



Market Liquidity and Price Discovery in the Pakistan Stock Exchange: The Role of Trading Volume and Investor Participation

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Abstract

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This paper looks at the dynamic interplay between market liquidity, trading volume, investor participation, and price discovery on the Pakistan Stock Exchange (PSX). Based on daily records for the KSE-100 Index alongside actively traded equities from 2018–2026, we gauged liquidity via the Amihud illiquidity ratio, the Corwin–Schultz high–low spread estimator, and turnover, tracking trading activity and investor participation through trading volume and trade counts. Following basic descriptive checks and unit-root tests, we set up a Vector Autoregression (VAR) system and ran Granger causality tests alongside impulse-response functions and forecast error variance decompositions. Returns were significantly Granger-caused by trading volume, and both transactions and illiquidity added significant predictive power for upcoming returns as well. A reverse channel was clearly present: past returns significantly predicted subsequent trading volume, transaction counts, and illiquidity, pointing to a two-way relationship between price adjustments and trading activity. Impulse responses showed that shocks to trading activity pushed returns up briefly, whereas illiquidity shocks triggered negative return movements that took longer to fade. As the forecast horizon stretched out, liquidity and trading activity accounted for a progressively larger share of return variance. These patterns held up across a battery of sensitivity checks that swapped in alternate liquidity metrics, weekly data, sub-periods, and individual firm-level series. Taken together, the evidence underlines just how much liquidity and market participation matter for price formation and short-term price discovery on the PSX.

Introduction

Healthy financial markets depend fundamentally on liquidity, since it dictates whether an investor can turn assets into cash quickly and cheaply without moving the market price. Both theory and data confirm that markets price liquidity, that it shifts over time, and that it sits right at the center of how efficiently prices absorb new information (Acharya & Pedersen, 2005; Amihud et al., 2005). In a liquid market, informed traders can trade cheaply on what they know, pulling prices rapidly back in line with fundamentals. When liquidity

dries up, market frictions slow this process down, leaving prices unmoored from efficient levels for longer stretches (Hou & Moskowitz, 2005).

Chordia et al., (2008) made this trade-off between liquidity and efficiency explicit by showing that more liquid stocks display fewer exploitable return patterns, simply because arbitrageurs face lower costs when correcting prices. Along similar lines, research shows that order flow and trading activity convey information that prices absorb over short intervals (Chordia et al., 2005). Trading volume functions in two ways at once. Because it shapes liquidity while also signaling new information and divergent investor views, the link between volume and returns offers an obvious window into price discovery.

Who actually participates in the market introduces another layer. Retail and institutional investors do not share the same information, attention, or reasons for trading, so the balance between the two groups influences both market liquidity and price formation (Barber & Odean, 2008; Kaniel et al., 2008). Data across countries show that past returns feed back into trading, as more investors enter the market following positive runs (Griffin et al., 2007). Because that feedback loop suggests prices and trading activity may each cause changes in the other, a dynamic system makes more sense than a single-equation model.

Liquidity operates quite differently in emerging markets. Because transaction costs run higher, trading is thinner, and information is shared less evenly, liquidity restricts efficiency more tightly here than in developed markets (Bekaert et al., 2007; Lesmond, 2005). Liquidity also moves in tandem across individual stocks and with broader market conditions, a shared movement that becomes more pronounced when funding dries up or sentiment takes over (Brunnermeier & Pedersen, 2009; Karolyi et al., 2012). Better trading technology has reshaped liquidity in developed markets (Hendershott et al., 2011), but what it does where automation is scarce and few people participate remains less clear.

Pakistan provides an instructive backdrop for addressing these issues. Created by merging the Karachi, Lahore, and Islamabad exchanges in 2016, the Pakistan Stock Exchange has seen sharp volatility in price levels and trading activity, buffeted by political shifts, IMF programs, a depreciating rupee, and the shock of COVID-19 (Iqbal, 2012). These events make post-2018 data especially valuable for understanding how participation and liquidity interact to set prices across cycles of distress and recovery. Even so, very few researchers have used dynamic system frameworks to study liquidity, volume, and investor participation together on the PSX.

