

Research Article

Informational Efficiency in Dow Jones Industrial Average Companies: Pre-Announcement Leakage and Post-Announcement Price Adjustment

Running title: Informational Efficiency in DJIA Companies

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ABSTRACT

PURPOSE: This study examines two dimensions of informational efficiency among Dow Jones Industrial Average (DJIA) constituents: the leakage of price-relevant information before scheduled corporate disclosures and the speed at which prices absorb newly released information. Quarterly earnings announcements serve as the information event.

DESIGN/METHODOLOGY/APPROACH: Open, high, low, and closing prices for 26 DJIA constituents over 2010–2024 were obtained from Yahoo Finance, and announcement dates were identified from Form 8-K filings (Item 2.02) submitted to the U.S. Securities and Exchange Commission. Volatility, measured as the daily high–low range relative to the closing price, was examined over an eleven-day window around each announcement, yielding 1,568 events and 17,248 firm-day observations. Differences across event-window days were tested at the firm and pooled levels using one-way ANOVA and independent-samples t-tests, with effect sizes reported alongside p-values.

FINDINGS: Volatility differs across the event window ($F = 158.39$, $p < 0.0001$, $\eta^2 = 0.084$), a pattern significant for all 26 firms, and peaks on the announcement day at roughly 60% above the pre-announcement baseline (Cohen's $d = 0.95$). The elevation persists into the following trading day ($d = 0.46$, significant for 15 of 26 firms) before normalizing by day +2. Volatility in the two days preceding the announcement shows no economically meaningful difference ($d = 0.13$, significant for one firm), providing no support for systematic pre-disclosure leakage.

RESEARCH IMPLICATIONS: The results support a qualified view of semi-strong-form efficiency: reactions are large and essentially leakage-free, but full price discovery takes slightly more than one trading session for most firms. They also show why effect sizes, not p-values alone, are needed to interpret large financial panels.

ORIGINALITY/VALUE: The study jointly maps pre-disclosure leakage and post-disclosure adjustment speed using a single recurring event across a fifteen-year panel of DJIA constituents and explicitly separates statistical from economic significance.

RESEARCH HIGHLIGHTS

- Earnings-day volatility rises about 60% above baseline and persists into day +1.
- No economically meaningful pre-announcement information leakage is detected.
- Effect sizes show that large-sample significance can overstate economic impact.

1. Introduction

Information is one of the central concerns of financial economics: the way market participants acquire, process, and trade on information determines how well security prices reflect underlying economic value. When markets convert new information into prices quickly and completely, investors and firms can make better financing, investment, and risk-management decisions; when they do not, prices can remain stale long enough to create trading opportunities for informed participants and mispricing costs for everyone else. Understanding the channels through which information is impounded into prices—and the speed at which this happens—is therefore directly relevant to investors, to corporate managers making disclosure decisions, and to regulators designing disclosure and trading rules (Milgrom & Stokey, 1982; Sebenius & Geanakoplos, 1983).

A large body of research questions whether prices fully reflect fundamental values (Shiller, 1981) and documents that informational efficiency is not a fixed property of a market but varies with the incentives and behavior of its participants. Trading activity is widely regarded as the primary mechanism through which new information is incorporated into prices: without active trading, prices become stale and slow to reflect new information, which erodes informational efficiency (Hasbrouck, 2017). Consistent with this view, Zhang and Kalev (2021) show that trading activity—in particular, noise trading—is an important driver of variation in the informational efficiency of asset prices, with effects that differ between large, liquid stocks and smaller, less liquid ones. A related dimension of informational efficiency concerns the timing of investors' reactions to public news: markets in which investors react quickly and consistently to newly released information tend to exhibit more stable and predictable adjustment patterns, whereas markets in which reactions are slow, delayed, or erratic are more prone to mispricing. Fama (1970) formalizes this idea in his classic taxonomy of weak-form, semi-strong-form, and strong-form efficiency, which remains the organizing framework for most empirical work in this area, including the present study.

One strand of the literature investigates how the trading behavior of specific investor types shapes informational efficiency. Several studies focus on sophisticated, well-resourced traders such as institutional investors (e.g., Boehmer & Kelley, 2009; Chen *et al.*, 2020; Hendershott *et al.*, 2015; Yan & Zhang, 2009), whereas others examine the effect of retail traders (e.g., Barber *et al.*, 2009; Fong *et al.*, 2014; Foucault *et al.*, 2011; Kaniel *et al.*, 2008). Although each of these studies offers valuable insight into a particular group of participants, none provides a holistic picture of how aggregate trading activity affects financial markets, because real markets aggregate information from all participants simultaneously rather than from any single investor class.

Building on this literature, the present study investigates the informational efficiency of DJIA constituents by examining price volatility around quarterly earnings announcements—arguably the most important and most regularly scheduled information event generated by publicly traded firms, and one long established as price-relevant to investors (Ball & Brown, 1968). A large volume of information can arrive within a short window around such announcements, and understanding how quickly and how completely it is absorbed into prices is central to assessing market efficiency. Sharp price movements in the days before an official announcement are potentially informative about information leakage, whereas sharp movements that continue for several days after an announcement, rather than subsiding promptly, are potentially informative about slow price discovery.

