

“Realized annual price dispersion, trading activity, and contemporaneous price returns on the Amman Stock Exchange”

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REALIZED ANNUAL PRICE DISPERSION, TRADING ACTIVITY, AND CONTEMPORANEOUS PRICE RETURNS ON THE AMMAN STOCK EXCHANGE

Abstract

This study examines how realized annual price dispersion and trading activity co-moved with 2025 price returns in the cross-section of Amman Stock Exchange (ASE) equities. The official yearly sector bulletin contains 160 valid securities; transparent activity and data-validity filters yield a 142-stock baseline sample. Cross-sectional OLS models use HC3 standard errors and are complemented by broad-sector controls, outlier-resistant estimation, alternative range scaling, sample sensitivity, signed range decomposition, and a manual corporate-action audit of extreme observations. The annual high-low range is strongly positively associated with same-year price return: its baseline coefficient is 0.883 (HC3 SE = 0.075). Scaling the range by average price leaves the coefficient positive but reduces R^2 from .729 to .307. Decomposing the previous-close-scaled range produces an upside coefficient of 0.806 (SE = 0.071) and a downside coefficient of -0.630 (0.187), with equality strongly rejected (Wald $\chi^2 = 72.61$, $p < .001$). The extreme-observation audit identifies official 2025 capital reductions for PHNX, OFTC, NAQL, and DAFI. Excluding these four securities leaves the unsigned range coefficient positive at 0.850 (0.082; $N = 138$); the signed coefficients remain 0.792 (0.062) and -0.653 (0.186), respectively. Because return and range are constructed from the same annual price path, these results document robust contemporaneous directional co-movement rather than an ex-ante risk premium, causal liquidity effect, or forecasting relation.

Keywords

price extremes, corporate actions, market
microstructure, emerging markets, cross-sectional
analysis, Jordan

JEL Classification

G12, G14, G15, C21

INTRODUCTION

Cross-sectional return research normally asks whether information known before a holding period is associated with subsequent returns. Annual exchange bulletins invite a different empirical exercise. They summarize, for the same calendar year, opening or previous closing prices, annual high and low prices, year-end prices, trading activity, and market classification. Such data can reveal economically meaningful differences across securities, but the timing and construction of the variables place a strict boundary on what those differences can establish.

That boundary is particularly important when a realized price return is studied together with the annual high-low range. Both statistics are generated by the same price path. In the main construction used here, they also share the previous closing price as a denominator, while the year-end close necessarily lies within the year's observed price trajectory. A stock that rises strongly during the year may therefore display both a high return and a wide annual range even in the absence of any



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independently priced range-related characteristic. The empirical challenge is to distinguish a stable descriptive pattern from an interpretation that the data cannot identify.

The Amman Stock Exchange provides a useful setting for this problem. The market includes securities with markedly different trading intensity, continuity, visibility, and market-segment status. In such an environment, annual public data are valuable for broad coverage, but thin trading, non-synchronous adjustment, limited firm-level controls, and corporate actions can complicate comparisons across stocks. Trading value and turnover also describe activity during the same period in which returns are realized; they are not direct measures of transaction costs or predetermined liquidity conditions.

1. LITERATURE REVIEW

The distinction between realized association and expected-return pricing follows directly from the development of modern asset-pricing research. Portfolio theory and the capital asset pricing model connect expected return to exposure to non-diversifiable risk (Markowitz, 1952; Sharpe, 1964; Lintner, 1965), while early empirical work emphasized the difficulty of translating equilibrium models into clean tests (Black et al., 1972; Roll, 1977). Fama and MacBeth (1973) made the information-timing issue explicit in cross-sectional testing by relating returns to risk measures estimated from prior information. Later characteristic-based work documented associations involving size, valuation, momentum, and multifactor exposures (Fama & French, 1992, 2015; Jegadeesh & Titman, 1993; Brennan et al., 1998). The broad lesson, reinforced by the econometric asset-pricing literature, is that a claim about expected returns requires an information set that precedes the return being explained and sufficient repetition to separate persistent structure from realized noise (Campbell et al., 1997). Harvey et al. (2016) further caution that cross-sectional return findings can be overstated when empirical designs do not adequately distinguish robust evidence from specification-specific patterns.

High-low prices provide a different type of information. Parkinson (1980) showed that intraperiod extremes can be used efficiently to estimate variance under restrictive assumptions, and subsequent estimators incorporated combinations of open, high, low, and close prices to improve volatility measurement or accommodate drift (Garman & Klass, 1980; Beckers, 1983; Rogers & Satchell, 1991; Yang & Zhang, 2000). These studies establish that price extremes contain useful informa-

tion about realized within-period variation. They do not imply that an unsigned annual high-low range is a predetermined risk exposure. The annual range used here is a simple scale-normalized dispersion statistic. It compresses the entire year's path into two extreme prices and therefore cannot distinguish the timing, persistence, or direction of the movement that generated the extremes.

The distinction matters because extreme outcomes themselves are related to return characteristics. Ang et al. (2006) show that idiosyncratic volatility can have a nontrivial cross-sectional relation with expected returns, while Bali et al. (2011) link extreme positive daily returns to lottery-like stock behavior. Those constructs use higher-frequency information and address questions different from the present one-year realized range. A wide annual range can arise from sustained appreciation, a temporary spike, a severe decline followed by recovery, a corporate-action discontinuity, or combinations of these paths. Consequently, a strong contemporaneous coefficient on annual range cannot be read as evidence that investors required compensation for bearing an independently measured range-related risk.