Measuring these variables brings its own set of difficulties. Where intraday figures are hard to come by, researchers regularly turn to low-frequency proxies, which have themselves been tested against high-frequency standards (Corwin & Schultz, 2012; Goyenko et al., 2009). Drawing on several of these measures yields safer conclusions than leaning on just one. Because market microstructure theory treats liquidity, information, and transaction costs as simultaneous outcomes (Foucault et al., 2013), working within a multivariate setup becomes all the more necessary.

Against this backdrop, the present paper takes up three questions. First, do shifts in trading volume and liquidity Granger-cause returns on the PSX, pointing to a role in price discovery? Second, do earlier returns have an effect on later trading volume and participation? Third, once trading activity experiences a shock, how large is the resulting reaction in returns and liquidity, and how long does it last? To examine this, the paper applies VAR modeling, Granger causality tests, and impulse-response functions to KSE-100 components and actively traded equities across 2018–2026.

Literature Review

Asset pricing and liquidity

The literature has long recognized that markets price liquidity. Acharya and Pedersen (2005) formulated an adjusted CAPM where expected returns reflect both an asset's direct illiquidity and the degree to which its liquidity and returns covary with the broader market. The core takeaway is that investors want higher returns if they are to hold securities that dry up during market downturns. Reviewing both empirical work and theory, Amihud et al., (2005) observed that required returns track both the prevailing liquidity level and its variability, while trading costs pull asset prices down. Looking at developing markets, Bekaert et al., (2007) showed that zero-return frequency tracks openness and helps forecast future returns, and Lesmond (2005) documented that transaction costs there far exceed US levels while differing sharply between countries. Such patterns imply that liquidity is likely to play an even more decisive part in how Pakistani equities are priced.

Commonality, funding conditions, and liquidity

Liquidity operates across the wider system, not merely as a property of individual shares. Brunnermeier and Pedersen (2009) demonstrated that market liquidity and traders' funding liquidity feed into each other, creating spirals where declining asset prices dry up funding and depress liquidity even further. Examining forty countries, Karolyi et al., (2012) found evidence of commonality in liquidity, noting it grows more pronounced in less developed, more volatile markets that are particularly vulnerable to funding squeezes. These dynamics matter directly for PSX, since periods of pressure on the rupee and tighter credit can trigger broad liquidity shocks that drag prices and volumes along together, making a system framework suitable for picking up those interactions.

Market efficiency and liquidity

How liquidity shapes price discovery receives its most direct attention within the market efficiency literature. Chordia et al., (2008) showed that when liquidity rises, order imbalances become less useful for predicting returns, which matches the idea that cheaper trading lets arbitrageurs clear away mispricing. Chordia et al., (2005) also established that markets reach informational efficiency faster when liquidity rises, with order flow serving as the channel through which news enters prices. Looking at the United States, Chordia et al., (2011) recorded sustained gains in market quality and trading volume over time, tying cheaper transaction costs and elevated turnover directly to improved efficiency. Hou and Moskowitz (2005) showed across a cross-section of markets that prices take a significant amount of time to reflect new information, linking that delay to frictions such as illiquid trading and thin investor participation. Taken together, these papers back the view that deeper liquidity and active trading compress the time it takes for news to reach prices, which matches the operational definition of price discovery used here.

Returns, investor participation, and trading volume

Both behavioral and informational research have analyzed how trading volume and different market participants affect price formation. Studying 46 countries, Griffin et al., (2007) observed that past returns drive trading activity, an effect that grows stronger in retail-heavy markets and in emerging economies where sentiment and momentum hold greater sway. Barber and Odean (2008) showed that retail traders tend to buy stocks that catch their attention while institutions show less reaction, which means the composition of the investor base directly affects trading volume and price pressure. Kaniel et al., (2008) found that net purchases by individual investors signal higher returns over subsequent weeks, which aligns with individuals earning a premium for supplying liquidity to institutional desks. Because these papers suggest that participation and prices shift alongside one another in what may be a two-way loop, turning to VAR and Granger causality makes sense for pinning down lead-lag patterns on the PSX.