This study contributes to the literature in three ways. First, it jointly examines pre-disclosure leakage and post-disclosure adjustment speed using a single, regularly recurring, firm-specific event. Second, it applies this design consistently across a fifteen-year panel of DJIA constituents. Third, it reports effect sizes alongside significance tests, showing how conclusions about efficiency change when statistical and economic significance are distinguished. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature, identifies the research gap, and develops the hypotheses. Section 3 describes the data, the volatility measure, and the statistical procedures. Section 4 presents the empirical results, Section 5 discusses the findings, and Section 6 concludes and sets out the study's limitations and directions for future research.

2. Theoretical Background and Literature Review

2.1. Conceptual and theoretical foundations

This study builds on Fama's (1970) taxonomy of informational efficiency, which distinguishes weak-form efficiency (prices reflect historical price information), semi-strong-form efficiency (prices reflect all publicly available information, including scheduled disclosures such as earnings announcements), and strong-form efficiency (prices reflect all information, including private information). The empirical focus here is semi-strong-form efficiency, and specifically two distinct constructs within it that are often conflated in applied work and must be defined separately.

The first construct, pre-disclosure information leakage, refers to the possibility that price-relevant information about a firm's forthcoming earnings becomes available to some market participants before the official public release. Theoretically, this construct is grounded in the rational-expectations literature on price formation: Grossman (1976) and Grossman and Stiglitz (1980) show that prices aggregate the private information of informed traders through the trading process itself, so that if even a subset of traders acquires information ahead of a public announcement and trades on it, this should manifest as abnormal price movement—and, in the volatility-based framework used here, abnormal volatility—in the days preceding the announcement. Verrecchia (1979) formalizes the related idea that the degree to which prices reflect the true distribution of returns increases with the number of market participants who correctly perceive that distribution ahead of a disclosure event. As operationalized in this study, this construct must be distinguished from illegal insider trading: elevated pre-announcement volatility is a statistical signature consistent with early information diffusion, which may arise from legitimate channels such as analyst inference, supply-chain signals, or partial disclosures, rather than direct evidence of unlawful trading on material non-public information.

The second construct, the speed of price adjustment, refers to the number of trading sessions required for a market to fully impound newly released public information into prices. This construct differs from two adjacent and more commonly studied phenomena. First, it differs from post-earnings-announcement drift (PEAD), which concerns the direction and magnitude of returns in the weeks following an earnings surprise (Bernard & Thomas, 1989; Bhushan, 1994); the present study instead examines the persistence of volatility—a proxy for the market's residual uncertainty about the value of new information—regardless of the sign or size of the price reaction. Second, it differs from the magnitude of the announcement-day reaction itself, which reflects the size of the surprise rather than the speed of its incorporation. Hasbrouck (2017) and Zhang and Kalem (2021) provide the conceptual link used here: active trading is the mechanism through which information is impounded into prices, so that markets with faster and more complete trading responses to news should show volatility that decays to baseline levels within one trading session rather than persisting over several days.

Together, these two constructs—pre-disclosure leakage and post-disclosure adjustment speed—provide two complementary, testable windows onto the same underlying theoretical property: how efficiently the market processes a scheduled, firm-specific information event.

2.2. Empirical evidence and unresolved gap

The empirical literature on informational efficiency can be organized into three broad clusters, which converge on some points and diverge on others.

The first cluster examines how the behavior of specific investor types shapes efficiency. Studies of institutional and other sophisticated investors (Boehmer & Kelley, 2009; Chen *et al.*, 2020; Hendershott *et al.*, 2015; Yan & Zhang, 2009) generally converge on the finding that greater participation by informed, well-resourced traders is associated with faster and more complete price discovery. Studies of retail investors (Barber *et al.*, 2009; Fong *et al.*, 2014; Foucault *et al.*, 2011; Kaniel *et al.*, 2008) present a more mixed picture, with retail participation sometimes associated with increased short-term volatility rather than improved efficiency—a divergence that appears to depend on whether retail order flow is treated as noise or as a genuine, if smaller-scale, source of information.

The second cluster examines market-structure and regulatory determinants of efficiency, such as dark-trading restrictions (Ibikunle *et al.*, 2021), tick size and decimalization (Zhao & Chung, 2006), trade openness (Lim &

Kim, 2011), and exchange-traded fund (ETF) activity (Glosten *et al.*, 2021). An important boundary condition emerges here: Glosten *et al.* (2021) find that ETF activity improves informational efficiency mainly for stocks in weak information environments, with no comparable benefit for stocks already in strong information environments. This conditionality suggests that findings from this literature may not generalize uniformly to firms as large and closely followed as DJIA constituents, which sit toward the strong end of the information-environment spectrum.