A parallel measurement distinction arises for liquidity. Theory and empirical evidence connect expected returns to trading costs, price impact, market-wide liquidity risk, and the interaction between asset returns and liquidity conditions (Brennan & Subrahmanyam, 1996; Datar et al., 1998; Amihud, 2002; Pastor & Stambaugh, 2003; Acharya & Pedersen, 2005; Liu, 2006; Korajczyk & Sadka, 2008). Yet liquidity is multidimensional. Roll (1984), Lesmond et al. (1999), Stoll (2000), Hasbrouck (2009), Goyenko et al. (2009), and Fong et al. (2017) show that spread, zero-return, price-impact, and other low-frequency proxies capture

different aspects of trading frictions. Corwin and Schultz (2012) demonstrate that high-low information can be used to estimate bid-ask spreads under a specific daily-data construction, which is conceptually distinct from treating a single annual range as liquidity or volatility.

Trading activity is related to liquidity but is not synonymous with it. Chordia et al. (2000) document commonality in liquidity, and Chordia et al. (2001) emphasize the close empirical connection between market liquidity and trading activity. Annual value traded, turnover, and trading-day coverage can therefore be informative about participation and continuity, particularly when microstructure measures are unavailable. At the same time, value traded can increase because prices rise, news attracts attention, institutional demand changes, or a security becomes more visible. Karolyi et al. (2012) show that liquidity commonality varies internationally. These findings reinforce the need to interpret the ASE activity variables as contemporaneous trading measures rather than structural estimates of transaction costs or liquidity risk.

The emerging-market setting adds further complications. Infrequent trading and non-synchronous prices can distort conventional risk and return measures (Scholes & Williams, 1977; Dimson, 1979), and price delay can reflect broader market frictions (Hou & Moskowitz, 2005). Emerging markets can also differ in integration, investor access, trading intensity, and the importance of local factors (Harvey, 1995; Bekaert & Harvey, 1995; Rouwenhorst, 1999). Bekaert et al. (2007) show that liquidity is economically important in emerging markets, while Griffin et al. (2010) demonstrate that measures of market efficiency can behave differently across developed and emerging settings. These concerns make broad coverage valuable, but they also make it especially important not to infer a structural premium from a one-year realized cross-section.

Market segmentation provides an additional channel through which observed associations can arise. Merton (1987) shows how incomplete investor recognition can affect equilibrium pricing, and Fama (1970) frames informational efficiency in terms of the incorporation of available information into

prices. A first-market listing can therefore proxy simultaneously for disclosure standards, firm scale, investor recognition, institutional participation, and trading activity. The coefficient on market segment is consequently best read as a composite conditional association rather than a single economic mechanism.

The empirical gap addressed here is therefore specific rather than universal. Prior research has extensively studied volatility, price extremes, liquidity, market frictions, and emerging-market returns. Less attention has been paid to the interpretive problem created when a public annual bulletin is used to relate a same-year high-low dispersion statistic to a same-year closing-price return in a thinly traded market, while simultaneously conditioning on activity and market segment. The ASE cross-section permits that relationship to be documented transparently and its sensitivity to denominator choice, sector composition, outliers, and activity filters to be assessed.

Accordingly, the study aims to characterize these contemporaneous relationships without converting them into claims about expected-return pricing, prediction, or causal liquidity effects.

2. METHOD

The analysis uses a quantitative cross-sectional design in which the security is the unit of observation. All variables are drawn from the ASE yearly sector bulletin covering January 2 through December 31, 2025 (Amman Stock Exchange, 2026). The design is intentionally descriptive: price return, annual range, and trading variables are observed over the same calendar year. HC3 inference, sector controls, alternative scaling, robust estimation, multicollinearity diagnostics, and sample sensitivity are used to evaluate the stability of conditional associations, not to create temporal identification.

2.1. Data and variable construction

The equity section of the bulletin contains 160 listed securities in the Financial, Services, and Industrial sectors. The recorded fields include the official symbol, market, previous close, annual high, annual low, year-end close, average price,

value traded, shares traded, transactions, turnover, trading days, and broad sector. The baseline sample retains securities with a positive previous close, a nonnegative high-low difference, annual value traded of at least JD 10,000, and at least 30 trading days. These rules yield 142 observations. Sensitivity samples lower the trading-day requirement to 10 observations ($N = 151$) and then use all 160 securities with valid price fields and positive trading value.

The ASE bulletin states that historical previous-close, high, low, and average-price fields are not adjusted for corporate actions. Splits, rights issues, capital changes, bonus issues, or other restructurings can therefore create discontinuities that are not ordinary market performance. Cash dividends are also excluded from the dependent variable. The outcome is thus a closing-price return rather than total shareholder return. To address the corporate-action concern directly, the empirical audit identifies the union of the ten largest annual ranges and the ten largest absolute price returns, then checks those extreme securities against the official ASE 2025 corporate-actions register. The baseline sample is never silently altered; confirmed corporate-action observations are excluded only in a separately labeled sensitivity analysis.