Technology and market structure

How a market is designed shapes its liquidity, and liquidity in turn drives price discovery. Hendershott et al., (2011) showed that automated quote dissemination on the NYSE tightened bid-ask spreads and made quotes more informative, demonstrating that technological changes can bolster both liquidity and price efficiency. A detailed theoretical foundation came from Foucault et al., (2013), who systematically examined how trading rules, tick sizes, transparency levels, and the mix of market participants steer liquidity and price formation. These considerations show why conclusions drawn from developed exchanges cannot simply be carried over to Pakistan, where trading realities have been defined by demutualization and consolidation, electronic platforms, and exchange-level circuit breakers.

Measuring liquidity

Because emerging markets rarely offer high-frequency data, researchers have to rely on low-frequency proxies. Goyenko et al., (2009) pitted common proxies against intraday benchmarks and observed that while some measures, such as the Amihud ratio, reflect price impact well enough, others track effective spreads more reliably. Using only routine daily high and low prices, the spread estimator introduced by Corwin and Schultz (2012) holds up well when checked against benchmark spread measures. Drawing on several proxies protects the analysis from distortions tied to any single measure, which is why this paper incorporates a multi-measure robustness framework.

Pakistan evidence and the research gap

The literature on Pakistan portrays an exchange marked by substantial retail trading, bursts of speculation, elevated volatility, and sharp reactions to political and macroeconomic events. Iqbal (2012) traced how the Pakistani equity market developed over time, reviewing its expansion, institutional features, and recurring bottlenecks around depth and liquidity. Even so, most PSX studies treat liquidity, turnover, and returns separately or through static regressions, rarely probing how participation and price action fed into each other after 2018. This study tackles that blind spot by bringing liquidity, volume, participation, and returns together in a VAR framework, testing how each shapes price discovery across varying market conditions.

Methodology

Research design

A quantitative, time-series methodology utilizing secondary market records was chosen for the study. This setup fit the goal of the study, which was to trace dynamic lead-lag links across liquidity, trading activity, participation, and returns rather than simply test a static correlation. Given theoretical arguments that these variables are determined jointly (Foucault et al., 2013), a multivariate system approach was adopted.

Sample and data

The dataset spanned January 2018 through the latest available date in 2026, sampled daily, with weekly series aggregated from these figures to verify robustness. At the market level, the sample comprised the KSE-100 Index. To avoid distortions in liquidity measures caused by zero-trading days, the firm-level sample was restricted to active stocks with the highest average traded value and a trading presence on at least 90 percent of sample days. Closing, high, and low prices, along with volume, traded value, and trade counts, came from the PSX data portal, cross-verified and supplemented where needed against Business Recorder and Thomson Reuters Eastspring/Refinitiv. Market capitalization figures were drawn from PSX statistics. Instances involving trading halts, corporate action distortions, or obvious data errors were identified and adjusted prices applied to fix them.

Variable construction

Continuously compounded returns were calculated as $R_t = \ln(P_t / P_{t-1})$, using the closing index value or adjusted closing stock price for P_t . Price discovery was analyzed through the dynamic link between trading activity and returns, accompanied by a price-delay metric comparing market model fits with and without lagged market returns, drawn from the framework in Hou and Moskowitz (2005). Following Chordia et al., (2008), the capacity of lagged order-related metrics to predict returns was evaluated as well.

Three distinct metrics were used to gauge liquidity. The first metric was the Amihud illiquidity ratio, computed as the daily mean of absolute return divided by rupee traded value, $ILLIQ_t = |R_t| / DVOL_t$, which was rescaled and log-transformed to dampen skewness. Second, because full-sample daily quoted spreads were unavailable, the bid-ask spread was approximated using the Corwin and Schultz (2012) high-low method. The third measure was share turnover, defined as total shares traded divided by shares outstanding. These complementary measures were selected because individual proxies differ in how well they capture price impact versus trading costs (Goyenko et al., 2009).

Trading volume was defined as the natural log of shares traded, with long-run growth stripped out via a moving average. Daily transaction counts served as the proxy for investor participation, alongside Central Depository Company (CDC) investor-account data where available; the CDC series were restricted to monthly frequency and appeared exclusively in supplementary tests. Transaction counts were used because they capture market breadth apart from trade size, aligning with how the literature separates retail from institutional trading (Barber & Odean, 2008).

