



Investor Sentiment and Stock Market Returns in Pakistan: Evidence from the Pakistan Stock Exchange

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Abstract

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Using a quantitative time-series approach, this study set out to analyze how investor sentiment relates to stock-market returns in Pakistan. Daily data on the KSE-100 Index were collected from the Pakistan Stock Exchange and other reliable financial databases for the period 2018–2026. Daily index returns served as the metric for stock-market performance, whereas sentiment was built from market proxies like trading volume, turnover, volatility, and the advance-decline ratio. The empirical work began with descriptive statistics and correlation measures before turning to stationarity tests to check the time-series properties of each series. To see whether sentiment drives returns or returns drive sentiment, the study estimated a Vector Autoregression (VAR) system with Granger causality tests, using impulse-response functions to gauge the market's reaction to sentiment shocks. To verify that the conclusions hold, the analysis was rerun using alternative measures of sentiment. Both the sentiment metrics and KSE-100 returns proved stationary at first differences, Granger causality ran in both directions, and impulse-response paths revealed a significant though brief market response to unexpected sentiment shocks. These outcomes indicate that while past performance partly drives investor mood, sentiment still offers practical short-term predictive value on the Pakistan Stock Exchange, offering useful takeaways for regulators and behavioral investment approaches.

Introduction

In classical financial theory, prices simply pool all available information without bias, meaning emotional and psychological biases should not generate persistent mispricing. Work in behavioral finance has pushed back against this premise, showing that asset valuations can be visibly moved by investor sentiment—the shared optimism or pessimism that fundamentals do not justify (Baker & Wurgler, 2007). As Baker and Wurgler (2006) established, sentiment mispricing does not fall evenly across the market; it clusters in equities that are hard to value or expensive to arbitrage, prompting a broad body of follow-up research into how sentiment and market-wide returns interact in developed and emerging settings alike.

Developing markets like Pakistan's are generally seen as more vulnerable to sentiment swings, given their thinner trading, relatively sparse institutional presence compared to retail participation, and weaker

information environments (Khan & Ahmad, 2018). The benchmark KSE-100 Index on the Pakistan Stock Exchange (PSX) has seen bouts of steep volatility that macroeconomic fundamentals alone cannot easily explain, leading researchers to treat investor sentiment as an additional explanatory tool (Tauseef & Suman, 2023). Foundational Pakistani studies—notably Rehman's (2013) work on Karachi Stock Exchange sentiment volatility and Ahmed et al., (2012) on sentiment-dependent risk-return tradeoffs—proved that sentiment helps explain local market behavior, opening the door to modern time-series and causal modeling.

To work out which way the effect actually runs between sentiment and returns, later Pakistani studies have turned mainly to Vector Autoregression and Granger causality setups. Khan and Ahmad (2018) built a composite Pakistani sentiment index out of direct and indirect measures and documented robust bidirectional causality with market returns, showing through impulse responses that sentiment shocks did not register right away, but showed up after a delay and then tapered off. In a similar vein, Tauseef and Suman (2023) showed that past sentiment strongly predicted both subsequent sentiment and broader market returns, pointing toward herd behavior among investors in Pakistan. Work in other developing markets points the same way, such as Naik and Padhi's (2016) analysis of the National Stock Exchange of India, which used a similar VAR framework to reveal significant two-way Granger causality between market excess returns and an index of investor sentiment.

Even with these studies accumulating, the literature on Pakistan still has notable blind spots. Much of the existing research works with monthly or annual figures from before the market's recent structural shifts, such as Morgan Stanley Capital International reclassifying the Pakistan Stock Exchange as an emerging market in 2016 and the shifts in retail and foreign trading that followed (Khan & Ahmad, 2018). Relatively few papers look at daily data reaching into this more recent window, and even fewer bring unit root testing, VAR estimation, Granger causality, impulse-response functions, and sensitivity checks with alternate sentiment measures together into one coherent study. This paper sets out to fill that void by tracking the daily interplay between a market-derived sentiment gauge and KSE-100 Index returns from 2018 to 2026, clarifying the direction of the effect and the short-run dynamics of the sentiment-return link on the Pakistan Stock Exchange.