For security i , the realized 2025 price return and the baseline annual high-low range are defined as follows.

$$Price\ Return_i = 100 \cdot \frac{Close_i - Previous\ Close_i}{Previous\ Close_i}, \quad (1)$$

$$Annual\ Range_i = 100 \cdot \frac{High_i - Low_i}{Previous\ Close_i}, \quad (2)$$

$$Average - Price - Scaled\ Range_i = 100 \cdot \frac{High_i - Low_i}{Average\ Price_i}, \quad (3)$$

$$Upside\ Range_i = 100 \cdot \frac{High_i - Previous\ Close_i}{Previous\ Close_i}, \quad (4)$$

$$Downside\ Range_i = 100 \cdot \frac{Previous\ Close_i - Low_i}{Previous\ Close_i}. \quad (5)$$

By construction,

$$Annual\ Range_i = Upside\ Range_i + Downside\ Range_i, \quad (6)$$

when the same previous-close denominator is used.

The components are signed distances from the previous close. If the previous close lies outside the year's observed high-low interval, one component can be negative; such cases are retained because changing their sign would break the algebraic identity and obscure the directional diagnostic.

The annual range and the price return are mechanically connected by timing and construction. They use the same 2025 price path; in the baseline specification, both are scaled by the previous close; and the year-end close is one point on the

Table 1. Variable definitions and measurement

Variable	Construction	Interpretive scope
Price return (%)	$100 \times (Close - Previous\ Close) / Previous\ Close$	Realized 2025 price change; excludes dividends
Annual range (%)	$100 \times (High - Low) / Previous\ Close$	Realized same-year price dispersion
Average-price-scaled range (%)	$100 \times (High - Low) / Average\ Price$	Denominator sensitivity; still contemporaneous
Log value traded	Natural log of annual JD value traded	Same-year trading-value activity proxy
Turnover (%)	ASE-reported annual turnover	Trading-intensity measure
Trading-day ratio	Trading days / 247	Trading-continuity/activity measure
First market	1 for first market; 0 otherwise	Composite market-segment indicator
Sector indicators	Services and Industrial dummies; Financial omitted	Broad-sector controls
Upside range (%)	$100 \times (High - Previous\ Close) / Previous\ Close$	Signed upward component of realized same-year price movement
Downside range (%)	$100 \times (Previous\ Close - Low) / Previous\ Close$	Signed downward component; can be negative when low exceeds previous close

Note: All fields originate in the official ASE 2025 yearly sector bulletin. Price fields are unadjusted for corporate actions.

path bounded by the observed annual extremes. A broad upward move can therefore raise both variables. Replacing the common denominator with average price is informative about shared scaling, while the signed decomposition separates the upward and downward distances embedded in the unsigned high-low range. Neither transformation makes the measure predetermined, so the resulting coefficients remain contemporaneous diagnostics rather than risk-price estimates.

The trading variables have a related timing limitation. Annual value traded, turnover, and trading-day coverage are realized during the same period as the return and can respond to news, prices, investor demand, and attention. Log value traded is therefore described as a trading-value activity proxy, not as a direct liquidity measure. First-market status is treated as a composite indicator of market segment and associated institutional differences.

2.2. Empirical specification and diagnostic procedures

$$\begin{aligned} \text{Return}_i = & \beta_0 + \beta_1 \text{Range}_i + \beta_2 \text{LogValue}_i \\ & + \beta_3 \text{Turnover}_i + \beta_4 \text{DayRatio}_i \\ & + \beta_5 \text{FirstMarket}_i + \varepsilon_i. \end{aligned} \quad (7)$$

The baseline model relates the 2025 price return to realized annual range, log value traded, turnover, trading-day coverage, and first-market status. Ordinary least squares is estimated with HC3 heteroskedasticity-robust standard errors (MacKinnon & White, 1985). A second specification adds Services and Industrial indicators, with Financial as the omitted sector. A third replaces the previous close-scaled range with the average-price-scaled range. Huber iteratively reweighted least squares (Huber, 1964) provides an outlier-resistant descriptive comparison. Predictor correlations and variance inflation factors (VIFs) assess near-linear dependence among regressors. The signed model replaces the unsigned annual range with both Upside Range and Downside Range while retaining the baseline controls; a one-degree-of-freedom Wald test evaluates equality of the two directional coefficients. The signed model is also estimated with broad-sector indicators. In Equation (8), U_i and D_i denote the upside and downside range components defined in Table 1.

$$\begin{aligned} \text{Return}_i = & \beta_0 + \beta_1 U_i + \beta_2 D_i + \beta_3 \text{LogValue}_i \\ & + \beta_4 \text{Turnover}_i + \beta_5 \text{DayRatio}_i \\ & + \beta_6 \text{FirstMarket}_i + \varepsilon_i. \end{aligned} \quad (8)$$

For the manual corporate-action audit, extreme observations are defined before examining event status as the union of the top ten securities by annual range and the top ten by absolute price return. This rule yields 12 unique securities. Official ASE corporate-action records (Amman Stock Exchange, 2025) are then searched by symbol. A missing match is reported only as ‘no corresponding 2025 entry identified’ and is not treated as proof that no action occurred. The core unsigned and signed models are re-estimated after excluding only extreme securities with a confirmed 2025 capital action; the original $N = 142$ baseline remains the primary sample.