The third cluster uses entropy- and complexity-based efficiency metrics (Risso, 2008; Siokis, 2018) or macro-level integration measures (Boamah, 2022; Hooy & Lim, 2013; Todea & Pleşoianu, 2013) and is largely applied to broad market indices, emerging markets, or non-equity instruments (Go & Lau, 2020) rather than to a matched panel of large-cap constituent firms around a common, recurring corporate event.

Across all three clusters, the evidence converges on the general proposition that active, informed trading improves informational efficiency but diverges on which mechanisms matter most and under what conditions efficiency gains materialize. Critically, none of these studies jointly examines pre-disclosure leakage and post-disclosure adjustment speed using a single, regularly recurring, firm-specific event applied consistently across a broad, long-horizon sample of index constituents. This is the gap the present study addresses: rather than inferring efficiency indirectly from investor type or market structure, it maps volatility behavior directly around quarterly earnings announcements—the most consistently available firm-specific information event—across 26 DJIA firms and fifteen years, treating leakage and adjustment speed as two separately testable and theoretically distinct outcomes of the same underlying process.

2.3. Hypothesis development

If price volatility reflects the arrival and processing of new information, volatility should not be uniform across an event window that contains a scheduled information release; instead, it should vary systematically with proximity to the announcement (Fama, 1970; Hasbrouck, 2017). This reasoning motivates the first, omnibus hypothesis, tested against the null that mean volatility is equal across all eleven trading days surrounding the announcement:

H1. *Mean price volatility differs across at least two of the eleven trading days surrounding the earnings announcement (days -5 to $+5$).*

If the announcement itself is the primary trigger of new information arrival, and if the market processes this information rapidly (Hasbrouck, 2017; Zhang & Kalev, 2021), volatility should be concentrated on the announcement day relative to the days immediately before and after it. This reasoning motivates the second hypothesis, which is tested in four stages:

H2. *Mean volatility on the announcement day exceeds mean volatility on (a) the pre-announcement days, (b) the post-announcement days, and (c) all other days combined; in addition, (d) mean pre-announcement volatility differs from mean post-announcement volatility.*

If price adjustment to earnings news is rapid, as the theoretical mechanism in Section 2.1 predicts for actively traded and closely followed securities such as DJIA constituents, volatility should decay to baseline levels within a single trading session rather than persisting over several days; by contrast, delayed price responses of the kind documented by Bernard and Thomas (1989) would imply that elevated volatility persists beyond the announcement day. This reasoning motivates two sequential tests, each against the null of equal volatility on adjacent days:

H3. *Mean volatility on day $+1$ exceeds mean volatility on day $+2$.*

H4. *Mean volatility on day $+2$ exceeds mean volatility on day $+3$.*

Finally, if information about a firm's earnings leaks into the market ahead of the official release, volatility should build up as the announcement approaches, consistent with the rational-expectations mechanism in Grossman (1976) and Grossman and Stiglitz (1980). This reasoning motivates the fifth hypothesis; support for it would be consistent with, although not on its own proof of, information leakage building closer to the announcement:

H5. *Mean volatility on day -1 exceeds mean volatility on day -2 .*

3. Data and Methodology

3.1. Research design and analytical framework

The study uses an event-study design in which quarterly earnings announcements are the information event and the firm-day is the unit of observation. Price volatility is compared across the eleven trading days surrounding each announcement, separately for each firm and for the pooled sample. Differences across event-window days are tested with one-way analysis of variance (ANOVA) and independent-samples t-tests, and effect sizes are reported alongside p-values so that economically meaningful patterns can be distinguished from patterns that are merely detectable in a large sample.

3.2. Population, sample, data sources, and study period

The study covers the fifteen-year period 2010–2024, which provides substantial statistical power and spans a broad range of market conditions, including the latter half of the post-2008 recovery, the 2020 COVID-19 shock, and the 2021–2023 period of inflation and interest-rate increases. The starting year was chosen deliberately. The SEC's Item 2.02 disclosure requirement, used to identify earnings-announcement dates, took effect only in mid-2004, and Visa Inc. (V), one of the sample firms, did not begin trading until its initial public offering in March 2008. Starting in 2010 therefore ensures a data buffer of at least two years after Visa's listing, and 2024 is the final complete calendar year of available data.

Daily open, high, low, and closing prices were obtained from Yahoo Finance, and quarterly earnings-announcement dates were identified from Form 8-K filings submitted to the U.S. Securities and Exchange Commission (SEC) under Item 2.02 ("Results of Operations and Financial Condition"), retrieved through the EDGAR system. Within the 27-firm study universe, 1,744 candidate Item 2.02 events fell within 2010–2024; after removing same-cycle duplicate filings (events within 40 calendar days of a previously retained event for the same firm), 1,591 distinct quarterly events remained.

One firm, The Walt Disney Company (DIS), was excluded from the final sample because only 23 of an expected 60 quarterly events could be retrieved: Disney's SEC filings since 2019 are recorded under a new Central Index Key (CIK) assigned after its 2019 corporate restructuring, which made the 2010–2018 filings unrecoverable through the automated CIK-based lookup used here. The final sample therefore comprises 26 firms and 1,568 quarterly earnings events over 2010–2024, which, combined with an eleven-trading-day event window (Section 3.3), yield a panel of 17,248 firm-day observations with complete price data; no observations required imputation.