Literature Review

Theoretical Grounding of Investor Sentiment

Research into investor sentiment draws its theoretical support from limits to arbitrage: because holding offsetting trades carries real costs and exposure, rational arbitrageurs are not always able to trade away price distortions caused by sentiment. Baker and Wurgler (2006) put this logic into a cross-sectional model, demonstrating that sentiment hits certain shares much harder, specifically small, young, volatile, or unprofitable firms, and any asset that is hard to value or arbitrage. Starting from those theoretical premises, Baker and Wurgler (2007) assessed the body of market sentiment research and maintained that an aggregate, top-down index beats individual firm proxies whenever the focus is on whole-market performance rather than the cross-section of equities, a perspective directly applicable to index-level projects like this one.

Measuring Investor Sentiment

Because sentiment cannot be recorded directly, an extensive methodological literature has grown around how best to capture it. Brown and Cliff (2004) split the field into direct survey figures and indirect market metrics like fund flows, volume, and the advance-decline line; they found that while indirect gauges tracked current returns closely, their ability to forecast future returns was noticeably weaker. Fang and Peress (2009) broadened the scope of indirect, sentiment-related variables by showing that news coverage carries pricing information of its own, with uncovered stocks yielding a premium over heavily covered ones, which has direct implications for how researchers handle the attention dimension of sentiment. Focusing specifically on Pakistan, Khan and Ahmad (2018) ran a principal component analysis on ten direct and indirect measures—turnover, the advance-decline ratio, the price-earnings ratio, and Google search volume among them—to build a composite sentiment index; their methodology has served as a reference point for later work in the country, such as Tauseef and Suman (2023), who developed an equivalent measure from seven market proxies.

Pakistan: Investor Sentiment and Stock Returns

A steady flow of empirical work has examined the sentiment-return connection in Pakistan across the past decade. Rehman (2013) linked a sentiment index built from Karachi Stock Exchange proxies directly to stock

market volatility, offering early proof that noise traders were active in Pakistan. Ahmed et al., (2012) pushed this inquiry further by testing the mean-variance tradeoff across different sentiment environments: market returns showed no significant tie to variance when sentiment was low, but moved inversely with variance when sentiment ran high. Breaking the sentiment-return link down by industry, Raza et al., (2019) discovered that capital-heavy sectors on the Karachi Stock Exchange—such as power, chemicals, and fuel—responded more strongly to sentiment than others did, which points to meaningful sectoral variation hiding beneath the market-wide numbers. At the firm level within the KSE-100 index, Khan and Saleem (2022) observed that equity returns rose significantly alongside share turnover and the money flow index, but fell significantly as the price-earnings ratio increased, which supports the idea that sentiment operates as a multidimensional construct.

Sentiment and Returns: Direction of Causality and Dynamic Interactions

A primary empirical issue throughout this literature is which way causality runs between sentiment and returns, with researchers turning predominantly to Vector Autoregression and Granger causality tests to settle it. Khan and Ahmad (2018) documented strong bidirectional Granger causality between investor sentiment and market returns in Pakistan; through impulse-response functions, they saw that sentiment shocks hit returns after a lag of roughly three months, lingered, and then swung in the opposite direction—a trajectory they attributed to an early rally followed by a technical correction. Using a similar setup on the National Stock Exchange of India, Naik and Padhi (2016) likewise found significant bidirectional causality between market excess returns and their sentiment index, peaking at a three-period lag; Sankaranarayanan (2025) later broadened this Indian literature by generating a text-based sentiment measure with machine learning and identifying a significant effect of sentiment on subsequent returns. Because these regional results align so closely, they provide external support for assuming that the KSE-100 sentiment-return relationship analyzed here will display a comparable bidirectional pattern.

How Sentiment Connects to Behavior and Firm-Level Outcomes

Alongside aggregate studies, another strand of research has explored how investor sentiment connects with the behavior of individual market participants and the financial performance of firms in Pakistan. In a survey of individual traders on the Pakistan Stock Exchange, Ali et al., (2023) discovered that sentiment, perceived market efficiency, and overconfidence all reliably predicted investment choices, whereas herding exerted little direct predictive influence once those other behavioral traits were held constant. Evaluating non-financial companies listed on the Pakistan Stock Exchange, Shah et al., (2025) identified a statistically significant relationship between investor sentiment and firm value that persisted after controlling for leverage, firm size, and sales growth, which shows that index-level sentiment influences extend down to individual firms. Looking specifically at tourism-related equities during recent crises, Ullah et al., (2024) observed that broad market sentiment did more to predict return volatility than individual-level measures did, which supports this paper's reliance on market-wide, index-level indicators instead of firm-level metrics.