Two additional checks address sample composition. The baseline equation is re-estimated after lowering the trading-day threshold to 10 and after removing both baseline activity thresholds. Range quartiles provide a complementary non-parametric description of the same cross-section. Because the quartiles are formed from the same realized range used in the regressions, they are not an independent predictive test. The Q4-minus-Q1 return difference is evaluated using a Welch unequal-variance t-test and a 10,000-repetition percentile bootstrap with fixed seed 18890.

No human participants, private records, surveys, interviews, or personal data are used. The underlying fields are public exchange data. The empirical interpretation throughout is limited to contemporaneous cross-sectional association.

3. RESULTS

The empirical evidence is presented in a sequence that separates distributional facts from conditional estimates and diagnostic sensitivity checks. The first stage summarizes the 142-stock baseline sample and the dependence among predictors. The second stage reports contemporaneous regressions and denominator sensitivity. The final stage adds the signed directional decomposition, the manual corporate-action audit, corporate-action

exclusion sensitivity, sample-filter checks, and the high-minus-low range-quartile spread.

3.1. Descriptive patterns and baseline estimates

The baseline cross-section is heterogeneous. The mean 2025 price return is 27.57%, compared with a median of 18.47%, and observed returns range from -79.81% to 237.50%. The realized annual range averages 57.81% and reaches 268.75%. The right tails of both variables indicate that a small group of securities experienced unusually large movements during the year, which motivates heteroskedasticity-robust and outlier-resistant estimation. These descriptive statistics do not establish whether the range-return relation is economic, mechanical, or both.

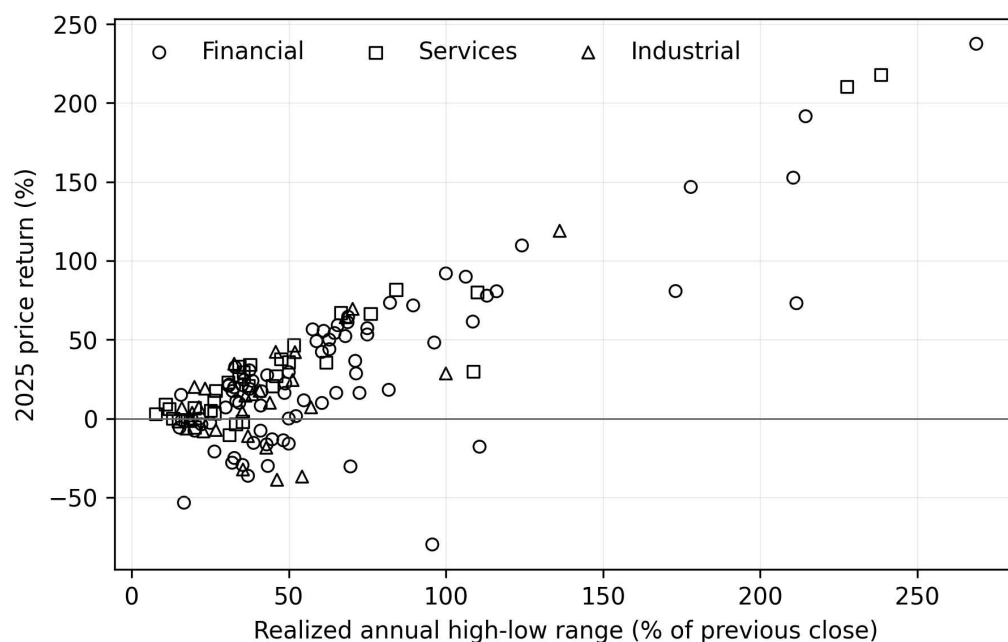
Figure 1 maps realized annual range against the 2025 price return by broad sector. The upward pattern is visually strong, but its interpretation is deliberately limited. The points use the same annual price path for both axes, and the baseline variables share the previous-close denominator. The figure therefore visualizes realized co-movement rather than a pricing line or a forecasting relationship.

The predictor diagnostics indicate moderate rather than extreme collinearity. The largest pairwise correlation is 0.724 between log value traded and the trading-day ratio. Their VIFs are 2.48 and 2.14, respectively, and all predictor VIFs remain below 2.5. The activity measures are related, as expected, but the diagnostics do not indicate a near-linear dependency that would mechanically prevent separate estimation of their conditional associations.

Table 2. Descriptive statistics for the 142-stock baseline sample

Variable	N	Mean	SD	Min	Median	Max
Price return (%)	142	27.57	48.34	-79.81	18.47	237.50
Annual range (%)	142	57.81	47.28	7.61	43.24	268.75
Log value traded	142	14.27	1.95	9.55	13.98	19.83
Turnover (%)	142	35.66	68.28	0.02	11.40	453.26
Trading-day ratio	142	0.66	0.28	0.12	0.67	1.00
First market	142	0.35	0.48	0.00	0.00	1.00

Note: Baseline filters require annual value traded $\geq$ JD 10,000 and trading days $\geq$ 30.



Note: N = 142. Marker shapes distinguish broad sectors. The figure depicts a contemporaneous relationship, not risk pricing or predictability.

Figure 1. Realized annual range and price return in the ASE cross-section, 2025

Table 3. Predictor correlation matrix and variance inflation factors

Variable	(1)	(2)	(3)	(4)	(5)	VIF
Annual range	1.000					1.13
Log value traded	0.117	1.000				2.48
Turnover	0.255	0.284	1.000			1.31
Trading-day ratio	0.167	0.724	0.228	1.000		2.14
First market	−0.227	0.313	−0.265	0.177	1.000	1.37

Note: Pearson correlations use N = 142. VIFs are calculated for the baseline regressors with an intercept.

