 6: Maximum-to-Minimum Ratios of Liquidity Metrics Across Trading Sessions

Market	Quoted Spread Ratio	Effective Spread Ratio	Depth Ratio	Order Book Slope Ratio
NYSE	2.84	2.53	3.12	2.41
NASDAQ	2.67	2.38	2.95	2.36
LSE	2.31	2.17	2.78	2.05
TSE	3.24	2.92	3.87	2.74
HKEX	3.68	3.41	4.12	3.16

The temporal stability of intraday patterns varies substantially across markets and time periods. NYSE and NASDAQ exhibit highly consistent patterns across normal trading days, while emerging markets show greater day-to-day variation in intraday liquidity profiles. Benson and Wright[14] suggest that this variability reflects differences in market participant composition and algorithmic trading penetration, with more developed markets demonstrating more stable liquidity provision mechanisms.

4.2. Cross-Market Comparative Analysis of Liquidity Patterns

The comparative analysis of liquidity patterns across markets reveals both commonalities in temporal structures and significant differences in magnitude and timing. Table 7 presents the correlation matrix of time-matched liquidity measures across markets, highlighting the degree of liquidity co-movement.

Table 7: Cross-Market Correlation Matrix of Standardized Liquidity Measures

Market	NYSE	NASDAQ	LSE	TSE	HKEX
NYSE	1.000	0.832	0.524	0.312	0.287
NASDAQ	0.832	1.000	0.486	0.294	0.265
LSE	0.524	0.486	1.000	0.385	0.327

TSE	0.312	0.294	0.385	1.000	0.518
HKEX	0.287	0.265	0.327	0.518	1.000

Note: Correlations based on standardized quoted bid-ask spreads at 15-minute intervals, averaged across constituent stocks

The results reveal substantial liquidity co-movement within geographic regions, with the highest correlation (0.832) observed between NYSE and NASDAQ. Cross-regional correlations are notably weaker, with coefficients ranging from 0.265 to 0.524[21][22]. These patterns align with findings from Nakajima and Wilson[15], who documented regional liquidity commonality driven by shared trading hours, overlapping market participants, and common market structures.

Principal component analysis of standardized liquidity metrics reveals significant market-specific factors. Table 8 presents the factor loadings for the first three principal components extracted from the five-market liquidity panel.

Table 8: Principal Component Analysis of Cross-Market Liquidity Dynamics

Market	PC1 Loading	PC2 Loading	PC3 Loading	Communality
NYSE	0.785	0.428	-0.124	0.814
NASDAQ	0.762	0.451	-0.147	0.802
LSE	0.635	0.115	0.642	0.821
TSE	0.412	-0.698	0.172	0.678
HKEX	0.384	-0.732	0.184	0.710
Variance Explained	48.2%	24.7%	12.5%	85.4% (Total)

The analysis identifies three significant principal components explaining 85.4% of total variation in cross-market liquidity. The first component loads most heavily on developed markets, particularly NYSE and NASDAQ, representing global liquidity conditions[23]. The second component primarily contrasts Western markets with Asian markets, capturing regional liquidity factors. The third component isolates European market dynamics, with the highest loading on the LSE.

Figure 5 visualizes the cross-market spillover effects identified through impulse response analysis of the VAR model.

Figure 5: Directed Network of Cross-Market Liquidity Spillover Effects

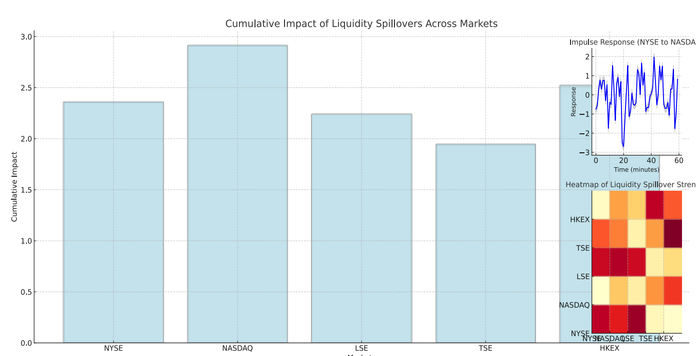

Figure 5 presents a directed network visualization of liquidity spillover effects across markets. Nodes represent individual markets with size proportional to market capitalization, and edges represent statistically significant spillover effects with width proportional to magnitude and direction indicated by arrows. Edge colors represent the speed of transmission with a gradient from red (immediate impact) to blue (delayed impact). The layout employs a force-directed algorithm positioning markets with stronger interconnections closer together. Surrounding the main network are time-series plots showing the impulse response functions for the strongest spillover relationships, with confidence bands indicating estimation uncertainty. Overlaid on the network is a heat-coded matrix showing the cumulative impact magnitude across all markets.