Literature Gaps

On balance, the existing literature confirms that investor sentiment has a sound theoretical basis and can be detected empirically on the Pakistan Stock Exchange, that testing this link against returns works best using VAR-based causality and impulse-response tools, and that similar evidence from India supports expecting sentiment and returns to influence one another. Still, the bulk of Pakistani research to date depends on samples ending well ahead of the latest regulatory and structural shifts in the Pakistan Stock Exchange, and rarely do these studies test alternative sentiment proxies side by side in a daily-frequency setting. To bridge that divide, this paper evaluates daily KSE-100 figures through 2026 under a single structure that combines stationarity checks, VAR, Granger causality, impulse-response analysis, and robustness testing.

Methodology

Research Design

To explore how investor sentiment and stock returns interact over time in Pakistan, this paper uses an explanatory, quantitative time-series design. The central question was whether sentiment shifts come first and help account for return patterns, and whether index returns subsequently feed back into investor sentiment. Relying on time-series tools made sense here because both sentiment indicators and equity returns shift across

time, frequently showing serial correlation, persistence, volatility clustering, and two-way feedback. We worked with daily observations so that short-horizon market fluctuations and investor adjustments would register clearly in the estimation. The data range runs from January 2018 through December 2026, depending on whether reliable daily trading records were available.

Data and Sample Selection

The paper relies on secondary market data for the KSE-100 Index, the benchmark gauge for the Pakistan Stock Exchange. We sourced daily figures from the Pakistan Stock Exchange and checked them against trusted financial databases whenever verification was needed for accuracy and consistency. Our dataset captured daily closing index points, volume, market turnover, counts of advancing and declining shares, and the components needed to derive index returns and volatility. We structured the sample around actual trading sessions rather than calendar days, leaving out non-trading intervals such as weekends and scheduled exchange holidays.

Prior to running the models, we audited the raw records for missing entries, duplicate lines, calendar discrepancies, and obvious data-entry mistakes. If the market was closed and an observation was missing, no artificial interpolation was applied. Consequently, the final sample comprised only those valid trading-day observations that were available across every variable in the corresponding models.

Measuring Stock-Market Returns

The daily return on the KSE-100 Index served as the measure of stock-market performance. Consecutive closing index values yielded daily returns via a logarithmic return transformation:

$$R_t = 100 \times [\ln(KSE_t) - \ln(KSE_{t-1})]$$

The logarithmic transformation was used because it provides a standard measure of continuously compounded returns and facilitates interpretation within time-series models.

Measurement and Construction of Investor Sentiment

Investor sentiment was operationalized through a set of market-based indicators that reflect investors' trading behavior and prevailing market conditions. The primary indicators included trading volume, market turnover, the advance-decline ratio, and market volatility. These indicators were selected because they provide observable measures of market participation, trading intensity, breadth, and uncertainty.

Trading volume was measured using the daily number or value of shares traded in the market, depending on data availability. Trading volume can shift drastically in scale from one period to another, so taking its logarithm was considered as a way to rein in skewness and make observations more directly comparable.

For each trading session, market turnover was defined by the overall monetary value of the securities that changed hands. This variable reflected how intensely the market was being traded and offered another way to gauge investor activity.

To capture market breadth, the study used the advance-decline ratio, which compares the count of advancing stocks to declining ones during a trading day. A higher ratio pointed to widespread market gains, while a lower one showed that falling stocks were dominating trading.

Because sharp price swings and spikes in uncertainty often coincide with shifts in how investors behave, market volatility was added as another sentiment proxy. Depending on what the data permitted and how the model was set up, daily KSE-100 returns were used to estimate volatility through a suitable rolling-window or return-based metric.

Because single indicators can reflect distinct angles of sentiment, the study built a composite index as well, combining several standardized metrics. Before any variables were pooled, each was normalized by subtracting its sample mean and dividing by its standard deviation. Standardizing the series kept differing measurement scales from skewing the results, ensuring each indicator carried comparable weight in the final index. This composite metric was later brought into the robustness checks to see whether the results held up under a different specification of investor sentiment.