The baseline HC3 regression produces an annual-range coefficient of 0.883 (SE = 0.075, $p < .001$). Adding broad-sector indicators leaves the estimate essentially unchanged at 0.887 (0.071, $p < .001$), while R^2 rises from .729 to .743. The Services indicator is positive at 14.019 percentage points (SE = 4.378) relative to financial firms, whereas the Industrial coefficient is small and imprecise. The stability of the range coefficient across these two specifications shows that broad sector composition does not account for the observed same-year relationship.

Trading-value activity is also positively associated with return in the baseline model: the log-value coefficient is 3.075 (SE = 1.503, $p = .041$), and it is 3.019 (1.539, $p = .050$) with sector controls. These estimates do not identify a liquidity premium.

Value traded can increase as a consequence of price appreciation, news, investor attention, and demand during the same year. Turnover and trading-day coverage are statistically indistinguishable from zero conditional on the other observed variables. First-market status is positive in the baseline (17.082; SE = 4.261) and sector-adjusted model (15.416; 4.347), consistent with a segment-level association that may combine listing standards, scale, recognition, and participation.

3.2. Robustness, directional decomposition, corporate-action audit, and sample sensitivity

Replacing the previous-close denominator in the range variable with the ASE-reported average

Table 4. Contemporaneous cross-sectional regressions of 2025 price returns

Variable	(1) Baseline HC3	(2) Sector HC3	(3) Alt. scale HC3	(4) Huber IRLS
Intercept	−67.766*** (16.870)	−71.787*** (17.429)	−85.799** (36.669)	−67.045*** (15.524)
Annual range (%)	0.883*** (0.075)	0.887*** (0.071)	—	0.949*** (0.038)
Average-price-scaled range (%)	—	—	0.929*** (0.350)	—
Log value traded	3.075** (1.503)	3.019** (1.539)	4.465* (2.519)	3.261** (1.376)
Turnover (%)	−0.026 (0.039)	−0.018 (0.039)	−0.001 (0.053)	−0.028 (0.029)
Trading-day ratio	−7.163 (10.831)	−5.182 (11.260)	1.868 (18.637)	−11.221 (8.933)
First market	17.082*** (4.261)	15.416*** (4.347)	9.507 (6.088)	14.318*** (4.168)
Industrial sector	—	1.379 (5.374)	—	—
Services sector	—	14.019*** (4.378)	—	—
N	142	142	142	142
R^2	.729	.743	.307	—

Note: Dependent variable: 2025 price return (%). HC3 standard errors or Huber H1 standard errors are in parentheses. Financial is the omitted sector. Model 3 replaces the previous-close-scaled range with the average-price-scaled range. ***, **, and * indicate $p < .01$, $p < .05$, and $p < .10$, respectively.

price yields a coefficient of 0.929 (SE = 0.350, $p = .008$). Model R^2 falls from .729 in the baseline specification to .307 under the alternative scaling. The direction of the range coefficient is therefore unchanged, while the overall model fit is substantially lower. The implications of this change in fit are considered in the Discussion.

Huber estimation yields an annual-range coefficient of 0.949 (SE = 0.038). The signs of the activity and market-segment coefficients are similar to those in the OLS specification. These estimates are reported as an outlier-resistant descriptive comparison.

When the minimum trading-day requirement is reduced to 10, the annual-range coefficient is 0.852 (SE = 0.078) with $N = 151$. Using all 160 valid equities produces a coefficient of 0.846 (SE = 0.079). Log value traded and first-market status remain positive in both samples. These estimates provide the sample-filter sensitivity reported in Table 5.

In the signed-range specification with baseline controls, the upside component is 0.806 (HC3 SE = 0.071, $p < .001$) and the downside component is -0.630 (0.187, $p < .001$). Model R^2 is .887, and the Wald test rejects equality of the two directional coefficients, $\chi^2(1) = 72.61$, $p < .001$. With broad-sector indicators, the corresponding coefficients are 0.815 (0.068) and -0.604 (0.188), $R^2 = .892$, and the equality restriction is again rejected, $\chi^2(1) = 68.25$, $p < .001$. Table 6 reports these estimates together with the corporate-action exclusion sensitivity.

The manual audit begins with 12 securities selected solely by the pre-specified extreme-observation rule. Four of them have confirmed 2025 capital reductions in the official ASE register. PHNX reduced capital from 86,840,292 to 42,803,502 shares on January 28 (reference price JD 0.34); NAQL from 13,915,000 to 7,000,000 on July 1 (JD 0.72); OFTC from 31,239,728 to 12,612,543 on July 7 (JD 0.99); and DAFI reduced capital twice, from 16,000,000 to 8,000,000 on July 24 (JD 0.62) and from 8,000,000 to 5,000,000 on October 9 (JD

Table 5. Sensitivity to activity and trading-day filters

Sample	Annual range	Log value traded	First market	N	R ²
Baseline filters	0.883*** (0.075)	3.075** (1.503)	17.082***	142	.729
Trading days ≥ 10	0.852*** (0.078)	3.894** (1.553)	14.759*** (4.167)	151	.696
All valid equities	0.846*** (0.079)	2.930** (1.404)	15.857*** (3.981)	160	.698

Note. Each model includes turnover and the trading-day ratio. HC3 standard errors are in parentheses. ***, **, and * indicate $p < .01$, $p < .05$, and $p < .10$, respectively.