For three firms—3M (MMM; 64 retained events against an expected 60), Honeywell (HON; 63), and Johnson & Johnson (JNJ; 61)—a small number of retained dates (4, 1, and 1, respectively; six firm-quarters in total, or less than 0.4% of the sample) fall within 45 days of another retained date for the same firm and may reflect a non-earnings Item 2.02 disclosure rather than the firm's principal quarterly release. We retain and report these events rather than forcing every firm to exactly 60 events.

The sample reflects DJIA membership close to the present day, not the index's actual composition at each point between 2010 and 2024. The composition of the DJIA changed several times during this period; firms that were constituents for part of the window but are not included here include Alcoa, Bank of America, and Hewlett-Packard (removed in 2013), AT&T (removed in 2015), General Electric (removed in 2018), and ExxonMobil and Pfizer (removed in 2020). By analyzing only current constituents, the design implicitly conditions the sample on firms that performed well enough over the full window to remain in—or later join—the index. This is a form of survivorship bias: to the extent that firms removed from the index for poor performance also exhibited weaker informational efficiency around their earnings announcements, the results may overstate the average informational efficiency of the DJIA as it existed at each point in time. This limitation does not invalidate the findings for the 26 firms analyzed, but it means that the results describe the informational efficiency of current DJIA constituents evaluated retrospectively over 2010–2024, rather than that of the DJIA as a time-varying index.

3.3. Variables, constructs, and measurement

Volatility. Daily price volatility is proxied by the intraday high–low range expressed as a percentage of the closing price:

$$\text{Vol}_{i,t} = \frac{\text{High}_{i,t} - \text{Low}_{i,t}}{\text{Close}_{i,t}} \times 100 \quad (1)$$

where $\text{High}_{i,t}$, $\text{Low}_{i,t}$, and $\text{Close}_{i,t}$ are the highest, lowest, and closing prices of firm i on trading day t .

Across the 17,248 firm-day observations, this measure has a mean of 1.98% and a median of 1.67% of the closing price, with a standard deviation of 1.21 percentage points and a maximum of 38.4%—an extreme value very plausibly associated with the March 2020 COVID-19 market shock and addressed in the outlier-sensitivity analysis (Sections 3.5 and 4.3).

Event window. For each of the 1,568 retained quarterly events, an eleven-trading-day window was constructed: day 0 (the SEC filing date, or the next trading day if the filing date fell on a weekend or market holiday), days -5 to -1 (the five trading days before), and days $+1$ to $+5$ (the five trading days after). Each firm's own trading-day calendar was used, so that the window is always defined in trading days rather than calendar days. All 1,568 events had a complete eleven-day window within the underlying 2000–2025 price history, so no events were dropped for insufficient surrounding data. Table 1 summarizes the variables.

Table 1. Variable definitions and measurement

Variable / construct	Role	Operational definition	Data source	Expected sign
Volatility (high–low %)	Dependent	Daily (High – Low)/Close $\times 100$ for firm i on day t (Equation 1)	Yahoo Finance	—
Day group (event-window position)	Main predictor	Categorical indicator for the eleven trading-day positions $\{-5, \dots, -1, 0, +1, \dots, +5\}$; day 0 = next trading day at or after the SEC Item 2.02 filing date	SEC EDGAR (Form 8-K, Item 2.02)	Day 0 and day +1 > other days
Firm	Fixed effect	Firm identifier (ticker), absorbing time-invariant firm characteristics	—	Absorbs firm heterogeneity
Quarter	Fixed effect	Fiscal-quarter identifier (e.g., 2015Q3), absorbing market-wide shocks common to a quarter	Derived from event date	Absorbs period shocks
Firm size †	Control	Natural logarithm of market capitalization at the start of each fiscal year	Not used in the present analysis	–
Trading volume / liquidity †	Control	Logarithm of average daily dollar volume over the $[-30, -6]$ pre-window period	Not used in the present analysis	–
Market-wide volatility †	Control	CBOE VIX closing level on day t , for market-adjusted (abnormal) volatility	Not used in the present analysis	Absorbs market-wide shocks
Earnings surprise †	Control	Actual EPS minus consensus estimate, scaled by price	Not used in the present analysis	+

Notes: Volatility is winsorized at the 1st and 99th percentiles in the robustness analysis (Section 4.3; 2.01% of observations affected). Variables marked † belong to the panel-regression specification in Equation (2), which is proposed for future confirmatory analysis; they are not used in the analyses reported in Section 4. Table 2 reports mean volatility by event-window day.

3.4. Statistical tests and model specification

The results in Section 4 are based on one-way ANOVA and independent-samples t-tests applied separately at the firm level and at the pooled level, at the 5% significance level. Levene's test is applied before every ANOVA and t-test; because the panel is large, Welch-adjusted (unequal-variance) test statistics are reported whenever Levene's test rejects the homogeneity assumption. Given the sample size, statistical significance is interpreted together with effect size—Cohen's d for pairwise comparisons and η^2 for the omnibus ANOVA.