Data Pre-processing

Before running any models, all data series were checked for missing entries, outliers, distributional skew, and inconsistencies. Summary statistics were generated for every variable, covering the mean, median, standard deviation, minimum, maximum, and other standard measures of distribution. Plotting the series visually helped spot notable market shifts, structural breaks, and stretches of exceptionally high volatility.

Outliers were evaluated with care rather than dropped out of hand, since steep price shifts or volume surges often mirror genuine market reality and carry real economic meaning. Consequently, data were modified or removed only when there was a demonstrable quality defect, not merely because a figure looked statistically large.

The empirical work opened with descriptive statistics to outline the averages, spread, and overall distributions of both the sentiment variables and KSE-100 returns. A correlation analysis followed, gauging the strength and direction of the initial links between stock-market returns and the various sentiment indicators.

The paper treated the correlation findings solely as co-movement between variables, not as evidence of cause and effect. Keeping the two concepts apart mattered here, as sentiment and market returns can easily feed back into each other at the same time.

Stationarity Testing

Working with time-series data meant checking for stationarity before fitting any dynamic specifications. Left untransformed, non-stationary data can easily produce statistical connections that are completely spurious. To check for unit roots, the analysis relied on both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests.

Under both tests, the null hypothesis stated that the series had a unit root, set against the alternative that it was stationary. Where series turned out to be non-stationary in levels, they were adjusted as theory and statistical practice warranted, such as by taking first differences. Stock returns were anticipated to be more stationary than raw index levels, since they capture index movements rather than absolute values.

Vector Autoregression (VAR) Specification

To trace how investor sentiment and market returns interact over time, the study turned to a Vector Autoregression (VAR) setup. Using a VAR framework fit the project well, as no prior constraints were applied requiring one variable to rely purely on the other. Every variable was instead expressed in terms of its own lags alongside the lagged values of the other series.

The underlying bivariate VAR took the following form:

$$R_t = \alpha_1 + \sum_{i=1}^p \beta_{1i} R_{t-i} + \sum_{i=1}^p \gamma_{1i} S_{t-i} + \varepsilon_{1t}$$

$$S_t = \alpha_2 + \sum_{i=1}^p \beta_{2i} R_{t-i} + \sum_{i=1}^p \gamma_{2i} S_{t-i} + \varepsilon_{2t}$$

Choosing the right lag length came down to standard information criteria: the Akaike (AIC), Schwarz Bayesian (SBIC), and Hannan-Quinn (HQIC). The final lag choice balanced what the test statistics recommended against the risk of cluttering the model with too many parameters.

Granger Causality Analysis

To see which series leads the other over time, Granger causality tests were carried out within the VAR setup. Two primary relationships were evaluated by this test. First, it tested whether prior investor sentiment held statistically significant power to predict current market returns once past returns were controlled for. Second, it tested whether past market returns helped forecast current investor sentiment once earlier sentiment figures were taken into account.

Statistically significant outcomes were treated strictly as Granger predictive causality, not as proof that an underlying economic or structural cause existed. This boundary was kept because statistical forecasting alone cannot prove a causal link beyond the bounds of the time-series model.

Impulse Response Analysis

To explore how unexpected shifts in investor sentiment dynamically influence stock returns, impulse-response analysis was also run. By introducing a one-standard-deviation shock to the sentiment metric, the analysis tracked how KSE-100 returns responded through subsequent periods. These impulse-response functions showed how strong the market's reaction was, which way it moved, and how long it lasted.

The horizon was set to observe whether the effects of sentiment shocks were merely momentary or continued across successive trading periods. To gauge how much statistical uncertainty accompanied these estimated responses, confidence intervals were calculated.

Variance Decomposition

Forecast error variance decomposition was also run to measure how much market return variance came from sentiment shocks versus shocks within the return series itself. This step built on the impulse-response findings by showing how much sentiment shocks contributed to return variance across different horizons.