Table 6. Signed-range decomposition and corporate-action exclusion sensitivity

Specification	Annual range	Upside range	Downside range	N	R ²	Wald: $\beta_{up} = \beta_{down}$
Signed baseline	—	0.806*** (0.071)	-0.630*** (0.187)	142	.887	72.61***
Signed + sector indicators	—	0.815*** (0.068)	-0.604*** (0.188)	142	.892	68.25***
Exclude 4 confirmed CA securities	0.850*** (0.082)	—	—	138	.627	—
Signed, exclude 4 confirmed CA securities	—	0.792*** (0.062)	-0.653*** (0.186)	138	.875	78.72***

Note: Dependent variable: 2025 price return (%). All reported standard errors are HC3 and appear in parentheses. Signed specifications retain log value traded, turnover, trading-day ratio, and first-market status; the sector specification additionally includes Services and Industrial indicators, with Financial omitted. The original unsigned baseline is reported in Table 4. The corporate-action sensitivity excludes PHNX, OFTC, NAQL, and DAFI only. Wald statistics test $H_0: \beta_{up} = \beta_{down}$. ***, **, and * indicate $p < .01$, $p < .05$, and $p < .10$, respectively.

Table 7. Manual corporate-action audit of extreme annual range and absolute-return observations

Ticker	Return (%)	Range (%)	Extreme-observation reason	2025 ASE corporate-action audit	Sensitivity handling
PHNX	237.50	268.75	Top-10 annual range (rank 1); Top-10 return (rank 1)	Capital reduction, 28 Jan: 86.84m → 42.80m; ref. JD 0.34	Excluded in N = 138 sensitivity
OFTC	217.95	238.46	Top-10 annual range (rank 2); Top-10 return (rank 2)	Capital reduction, 7 Jul: 31.24m → 12.61m; ref. JD 0.99	Excluded in N = 138 sensitivity
NAQL	210.34	227.59	Top-10 annual range (rank 3); Top-10 return (rank 3)	Capital reduction, 1 Jul: 13.915m → 7.0m; ref. JD 0.72	Excluded in N = 138 sensitivity
AMAD	191.57	214.46	Top-10 annual range (rank 4); Top-10 return (rank 4)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained
DAFI	73.08	211.54	Top-10 annual range (rank 5)	Two reductions: 24 Jul 16m → 8m (JD 0.62); 9 Oct 8m → 5m (JD 0.57)	Excluded in N = 138 sensitivity
CEIG	152.63	210.53	Top-10 annual range (rank 6); Top-10 return (rank 5)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained
DMAN	146.75	177.92	Top-10 annual range (rank 7); Top-10 return (rank 6)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained
JDPC	80.77	173.08	Top-10 annual range (rank 8)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained
UCIC	118.97	136.21	Top-10 annual range (rank 9); Top-10 return (rank 7)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained
AQAR	109.68	124.19	Top-10 annual range (rank 10); Top-10 return (rank 8)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained
SPIC	89.87	106.33	Top-10 return (rank 10)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained
MHFZ	91.94	100.00	Top-10 return (rank 9)	No corresponding 2025 entry identified in the official register; absence is not treated as proof of no action	Retained

Note: Extreme securities are the union of the top ten annual-range observations and the top ten absolute-return observations, producing 12 unique symbols. Corporate-action verification uses the official ASE 2025 corporate-actions chronology and structured corporate-actions table. 'No entry identified' is deliberately weaker than 'no action occurred'.

0.57). For the other eight extreme securities, no corresponding 2025 entry was identified in the official corporate-actions register during the symbol-based audit; this finding is not treated as proof that no action occurred.

Excluding the four confirmed extreme corporate-action securities gives a sensitivity sample of $N = 138$. The unsigned annual-range coefficient is 0.850 (HC3 SE = 0.082, $p < .001$), with $R^2 = .627$. In the signed model, the upside coefficient is 0.792 (0.062, $p < .001$) and the downside coefficient is -0.653 (0.186, $p < .001$), with $R^2 = .875$; the equality restriction is rejected, $\chi^2(1) = 78.72$, $p < .001$. These sensitivity estimates are included in Table 6.