As a confirmatory extension of this univariate design, and as the specification to be estimated once the control variables in Table 1 are available, we specify the following panel regression on the same 17,248-observation firm-day panel:

$$\text{Vol}_{i,q,t} = \alpha + \sum_k \beta_k \text{Day}_{k,i,q,t} + \gamma' \text{Controls}_{i,q,t} + \mu_i + \lambda_q + \varepsilon_{i,q,t} \quad (2)$$

where $\text{Vol}_{i,q,t}$ is the volatility measure for firm i , fiscal quarter q , and event-window day $t \in \{-5, \dots, +5\}$; $\text{Day}_{k,i,q,t}$ is a set of ten day-offset indicator variables, with day 0 (the announcement day) as the omitted reference category, so that each β_k measures the difference in mean volatility between day k and the announcement day; $\text{Controls}_{i,q,t}$ is the vector of firm- and event-specific controls in Table 1 (firm size, liquidity, market-wide volatility, and earnings surprise); μ_i is a firm fixed effect; λ_q is a fiscal-quarter fixed effect; α is the intercept; and $\varepsilon_{i,q,t}$ is the error term. Standard errors are clustered by firm to account for within-firm serial correlation across events (Petersen, 2009).

Under this specification, H1 corresponds to a joint F-test of the null that all β_k coefficients are zero; H2 corresponds to individual tests of the β_k coefficients for the pre- and post-announcement days; and H3–H5 correspond to post-estimation Wald tests of linear combinations of adjacent coefficients (e.g., $\beta_{+1} = \beta_{+2}$ for H3). Because the control variables are not part of the analyzed dataset, Equation (2) is not estimated in this study, and the univariate findings in Section 4 should be read as descriptive evidence pending this confirmatory step.

3.5. Validity, robustness, and reproducibility

Two robustness analyses were conducted, and their results are reported in Section 4.3. First, because the maximum value of the volatility measure (38.4%) plausibly reflects extreme market-wide stress, the H1 and H2 analyses were re-estimated after winsorizing volatility at the 1st and 99th percentiles. Second, the H1 ANOVA was re-estimated on a narrower $[-3, +3]$ event window to assess whether the results depend on the width of the window.

Three further checks were not performed and are acknowledged as limitations (Section 6.1): a market-adjusted abnormal-volatility measure (net of contemporaneous VIX or S&P 500 realized volatility), screening of the event windows for confounding firm-specific news (e.g., guidance updates or merger announcements), and a placebo test based on randomly assigned pseudo-announcement dates. All data were obtained from Yahoo Finance (daily prices) and the SEC EDGAR submissions interface (Item 2.02 filing dates), with no imputed, estimated, or manually adjusted values, and the full construction pipeline—event de-duplication, window construction, and volatility calculation—is implemented in a single reproducible script.

4. Results

All statistical tests were conducted at the 5% significance level on the final panel of 26 firms, 1,568 quarterly earnings events, and 17,248 firm-day observations described in Section 3.

4.1. Descriptive statistics and preliminary analysis

Table 2 reports mean volatility by event-window day for the pooled sample.

Table 2. Mean volatility (high–low range as a percentage of the closing price) by event-window day, pooled sample

Day offset	Mean (%)	SD (%)	N
–5	1.754	1.012	1,568
–4	1.742	1.034	1,568
–3	1.740	0.998	1,568
–2	1.710	0.993	1,568
–1	1.834	0.979	1,568
0 (announcement)	2.799	1.470	1,568
+1	2.576	1.452	1,568
+2	1.984	1.099	1,568
+3	1.843	1.033	1,568
+4	1.825	1.107	1,568
+5	1.839	1.368	1,568

Notes: Day 0 is the announcement day (the SEC Item 2.02 filing date or the next trading day). SD = standard deviation; N = number of events.

The pattern in Table 2 is clear. Mean volatility on the announcement day (2.80%) is roughly 60% higher than the pre-announcement baseline (approximately 1.7–1.8%), remains elevated on day +1 (2.58%), falls roughly halfway back toward baseline by day +2 (1.98%), and normalizes by day +3.

4.2. Main findings

4.2.1. H1: Volatility across the eleven event-window days

At the pooled level, Levene's test rejects the equality of variances ($F = 41.57$, $p < 0.0001$), so Welch-type statistics are used. The one-way ANOVA strongly rejects the null hypothesis of equal mean volatility across the eleven event-window days ($F = 158.39$, $p < 0.0001$), and H1 is supported. Event-window position accounts for $\eta^2 = 0.084$ of the total variance in daily volatility—a moderate effect for a single categorical predictor in firm-day financial data, and one that, as the results below show, is concentrated almost entirely on the announcement day and the following day rather than spread evenly across the window.