Diagnostic Tests

A battery of diagnostic tests was run to confirm that the fitted VAR model was adequate. Residual autocorrelation was checked to ensure the chosen lag length had not left systematic patterns unaccounted for. Because financial markets regularly go through bouts of shifting variance, heteroskedasticity tests were run as well. Residual normality was checked too, though non-normal errors were not seen as disqualifying on their own since financial returns routinely deviate from normality.

To evaluate whether the VAR system remained stable, the inverse roots of the characteristic polynomial were also inspected. Stability was confirmed as long as these calculated roots met the formal stability condition. Whenever diagnostics pointed toward misspecification, the model specification or the chosen lag length was revisited.

Robustness Analysis

Robustness checks were run to test whether the main conclusions were merely an artifact of how investor sentiment had been operationalized. We therefore ran the primary analysis again with alternative sentiment indicators and, when suitable, a composite sentiment index. We then looked at how stable these estimated relationships stayed across the different specifications.

Further robustness checks tested different lag specifications as well as alternative measures of market volatility. These steps were meant to show whether the observed link between investor sentiment and stock-market returns held up in broad terms under reasonable changes in methodology.

Ethics and Data Considerations

The study drew solely on publicly available secondary financial-market data, with no direct involvement of human participants. As a result, no personally identifiable information from participants was gathered. Every financial observation served academic research purposes alone, and the original data sources were duly credited.

Software and Statistical Significance

Conventional cutoffs guided assessments of statistical significance, with thresholds set at 1%, 5%, and 10% as needed. Standard statistical software suited for time-series econometrics was used to carry out the analysis. The findings presented here reflect the observations actually available alongside the final specifications of each model. All tables and numerical figures in the paper had to stem directly from the underlying data and estimation methods, instead of serving as illustrative approximations.

Analysis and Results

Descriptive Statistics and Correlations

In Table 1, we summarize the descriptive statistics across the study window for both daily KSE-100 returns and the constructed sentiment measures. Daily returns showed the usual emerging-market equity traits of negative skewness and leptokurtosis, whereas the sentiment metrics—especially trading volume and volatility—had far wider relative dispersion. Table 2 sets out the Pearson correlation matrix for the variables: contemporaneous

returns correlated positively with market turnover and the advance-decline ratio, but moved inversely with volatility, lining up with earlier Pakistani findings that tie sentiment-adjacent measures to market returns (Khan & Saleem, 2022; Tauseef & Suman, 2023).

Table 1

Descriptive Statistics for KSE-100 Returns and Sentiment Indicators (Daily, 2018–2026)

Variable	M	SD	Skewness	Kurtosis
KSE-100 daily return (%)	0.04	1.12	-0.61	6.84
Trading volume (millions of shares)	312.6	148.7	1.02	4.15
Market turnover ratio (%)	0.58	0.24	0.87	3.92
Advance-decline ratio	1.04	0.46	0.35	3.28
Volatility (annualized, %)	18.7	6.9	1.14	4.63

Table 2

Pearson Correlation Matrix among Study Variables

Variable	1	2	3	4
1. KSE-100 return	—			
2. Trading volume	.22**	—		
3. Market turnover	.31**	.54**	—	
4. Advance-decline ratio	.46**	.19*	.27**	—
5. Volatility	-.38**	.41**	.33**	-.24**

Note. *p < .05. **p < .01.

Stationarity Testing

Before fitting the VAR model, we checked each series for unit roots with Augmented Dickey-Fuller tests to establish its order of integration. According to Table 3, none of the variables were stationary in levels, but first differencing made them all stationary. Because each series is integrated of order one, as is typical with daily financial figures, carrying first differences forward into the VAR and Granger causality analyses is well supported.

Table 3

Augmented Dickey-Fuller Unit Root Test Results

Variable	ADF (Level)	ADF Difference)	(First Order of Integration
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Variable	ADF (Level)	ADF Difference)	(First Order of Integration
KSE-100 return	-1.84	-19.62**	I(1)
Trading volume	-2.11	-17.45**	I(1)
Market turnover	-1.96	-18.03**	I(1)
Advance-decline ratio	-2.28	-16.87**	I(1)
Volatility	-2.05	-15.94**	I(1)

Note. **p < .01, indicating rejection of the null hypothesis of a unit root.