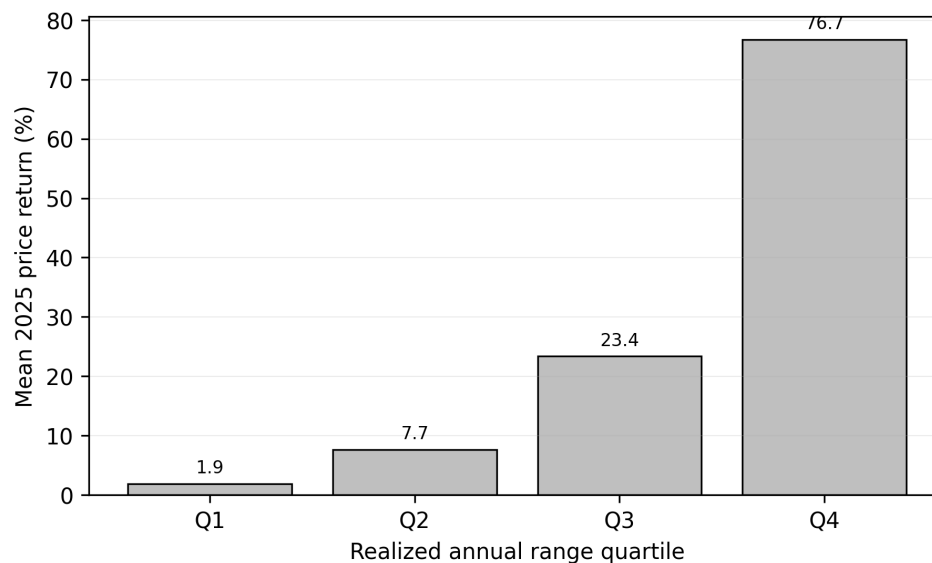
Mean price return rises from 1.90% in the lowest annual-range quartile to 76.72% in the highest. The Q4-minus-Q1 mean difference is 74.82 per-

centage points. A Welch test gives $t = 6.62$ with 38.08 degrees of freedom and $p < .001$; the 95% confidence interval is [51.95, 97.69]. A 10,000-repetition percentile bootstrap produces [53.90, 96.81]. Table 8 and Figure 2 report this complementary descriptive evidence.

Table 8. Price returns by realized annual range quartile

Range quartile	N	Mean range (%)	Mean return (%)	Median return (%)
Q1	36	21.05	1.90	1.44
Q2	35	36.60	7.65	15.38
Q3	35	54.22	23.35	27.03
Q4	36	118.69	76.72	70.58

Note: Q4 – Q1 mean return difference = 74.82 percentage points; Welch $t = 6.62$, $df = 38.08$, $p < .001$, 95% CI [51.95, 97.69]. Percentile bootstrap 95% CI [53.90, 96.81], 10,000 repetitions, seed 18890. The sort uses the same observations and variables as the regressions.



Note: The figure visualizes Table 8. Quartiles are formed from the same-year realized range and are not an independent predictive exercise.

Figure 2. Mean 2025 price return by realized annual range quartile

4. DISCUSSION

The central empirical fact is unusually strong realized co-movement between annual price dispersion and the 2025 closing-price return. The relationship survives broad-sector controls, Huber estimation, and less restrictive samples, so it is not well described as an artifact of a single sector, one conventional least-squares outlier, or the baseline activity filters. At the same time, robustness of a contemporaneous coefficient is not equivalent to identification of a risk premium. The range and return are outcomes of the same annual price process, and a sustained rise in price can mechanically widen the observed distance between the annual high and low while raising the year-end return.

This interpretation separates the study from the classical range-volatility literature. Parkinson (1980), Garman and Klass (1980), Beckers (1983), Rogers and Satchell (1991), and Yang and Zhang (2000) use price extremes as inputs to volatility estimators with specific statistical properties. Their contribution is that high-low information can improve measurement of within-period variation. The present annual statistic is intentionally simpler and is not a replacement for those estimators. Its coefficient with the same-year closing-price return combines information about realized dispersion with information about the direction

and path of prices. The evidence is therefore compatible with the informational value of price extremes while demonstrating why a high-low range cannot automatically be relabeled as a priced risk characteristic.

The distinction is also important relative to research on volatility and extreme returns. Ang et al. (2006) study the cross-section of idiosyncratic volatility and expected returns using repeated higher-frequency observations, and Bali et al. (2011) examine extreme positive daily returns as a lottery-like characteristic. Those designs separate the characteristic-measurement window from the future-return interpretation more clearly than a same-year annual bulletin can. The ASE evidence does not contradict those studies; it answers a different question. It shows that, within a single realized year, securities with wider annual price paths also tended to finish with much larger price gains.

The denominator sensitivity is especially revealing. Scaling the range by average price instead of the previous close leaves the coefficient positive but reduces R^2 from .729 to .307. Two conclusions follow simultaneously. First, shared scaling by the previous close is not the only source of the positive association. Second, it is quantitatively important for the overall fit of the baseline model. The sharp fall in explanatory power means that the high

baseline R^2 should not be interpreted as evidence that an independently measured economic factor explains almost three quarters of cross-sectional returns. A substantial part of that fit is tied to how the same-year price variables are normalized and constructed.

The trading-value result requires similar restraint. A positive log-value coefficient differs in sign from the simplest interpretation of an illiquidity premium in which harder-to-trade securities command higher expected returns. But the variable here is annual value traded, not a bid-ask spread, Amihud price-impact measure, or market-wide liquidity-risk exposure. Brennan and Subrahmanyam (1996), Datar et al. (1998), Amihud (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005) study explicit trading-friction or liquidity-risk channels, while Goyenko et al. (2009) and Fong et al. (2017) show that proxy choice matters materially. The ASE coefficient instead says that securities with more trading-value activity during 2025 also had higher realized price returns after conditioning on the other observed annual measures. Joint determination by prices, attention, demand, and news remains a plausible explanation.