At the firm level, the null hypothesis of equal volatility across the eleven days is rejected for all 26 firms ($p < 0.05$ in every case). The effect is strongest for Coca-Cola (KO; $F = 24.05$, $p < 10^{-38}$), IBM ($F = 23.98$), Travelers (TRV; $F = 21.42$), and 3M (MMM; $F = 20.16$) and weakest—although still statistically significant—for Procter & Gamble (PG; $F = 2.61$, $p = 0.004$) and Chevron (CVX; $F = 4.50$). This spread suggests that, although an announcement-day volatility effect is close to universal among the sample firms, its magnitude varies meaningfully across firms, plausibly reflecting differences in analyst coverage, business predictability, or typical earnings-surprise magnitude—factors not modeled in the present univariate design (Section 6.1).

4.2.2. H2: Announcement-day volatility versus other days

Table 3 reports the four-stage t-tests for H2.

Table 3. Independent-samples t-tests for H2, pooled sample

Stage	t	p-value	Mean difference	Cohen's d	Firms significant (of 26)
1. Day 0 vs. before	26.88	< 0.0001	+1.043 pp	0.95 (large)	22
2. Day 0 vs. after	19.77	< 0.0001	+0.786 pp	0.61 (medium)	20
3. Day 0 vs. all others	23.92	< 0.0001	+0.914 pp	0.78 (medium–large)	19
4. Before vs. after	−14.18	< 0.0001	−0.258 pp	0.23 (small)	19

Notes: pp = percentage points. Mean difference is the first group minus the second group. Effect sizes are classified using conventional Cohen's d benchmarks. The last column reports the number of firms (of 26) for which the firm-level test is significant at the 5% level.

The first three stages confirm a substantively large announcement-day volatility premium, and H2(a)–(c) are supported. A Cohen's d of 0.95 for the comparison of day 0 with the pre-announcement days is conventionally classified as a large effect, indicating that the difference is not merely an artifact of sample size; at the firm level, this comparison is significant for 22 of the 26 firms. Stage 4 yields a result that differs from the pattern a leakage-driven account would predict: pre-announcement volatility (mean 1.76%) is significantly lower, not higher, than post-announcement volatility (mean 2.01%), although the effect size is small ($d = 0.23$). This pattern is more consistent with a lagged adjustment process, in which part of the announcement's informational content continues to be processed for one additional trading day, than with pre-announcement leakage, and it anticipates the H3 result below.

4.2.3. H3: Day +1 versus day +2

The pooled test rejects the null hypothesis of equal volatility on days +1 and +2 ($t = 12.88$, $p < 0.0001$, Cohen's $d = 0.46$, a small-to-medium effect), and H3 is supported. At the firm level, 15 of the 26 firms individually show a significant difference. Thus, for a majority of the sample firms, the market's reaction to quarterly earnings news is not fully absorbed within a single trading session; an economically non-trivial portion of the announcement-day volatility premium persists into the following day before decaying substantially.

4.2.4. H4: Day +2 versus day +3

The null hypothesis is formally rejected at the pooled level ($t = 3.70$, $p = 0.0002$), but the effect size is negligible (Cohen's $d = 0.13$), and only 2 of the 26 firms show a significant firm-level difference. This result illustrates the distinction between statistical and practical significance in a large panel: with 17,248 observations, even a mean difference of 0.14 percentage points is detectable at conventional significance levels, yet it is too small to constitute economically meaningful evidence of continued price adjustment two to three days after the announcement. Substantively, therefore, H4 is not supported in any economically meaningful sense: for practical purposes, volatility has normalized by day +2.

4.2.5. H5: Day -1 versus day -2

The same pattern recurs. The pooled test is nominally significant ($t = 3.54$, $p = 0.0004$), but the effect size is negligible (Cohen's $d = 0.13$), and only 1 of the 26 firms shows a significant firm-level difference. As with H4, we interpret this result as providing no economically meaningful evidence of pre-announcement information leakage: the statistically detectable difference (0.12 percentage points) is an order of magnitude smaller than the announcement-day effect itself (Table 3) and is consistent with normal day-to-day variation in volatility rather than a systematic leakage pattern. H5 is therefore not supported in economic terms.

4.3. Robustness, sensitivity, and additional analyses

Outlier sensitivity. After winsorizing volatility at the 1st and 99th percentiles (affecting 346 of the 17,248 observations, or 2.01% of the panel), the H1 result is materially unchanged and, if anything, marginally stronger: $F = 192.28$ ($p < 0.0001$) and $\eta^2 = 0.100$ (versus 0.084 without winsorization), and the comparison of day 0 with the pre-announcement days yields Cohen's $d = 1.02$ (versus 0.95). The core H1 and H2 findings are therefore not driven by a small number of extreme observations.

Event-window width. Re-estimating the H1 ANOVA on a narrower $[-3, +3]$ window (dropping days ± 4 and ± 5) yields $F = 220.18$ ($p < 0.0001$), consistent in direction and significance with the full $[-5, +5]$ window result ($F = 158.39$). The announcement-day effect is therefore not an artifact of the specific window width.

5. Discussion

5.1. Interpretation relative to theory and prior evidence

The results tell a more nuanced story than a simple efficient-versus-inefficient verdict. Three findings, taken together, characterize the informational efficiency of DJIA constituents around quarterly earnings announcements over 2010–2024.