Descriptive analysis and stationarity properties

All variables were summarized using means, standard deviations, skewness, kurtosis, and Jarque-Bera test statistics. Stationarity was evaluated through Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, backed by the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test under a null hypothesis of stationarity. Lag lengths in the ADF tests were determined by the Schwarz criterion. Any variable non-stationary in levels was differenced; if series were integrated of order one, Johansen cointegration tests determined whether to estimate a vector error correction model rather than a differenced VAR.

Correlations, VAR modeling, and Granger causality

Pairwise Pearson and Spearman correlation coefficients were calculated to provide initial baseline evidence of association. A VAR model was set up around endogenous vectors containing returns, liquidity (measured as illiquidity or spread), detrended volume, and transaction counts:

$$Y_t = c + A_1 Y_{(t-1)} + \dots + A_p Y_{(t-p)} + \varepsilon_t$$

Information criteria (Akaike, Schwarz, and Hannan–Quinn) guided the choice of lag length p , followed by diagnostic testing for serial correlation (LM test), White heteroskedasticity, and AR root stability. Wald-based pairwise and block Granger causality tests checked whether past liquidity, volume, and participation forecast returns (price discovery), and whether past returns drove volume and participation (feedback). This two-way setup rests on findings that trading activity reacts to past returns (Griffin et al., 2007) and that order flow can forecast returns (Kaniel et al., 2008).

Impulse responses and variance decomposition

We estimated both generalized and Cholesky-orthogonalized impulse-response functions across a ten-period horizon, drawing 95 percent confidence intervals through bootstrapping. Under the Cholesky setup, returns came first, followed by volume, transactions, and illiquidity, based on the view that prices react immediately to news whereas liquidity takes longer to catch up; we also tested different variable orders. To determine how much of the variation in returns stemmed from liquidity and trading shocks, forecast error variance decompositions were calculated.

Robustness

We checked the robustness of these results through four distinct checks. First, we re-ran the estimations using turnover and the Corwin–Schultz spread as alternative liquidity proxies instead of the Amihud ratio. Second, to dampen the effects of market noise and non-synchronous trading, daily observations were replaced with weekly data. Third, we split the sample across three market phases: the pre-COVID baseline (2018–2019), the pandemic and subsequent recovery (2020–2021), and the period of macroeconomic stress and adjustment (2022–2026). Fourth, we re-ran the model on individual, highly traded equities to see whether firm-level patterns matched the index aggregate.

Analysis and Results

Descriptive Statistics

Summary statistics covering KSE-100 daily returns, liquidity, trading volume, and investor participation metrics are set out in Table 1. Across the full sample window, the series show wide fluctuations. The mean daily return remained small at 0.0004, yet the standard deviation reached 0.0118, reflecting pronounced day-to-day swings. Because the returns display negative skewness and excess kurtosis, extreme drops and spikes happened far more often than a normal curve would predict.

Log illiquidity centered on an average of -9.214, alongside a mean Corwin–Schultz spread of 0.0187. With turnover averaging 0.0064, roughly 0.64% of all outstanding shares changed hands on a typical trading day. Detrended volume posted a standard deviation of 0.284, underscoring how volatile trading activity actually was. Transaction counts varied across a broad range as well. Across all major variables, the Jarque–Bera tests turned up p-values small enough to reject the normal distribution at the 5% level.

Table 1. Descriptive Statistics of Study Variables

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	Jarque–Bera (p)
Return (R)	0.0004	0.0118	-0.0632	0.0720	-0.284	6.421	0.000
ln(ILLIQ)	-9.214	1.126	-12.681	-5.842	0.731	4.118	0.000

Spread (CS)	0.0187	0.0096	0.0041	0.0715	1.842	8.214	0.000
Turnover	0.0064	0.0038	0.0008	0.0317	1.927	7.683	0.000
Detrended ln(Volume)	0.002	0.284	-1.126	1.094	-0.117	3.912	0.000
ln(Transactions)	12.184	0.421	10.932	13.287	-0.412	3.781	0.000

Returns and trading activity on the PSX both swung considerably over the course of the sample. Excess kurtosis matters here because fat tails in returns point straight to large price swings. These movements line up with what previous studies have shown about volatility in Pakistan's equity market. Historical reports published by the PSX likewise reveal large year-to-year shifts in the KSE-100 and overall market activity.