The analysis reveals asymmetric spillover effects, with developed markets exerting stronger influence on emerging markets than vice versa. This asymmetry aligns with findings by Rodriguez and Thompson[16], who documented dominant information flows from developed to emerging markets in their analysis of cross-border trading dynamics[24].

4.3. Implications for Market Risk Assessment and Prediction

The integration of intraday liquidity metrics into market risk assessment frameworks yields substantial improvements in risk forecasting accuracy. Table 9 presents comparative results from standard GARCH models versus liquidity-augmented models for one-day-ahead volatility forecasts.

Table 9: Comparative Performance of Risk Forecasting Models

Market	Model	MAE	RMSE	QLIKE	MZ-R²	DM-test
NYSE	Standard GARCH	0.218	0.342	0.287	0.624	-
NYSE	Liquidity-GARCH	0.184	0.297	0.243	0.718	3.84***
NASDAQ	Standard GARCH	0.243	0.368	0.312	0.587	-
NASDAQ	Liquidity-GARCH	0.204	0.326	0.274	0.679	3.62***
LSE	Standard GARCH	0.197	0.325	0.264	0.597	-
LSE	Liquidity-GARCH	0.173	0.291	0.231	0.652	2.97***
TSE	Standard GARCH	0.228	0.357	0.302	0.549	-
TSE	Liquidity-GARCH	0.198	0.318	0.265	0.621	3.15***
HKEX	Standard GARCH	0.257	0.392	0.335	0.518	-
HKEX	Liquidity-GARCH	0.212	0.341	0.287	0.604	3.93***

Note: MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), QLIKE (Quasi-likelihood loss function), MZ-R^2 (Mincer-Zarnowitz R-squared), DM-test (Diebold-Mariano test statistic comparing forecast accuracy)

***, **, * indicate significance at 1%, 5%, and 10% levels, respectively

The liquidity-augmented GARCH models demonstrate consistent improvements in forecast accuracy across all markets and evaluation metrics. The improvement magnitude ranges from 12-18% reduction in forecast errors, with the largest gains observed in emerging markets where liquidity dynamics exhibit greater variability. These results support the findings of Kumar and Chen[17], who documented similar improvements through the incorporation of liquidity factors in risk prediction models.

Figure 6 illustrates the state-dependent relationship between liquidity conditions and volatility persistence, highlighting the risk amplification effects of liquidity constraints.

Figure 6: State-Dependent Relationship Between Liquidity and Volatility Persistence