First, the announcement-day volatility effect is large and economically meaningful, not merely statistically detectable. A Cohen's d of 0.95 for the comparison of day 0 with the pre-announcement days (Table 3) places this effect at the upper end of conventional benchmarks; the event-window effect is significant for all 26 firms (Section 4.2.1), and the day-0-versus-pre-announcement comparison is significant for 22 of them. This is clear evidence that quarterly earnings announcements are highly price-relevant events for DJIA constituents, consistent with the foundational finding of Ball and Brown (1968) that accounting earnings carry information that the market prices, and with Fama's (1970) prediction that a semi-strong-form efficient market should react sharply to newly public information.

Second, price adjustment is not complete within the announcement day itself. Volatility remains meaningfully elevated on day +1 (a small-to-medium effect, $d = 0.46$, significant for 15 of 26 firms; Section 4.2.3) before decaying to a level that is statistically, but not practically, distinguishable from baseline by day +2 ($d = 0.13$; Section 4.2.4). Substantively, for more than half of the sample firms the market requires slightly more than one trading session to fully impound quarterly earnings information into prices—a pattern more consistent with the gradual-adjustment mechanisms documented in the post-earnings-announcement-drift literature (Bernard & Thomas, 1989; Bhushan, 1994) than with instantaneous, single-session semi-strong-form efficiency. This also explains the sign of the H2 Stage 4 comparison (Section 4.2.2): post-announcement volatility (2.01%) exceeds pre-

announcement volatility (1.76%) because the day +1 spillover raises the post-announcement average, not because of any pre-announcement phenomenon.

Third, and most directly relevant to the leakage question motivating H5, we find no economically meaningful evidence of abnormal volatility build-up in the two trading days immediately preceding the announcement ($d = 0.13$, significant for only 1 of 26 firms). Combined with the small effect size for H4, this result illustrates a point of direct relevance to how such results should be read: with 17,248 observations, conventional significance testing alone is not a reliable guide to economic importance. Distinguishing statistical from practical significance—as done throughout Section 4 by means of Cohen's d —is therefore a necessary step for correctly interpreting a panel of this size, and it is this distinction, rather than the raw p-values, that supports the paper's central claim: DJIA constituents show little to no detectable pre-disclosure leakage but only partial, not instantaneous, post-disclosure price discovery.

The substantial firm-level heterogeneity documented in Section 4.2.1—from very strong announcement-day effects at Coca-Cola, IBM, Travelers, and 3M to comparatively muted effects at Procter & Gamble and Chevron—is also informative. This variation is unlikely to be random; it plausibly reflects cross-firm differences in the intensity of analyst coverage, the typical magnitude of earnings surprises, or the extent to which a firm's fundamentals are otherwise predictable between reporting dates (Hasbrouck, 2017; Zhang & Kalev, 2021). The present univariate, firm-by-firm design cannot formally test which of these channels drives the heterogeneity; doing so requires the firm-level controls and the panel-regression framework set out in Section 3.4.

5.2. Theoretical and methodological contributions

Theoretically, the results support a qualified rather than an unqualified reading of semi-strong-form efficiency for DJIA constituents: the market reacts sharply and, for most firms, within one to two trading sessions to quarterly earnings news, with no detectable systematic leakage beforehand, but the process is not instantaneous, and a majority of firms show a statistically and economically meaningful continuation of the price reaction into the day after the announcement. Methodologically, the study shows that in large financial panels, reporting effect sizes (Cohen's d and η^2) alongside p-values changes substantive conclusions: two of the five hypothesis tests that are statistically significant would be misread as evidence of continued adjustment or leakage if significance alone were considered.

5.3. Managerial, regulatory, investment, and policy implications

For investors and portfolio managers, the persistence of elevated volatility into day +1 implies that risk exposure around earnings announcements extends beyond the announcement session, which is relevant to position sizing, hedging, and option pricing around earnings dates. For regulators, the absence of economically meaningful pre-announcement volatility build-up among DJIA constituents offers no indication of systematic information leakage in this segment of the market, although this conclusion should not be extended to smaller or less closely followed firms. For corporate managers, the results confirm that scheduled earnings disclosures are among the most price-relevant communications a firm makes. These implications are subject to the study's univariate design and to the survivorship and measurement limitations discussed in Section 6.1.

6. Conclusion

This study set out to answer a direct question: around scheduled quarterly earnings announcements, do DJIA constituents show signs of pre-disclosure information leakage, and how quickly does the market absorb new information once it is released? Using a fifteen-year panel of 26 DJIA firms, 1,568 quarterly earnings events, and 17,248 firm-day volatility observations, the answer is a qualified one. On leakage, the evidence is reassuring but not absolute: volatility in the two trading days immediately before an announcement shows no economically meaningful difference (Cohen's $d = 0.13$, significant for only 1 of 26 firms), which does not support systematic, sample-wide pre-disclosure information diffusion. On the speed of adjustment, the picture is more nuanced: the announcement triggers a large volatility spike ($d = 0.95$), with the event-window effect significant for all 26 firms, but this reaction is not complete within a single trading session; a small-to-medium share of it ($d = 0.46$, significant for 15 of 26 firms) carries over into the following day before settling to baseline by day +2.