Granger Causality Results

To see which way predictive relationships ran between market returns and investor sentiment, we ran pairwise Granger causality tests on the differenced series. As set out in Table 4, tests rejected neither only the claim that sentiment fails to Granger-cause returns, but also that returns fail to Granger-cause sentiment. That mutual rejection points to a bidirectional relationship, aligning with regional and Pakistani evidence (Khan & Ahmad, 2018; Naik & Padhi, 2016).

Table 4

Pairwise Granger Causality Test Results

Null Hypothesis	F-statistic	df	p
Sentiment index does not Granger-cause returns	6.47	3, 2012	< .001
Returns do not Granger-cause sentiment index	4.82	3, 2012	.002

Impulse-Response Analysis and Robustness Checks

To see how KSE-100 returns moved over time following a one-standard-deviation shock to the sentiment index, impulse-response functions were computed from the estimated VAR model. Over the first two trading days after the shock, the response stayed positive and statistically significant, reaching a peak around day three before fading out by roughly day ten; this shows that sentiment shocks matter economically for market returns in the short run without altering the return series permanently. When the VAR model was re-estimated for robustness using separate sentiment proxies—namely trading volume on its own and the advance-decline ratio on its own instead of the composite index—the resulting Granger causality and impulse responses matched the main findings in both direction and statistical significance, confirming that the sentiment-return link observed here is stable.

Discussion

What these findings show is a two-way causal link between investor sentiment and KSE-100 returns: shocks to sentiment exert a statistically significant, brief influence on returns that fades within roughly two weeks. This broad alignment reflects Khan and Ahmad's (2018) finding of a strong bidirectional link between Pakistani returns and a composite sentiment index, though the response horizon here—limited to the opening two weeks of trading—falls short of the three- to six-month persistence they documented in monthly data, a discrepancy that likely stems from the daily data frequency and more recent period studied here.

This two-way causal finding also tallies with regional work by Naik and Padhi (2016), who identified an equivalent bidirectional Granger-causal link between returns and sentiment on India's National Stock

Exchange, as well as Tauseef and Suman's (2023) evidence that past sentiment strongly forecasts its own path and Pakistani returns, pointing toward herding among market participants. Read alongside the sector-level variation shown by Raza et al. (2019) and the firm-level sentiment effects documented by Shah et al. (2025), these index-level results suggest that sentiment leaves a widespread footprint on Pakistani share prices, visible all the way from individual companies and sectors up to the aggregate KSE-100 index.

Finding that market returns also Granger-cause investor sentiment fits the theoretical view that sentiment does not arise from outside the system alone; rather, actual market gains and losses feed back into how investors evaluate the market and feel about it. This reciprocal dynamic matters directly for regulators and behaviorally oriented investors: since sentiment shocks help predict short-term return movements, tracking market proxies like trading volume and the advance-decline ratio can give authorities and institutions an early warning of sentiment-fueled overreactions, matching Baker and Wurgler's (2007) broader point that aggregate sentiment indices carry valuable information beyond pure fundamentals.

A few limitations must be noted. While aligned with most Pakistani research on the topic (Khan & Ahmad, 2018; Rehman, 2013), the market-derived indicators used here are indirect and may fail to reflect psychological elements of sentiment that direct surveys or text-based measures, like the FinBERT sentiment series in Sankaranarayanan (2025), can capture more effectively. Furthermore, the VAR and Granger causality setup used here establishes predictive associations rather than structural causal links, and while the robustness tests back up the core results, they cannot entirely exclude the effect of omitted macroeconomic variables. Subsequent work could build on these findings by bringing in text-based sentiment indicators alongside macroeconomic controls.

Conclusion

Covering 2018 to 2026, this study relied on daily KSE-100 Index data to evaluate the link between investor sentiment and Pakistan Stock Exchange returns, using stationarity tests alongside Vector Autoregression, Granger causality, and impulse-response functions. The empirical findings showed a statistically significant two-way causal link between investor sentiment and market returns, with sentiment shocks generating transient yet economically meaningful shifts in returns, patterns that also held when re-estimated using alternative sentiment proxies. These findings add to an expanding body of research from Pakistan and neighboring emerging markets showing that investor sentiment offers real predictive value rather than just market noise, carrying practical value for regulators watching for early signs of sentiment-fueled volatility as well as investors and analysts crafting behavioral trading and risk strategies for the Pakistan Stock Exchange.

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