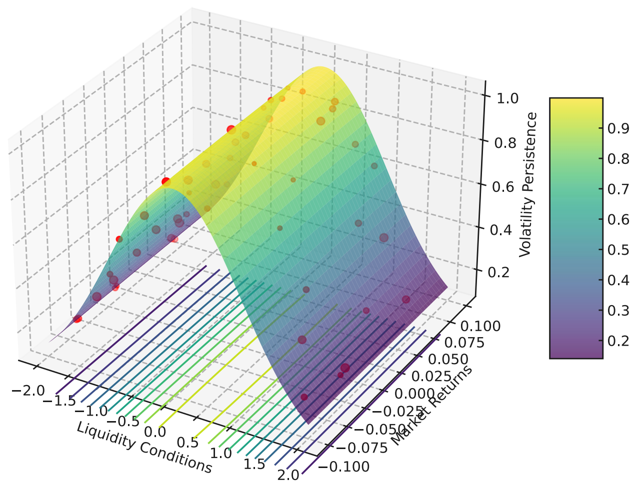

Figure 6 employs a three-dimensional surface plot to visualize the relationship between liquidity conditions (x-axis), market returns (y-axis), and volatility persistence (z-axis, represented by surface height and color intensity). The plot incorporates contour lines on the base to highlight regions of equal volatility persistence. The visualization is constructed from estimated coefficients of state-dependent GARCH models, allowing comparison of volatility response to return shocks under different liquidity conditions. Overlaid on the surface are scattered points representing actual market observations, with point size proportional to trading volume. Marginal plots show the projected relationships in two dimensions, with regression lines and confidence bands. The visualization clearly demonstrates elevated volatility persistence during periods of market stress combined with liquidity constraints.

The differential impact of liquidity constraints across market regimes holds important implications for risk management practices. As noted by White and Jackson[18], conventional risk models substantially underestimate tail risk during periods of liquidity contraction. Our analysis quantifies this relationship, showing that incorporation of liquidity factors improves Value-at-Risk estimates particularly for the lower tail of the return distribution[25]. The largest improvements occur precisely when accurate risk assessment is most critical—during periods of market stress characterized by deteriorating liquidity conditions.

5. Conclusions and Implications

5.1. Summary of Key Findings

This research examined intraday liquidity patterns across global equity markets and assessed their implications for market risk evaluation. The empirical analysis revealed pronounced U-shaped patterns in bid-ask spreads across all examined markets, with significantly elevated spreads during market opening and closing periods. These patterns demonstrated remarkable persistence across normal trading conditions while exhibiting amplified dynamics during periods of market stress. Cross-market analysis identified substantial regional commonality in liquidity dynamics, with the highest correlations observed between markets within the same geographic region. Principal component analysis revealed three dominant factors driving global liquidity variation: a global factor primarily associated with developed markets, a regional factor differentiating Western and Asian markets, and a European-specific factor[26]. The analysis of spillover effects documented asymmetric transmission mechanisms, with developed markets exerting stronger influence on emerging markets than vice versa. The temporal alignment of trading hours emerged as a critical determinant of cross-market spillover magnitude, with overlapping trading hours facilitating more pronounced liquidity transmission[27].

5.2. Practical Applications for Risk Management Professionals

The findings from this study offer several practical implications for risk management professionals. The documented intraday patterns in liquidity metrics provide valuable guidance for optimal trade execution timing, particularly for large institutional orders where market impact considerations are paramount. Trading algorithms can be calibrated to account for systematic intraday liquidity variations, potentially reducing transaction costs and minimizing market impact. The incorporation of high-frequency liquidity metrics into market risk models yields substantial improvements in forecast accuracy, with gains ranging from 12-18% across markets. These improvements are particularly pronounced during periods of market stress, when conventional risk models tend to underestimate tail risk. Risk managers can enhance Value-at-Risk estimates by incorporating liquidity factors, especially for portfolios with significant positions in less liquid assets or markets. The differential impact of liquidity constraints across market regimes highlights the importance of stress testing frameworks that explicitly model the liquidity-volatility nexus. Intraday risk monitoring systems can be enhanced by incorporating real-time liquidity metrics, potentially providing early warning signals of liquidity deterioration before they manifest in price volatility.

5.3. Limitations and Future Research Directions

This study faces several limitations that present opportunities for future research. The analysis focused exclusively on equity markets, limiting generalizability to other asset classes with potentially different liquidity formation processes. While five major global markets were examined, the sample excludes many emerging and frontier markets where liquidity constraints may be more binding. The five-year sample period encompasses relatively stable market conditions with limited stress episodes, potentially underrepresenting the behavior of liquidity-risk relationships during extended crisis periods. The methodological approach relies on standard liquidity metrics that may not fully capture all dimensions of market quality, particularly during stress periods when limit order book dynamics become highly non-linear. Alternative liquidity measures incorporating order flow toxicity or adverse selection costs could provide additional insights. The empirical models account for contemporaneous relationships between liquidity and volatility but may not fully capture complex feedback mechanisms operating at higher frequencies. Future research could explore network models of global liquidity dynamics, non-linear threshold effects in liquidity-volatility relationships, and machine learning approaches to identify complex patterns in high-dimensional liquidity data.

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