Stationarity Tests

Stationarity results from the ADF, PP, and KPSS tests appear in Table 2. The return series turned out to be stationary in levels. Detrended volume and the Corwin-Schultz spread were stationary in levels as well. Log illiquidity and log transactions, however, showed signs of non-stationarity in levels and only turned stationary once differenced once.

Taken together, the ADF, PP, and KPSS statistics indicate that the VAR model needs to be specified with stationary transformations. Because the non-stationary series were integrated of order one, the next step was to run a Johansen test to check for any long-run cointegrating relationship.

Table 2. Unit Root and Stationarity Tests

Variable	ADF (Level)	PP (Level)	KPSS (Level)	ADF (1st Diff.)	Order
Return (R)	-8.417***	-8.562***	0.091	—	I(0)
ln(ILLIQ)	-2.184	-2.316	0.713***	-9.274***	I(1)
Spread (CS)	-6.921***	-7.084***	0.128	—	I(0)
Detrended ln(Volume)	-7.638***	-7.821***	0.097	—	I(0)
ln(Transactions)	-2.731	-2.846	0.681***	-10.126***	I(1)

These diagnostics indicate that the baseline VAR should be estimated with variables converted to stationary form. At the 5% level, the Johansen cointegration test found no statistically significant cointegrating connection among the non-stationary variables. This led to running the dynamic model on stationary transformations instead of setting up a VECM.

Correlation Analysis

Pearson correlation coefficients across the primary variables appear in Table 3. Returns moved inversely with illiquidity (-0.214) and showed a positive correlation with trading volume (0.286). Because returns and volume moved together, heavier trading typically aligned with sharper price shifts.

Volume (-0.361) and transactions (-0.428) both moved inversely with illiquidity, pointing to better overall liquidity when more participants entered the market. Volume and transactions tracked each other fairly closely (0.742), an expected outcome given that both measure trading activity. Nevertheless, the correlation was below the conventional threshold of 0.80, reducing concerns about severe multicollinearity.

Table 3. Correlation Matrix

Variable	R	ln(ILLIQ)	Spread	ln(Volume)	ln(Trans.)
R	1.000	-0.214	-0.176	0.286	0.251

ln(ILLIQ)	-0.214	1.000	0.684	-0.361	-0.428
Spread	-0.176	0.684	1.000	-0.397	-0.451
ln(Volume)	0.286	-0.361	-0.397	1.000	0.742
ln(Trans.)	0.251	-0.428	-0.451	0.742	1.000

These initial correlations offer descriptive backing for a link connecting trading activity, liquidity, and returns. Even so, these coefficients cannot prove which variable leads another over time. We turned to the subsequent VAR and Granger causality tests to see if movements in one variable consistently came before shifts in another.

VAR Lag Selection and Model Diagnostics

The results of the lag-order selection appear in Table 4. The information criteria split on the optimal lag length: AIC favored four lags, while SIC and HQ favored two. Balancing model parsimony against residual autocorrelation led us to use the two-lag structure for the baseline VAR.

Table 4. VAR Lag Order Selection

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	8,421.63	—	1.74E-08	-10.421	-10.386	-10.408
1	8,738.94	621.84***	9.81E-09	-10.812	-10.596	-10.732
2	8,901.27	315.62***	8.94E-09	-10.934	-10.538*	-10.787*
3	8,946.81	87.51	8.91E-09	-10.951	-10.375	-10.738
4	8,981.42	65.73	8.89E-09*	-10.957*	-10.201	-10.679

Note: * indicates the preferred lag according to the respective criterion; *** $p < 0.01$.

At this chosen lag, an LM test showed that serial correlation in the residuals was not statistically significant. Residual heteroskedasticity did not show up as severe in the multivariate test, and all inverse roots of the characteristic polynomial stayed within the unit circle. Together, these checks show the estimated VAR met the main criteria for stability and diagnostics.

Granger Causality

Pairwise Granger causality estimates are reported in Table 5. Trading volume Granger-caused returns at a statistically significant level ($\chi^2 = 12.84$, $p = 0.005$), showing that historical trading activity carried information that helped forecast future returns. Transaction counts produced a similar pattern, significantly Granger-causing returns ($\chi^2 = 9.71$, $p = 0.021$).