The central contribution of this study is therefore not a blanket confirmation of semi-strong-form efficiency but a more precise, fifteen-year empirical map of where DJIA constituents sit on the spectrum between instantaneous and gradual price discovery: price discovery is essentially complete within the announcement session for a minority of firms but measurably incomplete after one day for a majority (15 of 26), with no detectable systematic leakage in either group. This distinction—between statistically detectable and economically meaningful patterns, made possible by reporting effect sizes alongside p-values—is itself a methodological contribution, because a design relying on significance testing alone would very plausibly have supported an overstated efficiency claim.

6.1. Limitations and future research

Design limitations. The study uses a univariate, firm-by-firm comparative design rather than a fully specified causal model. It does not include firm-level controls (size, liquidity, analyst coverage, or sector) that plausibly explain the substantial firm-level heterogeneity documented in Section 4.2.1, nor does it estimate a panel regression with firm and time fixed effects and clustered standard errors, such as the specification in Equation (2), which would allow the day effects, control variables, and standard errors to be estimated jointly.

Data limitations. Three data issues should be noted. First, The Walt Disney Company was excluded because a 2019 CIK reassignment in SEC records made its earlier filings unrecoverable through automated lookup, leaving 26 rather than 27 firms. Second, a small number of firm-quarters (6 of 1,568, or less than 0.4%) for 3M, Honeywell, and Johnson & Johnson may reflect non-earnings Item 2.02 disclosures rather than the firms' principal quarterly releases. Third, and most consequential for external validity, the sample reflects current DJIA membership rather than the index's time-varying composition between 2010 and 2024; firms removed from the index during this period (e.g., General Electric in 2018) are excluded, which introduces a survivorship bias that likely tilts the results toward higher informational efficiency than a point-in-time DJIA sample would show.

Measurement limitations. Volatility is proxied by the daily high–low range as a percentage of the closing price—an intuitive measure that is fully observable from daily price data but that is not adjusted for contemporaneous market-wide volatility and is statistically less efficient than range-based estimators such as those of Parkinson (1980) or Garman and Klass (1980). Because the reaction magnitudes are not benchmarked against a market or factor model, part of the announcement-day volatility premium could reflect market-wide conditions that coincide with earnings seasons rather than firm-specific news; an abnormal-volatility, market-adjusted event-study design (MacKinlay, 1997) is the natural next step. In addition, the $[-5, +5]$ window was not screened for confounding firm-specific or macroeconomic news. Moreover, day 0 is defined by the filing date without distinguishing announcements released before the market opens from those released after the close; for after-close releases, the first full trading-session reaction falls on day +1, so part of the day +1 effect may reflect announcement timing rather than slow price discovery.

External-validity boundaries. The findings describe large-capitalization, heavily traded, and closely followed U.S. equities—a setting in which, according to Glosten *et al.* (2021), the informational efficiency of prices is already high. The results should not be extrapolated to smaller firms, less liquid securities, or non-U.S. markets with different disclosure regimes, where both leakage and adjustment-speed dynamics could differ.

Future research. Three extensions follow directly from these limitations: (i) estimating the panel regression in Equation (2) with firm and quarter fixed effects, clustered standard errors, and the controls in Table 1, to test formally whether firm size, liquidity, or analyst coverage explains the cross-firm heterogeneity in announcement-day effects; (ii) reconstructing the DJIA's actual point-in-time membership, including removed constituents such as General Electric and Alcoa, to obtain a survivorship-bias-free estimate of index-level informational efficiency; and (iii) replacing the raw high–low proxy with a market-adjusted abnormal-volatility measure within a formal event-study framework (MacKinlay, 1997) and classifying announcements by release time, to isolate firm-specific informational effects from market-wide volatility.

Declarations and Transparency Statements

Author contributions (CRediT)

Both authors contributed to the conception and design of the study, data collection, analysis, and the writing and revision of the manuscript. All authors read and approved the final manuscript.

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Conflict of interest

The authors declare no competing interests.

Ethics approval

Not applicable. The study uses publicly available market and regulatory-filing data and does not involve human participants or animals.

Informed consent

Not applicable.

Data availability

The underlying data are publicly available from Yahoo Finance (daily prices) and the SEC EDGAR system (Form 8-K, Item 2.02 filings; <https://www.sec.gov/edgar>). The constructed firm-day panel (17,248 observations) is available from the corresponding author upon reasonable request.

Code availability

The script used to construct the dataset and perform the analyses is available from the corresponding author upon reasonable request.

Use of generative AI and AI-assisted technologies

During the preparation of this manuscript, an AI-assisted tool was used for language editing, formatting to the journal template, and checking the bibliographic details of the references. The authors reviewed and verified all content and take full responsibility for the accuracy, originality, and integrity of the manuscript.

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