The null turnover and trading-day coefficients reinforce the multidimensional nature of activity and liquidity. Turnover, trading continuity, and trading value are related but not interchangeable. Chordia et al. (2000, 2001) and Karolyi et al. (2012) emphasize common components in liquidity and trading activity, while Hasbrouck (2009), Lesmond et al. (1999), Roll (1984), and Stoll (2000) focus on trading-cost measurement. In the ASE cross-section, the positive value-traded coefficient alongside imprecise turnover and trading-day coefficients suggests that the scale of participation and visibility may be more closely associated with the realized 2025 return pattern than the other two annual activity measures. The annual data cannot isolate the mechanism.

The first-market coefficient is likewise best understood as a bundle of institutional differences. Merton's (1987) investor-recognition framework provides one reason more visible securities can behave differently, but first-market status can also reflect listing requirements, firm size, disclosure quality, institutional participation, and trading

activity. Its persistence after broad-sector controls is therefore descriptive evidence of segment heterogeneity, not a causal estimate of the value of first-market listing.

These measurement issues are magnified in a smaller emerging market. Scholes and Williams (1977) and Dimson (1979) show how infrequent trading affects conventional return-based measures, while Harvey (1995), Bekaert and Harvey (1995), Rouwenhorst (1999), Bekaert et al. (2007), and Griffin et al. (2010) document the importance of local factors, integration, liquidity, and market frictions in emerging markets. The ASE's wide dispersion in trading activity makes a full-population sensitivity useful, but annual aggregation can still conceal stale prices and irregular adjustment. The similarity of the 142- and 160-stock coefficients shows that filtering is not the main source of the result; it does not remove the limitations created by annual frequency and same-period measurement.

The corporate-action audit materially narrows one of the paper's principal measurement concerns. Four of the 12 pre-specified extreme securities experienced confirmed capital reductions during 2025, including two reductions for DAFI. These events are capable of altering unadjusted exchange price fields mechanically. Yet the positive unsigned-range coefficient remains 0.850 after PHNX, OFTC, NAQL, and DAFI are removed, and the signed asymmetry remains pronounced. The audit therefore shows both sides of the issue: unadjusted corporate actions matter enough to warrant explicit verification, but the central directional co-movement is not an artifact of only those four observations. The audit remains limited to the most influential extremes and should not be interpreted as a fully corporate-action-adjusted total-return dataset for all 142 securities.

The signed decomposition resolves the paper's earlier directional ambiguity and becomes central to interpretation. The unsigned range combines the distance from the previous close to the annual high with the distance from the previous close to the annual low. Once those components enter jointly, the upside coefficient is strongly positive while the downside coefficient is significantly negative, and the equality restriction is decisively rejected. This result is consistent with the concern

that broad annual appreciation mechanically expands the high-side distance while also raising the closing-price return. It also shows why the original 0.883 coefficient lacks a clean interpretation as a direction-neutral price of dispersion. The signed model is still contemporaneous, so the decomposition improves diagnosis of construction and direction without creating ex ante identification.

The practical implication is therefore methodological rather than prescriptive. Annual exchange bulletins can support transparent market diagnostics, screening of unusual realized observations, and

comparison of trading participation across securities. They are much less suited to claims about ex ante compensation, implementable portfolio rules, or causal liquidity effects unless the information set is lagged, price histories are adjusted for distributions and corporate actions, and conventional firm characteristics are incorporated. A stronger design would match multiple years of security-level data, construct lagged range and activity measures, verify corporate actions and dividends, add size, book-to-market, momentum, ownership, and other controls, and assess out-of-sample performance using only information available before each return period.

CONCLUSION

This study examined the contemporaneous cross-sectional relationship among realized annual price dispersion, trading activity, market segment, and 2025 price returns on the Amman Stock Exchange.

The realized annual high-low range is strongly positively associated with same-year price return: the coefficient is 0.883 (HC3 SE = 0.075) in the 142-stock baseline, 0.887 (0.071) with broad-sector controls, and 0.846 (0.079) in the full 160-stock sample. The signed decomposition shows that the relation is directional rather than symmetric: upside range enters at 0.806 (0.071) and downside range at -0.630 (0.187), with coefficient equality rejected at $p < .001$. A manual audit of 12 extreme observations identifies confirmed 2025 capital reductions for PHNX, OFTC, NAQL, and DAFI; excluding those four leaves the unsigned coefficient positive at 0.850 (0.082; $N = 138$), the signed coefficients at 0.792 (0.062) and -0.653 (0.186), and the realized Q4-minus-Q1 range-quartile return spread at 74.82 percentage points.

The evidence therefore supports a narrow conclusion: wide annual price dispersion and large positive price changes were tightly linked in the realized 2025 ASE cross-section, and much of that relationship is specifically associated with the upward component of the annual path. The denominator sensitivity and corporate-action audit show that measurement construction and a small number of verified restructuring events materially affect fit, but neither accounts for the directional pattern in full. The results do not demonstrate ex ante risk pricing, expected-return predictability, or a causal liquidity premium. A stronger asset-pricing design would require lagged or higher-frequency corporate-action-adjusted data, dividend-inclusive total returns, richer firm characteristics, and repeated cross-sections or panel evidence.

AUTHOR CONTRIBUTIONS

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DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

In preparing this manuscript, the author used ChatGPT (OpenAI) for language refinement, structural editing, and formatting support. After use, the author processed and edited the text and bears full responsibility for the content of the publication.

DATA AVAILABILITY STATEMENT

The source fields used in the analysis are publicly available from the Amman Stock Exchange yearly sector bulletin for 2025.

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