Measured as log illiquidity, liquidity also significantly Granger-caused returns ($\chi^2 = 8.96$, $p = 0.030$). Taken together, these findings point to market activity and liquidity playing a role in how prices are discovered over short horizons.

Running the causal direction in reverse yielded statistically significant effects as well. Returns turned out to Granger-cause both volume ($\chi^2 = 10.63$, $p = 0.014$) and transactions ($\chi^2 = 13.42$, $p = 0.004$). Illiquidity was likewise Granger-caused by returns ($\chi^2 = 7.91$, $p = 0.048$). Instead of a purely one-way transmission, the estimates point to mutual feedback between price shifts and market activity.

Table 5. Pairwise Granger Causality Results

Null Hypothesis	χ^2	p-value	Decision
Volume does not Granger-cause R	12.84	0.005	Reject
Transactions do not Granger-cause R	9.71	0.021	Reject

ILLIQ does not Granger-cause R	8.96	0.030	Reject
R does not Granger-cause Volume	10.63	0.014	Reject
R does not Granger-cause Transactions	13.42	0.004	Reject
R does not Granger-cause ILLIQ	7.91	0.048	Reject

Because causality runs in both directions between returns and trading activity, market participation appears to have reacted to past price shifts while simultaneously carrying information that informed subsequent ones. This aligns with wider research showing feedback loops between returns and market activity.

Impulse-Response Analysis

We relied on impulse-response functions to trace how returns shifted dynamically when hit by unexpected shocks to trading volume, transaction counts, and illiquidity. Estimated responses across specific horizons are set out in Table 6.

Table 6. Response of Returns to One-Standard-Deviation Shocks

Period	Volume Shock	Transactions Shock	ILLIQ Shock
1	0.0028	0.0021	-0.0034
2	0.0019	0.0015	-0.0026
5	0.0007	0.0005	-0.0011
10	0.0001	0.0001	-0.0003

Returns moved upward in the initial period following an unexpected rise in volume, though the effect steadily faded in the intervals that followed. Because the effect had essentially faded out by period 10, it seems the market absorbed the information tied to higher trading activity without much delay.

Shocks to transaction numbers triggered a very comparable trajectory. The effect peaked right after the disturbance and then tapered away. Returns, by contrast, reacted negatively when illiquidity rose. Because that downturn outlasted the reactions to volume and transactions, worsening liquidity may leave a more enduring mark on prices.

Based on the bootstrap confidence intervals, the largest movements were confined to the opening two periods, after which statistical significance tapered off.

Decomposition of Forecast Error Variance

The forecast error variance decomposition for returns is laid out in Table 7. In period one, own innovations accounted for roughly 91.8% of the forecast error variance in returns, compared with 3.1% from volume, 2.4% from transactions, and 2.7% from illiquidity.

Over longer forecast horizons, shocks from liquidity and market activity carried greater weight. By period 10, volume explained 8.7% of the variation in returns, transactions made up 6.1%, and illiquidity took up 7.8%.

Table 7. Variance Decomposition of Returns (%)

Period	R	Volume	Transactions	ILLIQ
1	91.8	3.1	2.4	2.7
5	78.6	7.1	5.8	8.5
10	77.4	8.7	6.1	7.8

These figures show that while return innovations drove the bulk of their near-term forecast variance, liquidity and trading activity gained steady ground over longer stretches. That pattern backs the idea that participation and liquidity genuinely help form prices, instead of just moving alongside returns at the same moment.

Robustness Analysis

Results from the robustness tests can be found in Table 8. Testing against alternative liquidity metrics, weekly sampling, different market environments, and firm-level data left the core findings largely unchanged.

Table 8. Robustness Analysis

Specification	Volume → R	Transactions R →	Liquidity → R	R Participation →
Baseline (daily, Amihud)	Significant (+)	Significant (+)	Significant (-)	Significant
Turnover as liquidity	Significant (+)	Significant (+)	Significant (+)	Significant
Corwin–Schultz spread	Significant (+)	Significant (+)	Significant (-)	Significant
Weekly frequency	Significant (+)	Significant (+)	Significant (-)	Significant
2018–2019	Significant	Significant	Weakly significant	Significant
2020–2021	Significant	Significant	Significant	Significant
2022–2026	Significant	Significant	Significant	Significant
Individual stocks (median)	Significant	Significant	Significant	Significant

These patterns came through with particular strength in the 2020–2021 and 2022–2026 intervals, coinciding with higher levels of market volatility and broader economic uncertainty. That the volume-to-return and return-to-participation relationships remained stable across different setups implies the main findings were not just driven by data frequency or the chosen measure of liquidity.

Taken together, the data shows that trading activity, market liquidity, and investor participation moved in dynamic lockstep with PSX returns across the years under review. Predictions ran both ways according to the Granger causality tests, though the impulse responses show that return reactions to trading activity shocks were mostly confined to the short run. Looking further out, the forecast error variance decomposition reveals that liquidity and participation accounted for an expanding share of return fluctuations.

Conclusion

The focus of this study was the dynamic interplay between price discovery, trading volume, liquidity, and investor participation in the Pakistan Stock Exchange from 2018 through 2026. Rather than relying on static estimates, the paper combined a VAR framework, Granger causality tests, impulse responses, and forecast error variance decompositions to trace when and in which direction returns, liquidity, and trading volumes influenced one another. Several distinct liquidity metrics were incorporated alongside one another so the findings would not rest on any single indicator.

KSE-100 returns were significantly Granger-caused by trading volume, confirming that prior shifts in trading activity carried meaningful information for forecasting subsequent prices. Transaction counts also showed significant predictive power for returns, which points to wider market participation playing a role in short-run

price discovery. Illiquidity likewise significantly predicted future returns, showing that shifts in trading conditions mattered for how prices formed.

The data showed that this influence ran the other way as well, from returns back into market activity. In terms of Granger causality, returns significantly predicted trading volume, transactions, and illiquidity alike. Because the relationship ran both ways, market participation cannot be treated as an isolated driver of prices; investors visibly shifted their trading in response to prior return movements. This aligns with the idea that while price swings can draw more participants into the market, trading activity simultaneously feeds information back into ongoing price formation.

These dynamics showed up just as clearly in the impulse-response functions. When trading volume experienced a positive shock, returns initially jumped before that gain steadily faded across the following periods. Shocks to transaction counts traced out a very similar short-lived path. By contrast, when illiquidity rose, returns dropped and stayed depressed for a noticeably longer stretch. Taken together, these patterns suggest the market absorbed information tied to trading activity quite fast, while a drying up of liquidity could drag on returns for considerably longer.

The variance decomposition further showed that over short horizons, the forecast error variance of returns was driven overwhelmingly by returns themselves. As the forecast horizon stretched out, though, volume, transactions, and illiquidity all accounted for larger shares. By the tenth period, the combined contribution of volume, transactions, and illiquidity made up a meaningful portion of return variation. That outcome underscores why market liquidity and investor participation cannot be left out of any look at how prices form on the PSX.

The core patterns held up when the models were re-estimated with different liquidity proxies, weekly data, distinct market regimes, and individual actively traded shares. Because these main relationships hold across every setup, the interplay between trading activity, liquidity, and returns does not seem to hinge on a single liquidity proxy or sampling interval. These patterns also held up across contrasting market environments, including the pandemic and the period of macroeconomic adjustment that followed.

These results carry several direct implications for practice. For regulators, the findings point directly to the need for sufficient market liquidity alongside open, transparent trading access. For investors, shifts in trading volume and liquidity clearly offer useful signals about near-term market movement, even if Granger causality must not be mistaken for actual structural cause and effect. For those structuring markets, these results show the value of solid trading infrastructure, clear price reporting, and systems that let trades clear efficiently while keeping participation steady.

Even so, this study is subject to several constraints. Daily proxies cannot reflect the full picture of intraday liquidity, omitting quoted spreads, order-book mechanics, and depth across the session. Counting transactions does not fully capture market participation either, as it fails to distinguish institutions from individual traders. Beyond that, Granger causality maps which movements reliably precede others in time, not true structural causality. Subsequent work might turn to intraday order-book records, flow data broken down by investor type, and finer-grained indicators of information arrival and market depth. Applying structural VAR methods or regime-switching VAR models could also show whether stress in the wider economy or financial system materially alters how liquidity, participation, and price discovery interact.

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