

Price Discovery or Price Pressure? High-Frequency Evidence from India's New Closing Auction Session

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Abstract:

India introduced a dedicated Closing Auction Session (CAS) for derivative-eligible cash equities on 3 August 2026. Using one-minute market data and official National Stock Exchange auction records, this study examines changes in closing-price formation and the persistence of auction-specific price movements. Closing movements increase after CAS, while stock-specific auction returns strongly reverse by the next trading-day open. The controlled mean daily cross-sectional reversal coefficient is -0.336 and is negative on 24 of 25 trading days. Reversal is stronger for large auction moves and high auction intensity. The evidence supports a hybrid interpretation combining information aggregation with temporary price pressure.

Keywords: closing auction; price discovery; price pressure; market microstructure; high-frequency data; India

JEL classification: G10; G14; G18

1. Introduction

The closing price is one of the most consequential outputs of an equity market. It is used in portfolio valuation, benchmark tracking, index calculation, derivatives settlement, margining, performance measurement, and the execution of large institutional orders. For that reason, the mechanism used to determine the close is not merely an operational detail. It affects how end-of-day liquidity is concentrated, how information is incorporated into prices, and how much transitory order-flow pressure can influence a widely referenced market price.

Closing auctions are intended to improve this process by pooling buy and sell interest at a common clearing price. Concentrating liquidity may reduce fragmentation and allow information dispersed across traders to be reflected in a single equilibrium price. The same concentration, however, can generate temporary price pressure when auction demand is large relative to immediately available liquidity. A closing price can therefore be more informative in an aggregate sense while still containing a stock-

specific transitory component. The relevant empirical question is not simply whether prices move more or less under an auction, but whether auction-induced adjustments persist when continuous trading resumes.

On 16 January 2026, the Securities and Exchange Board of India (SEBI) announced a Closing Auction Session (CAS) in the equity cash segment. Under the earlier closing mechanism, the official closing price was based on the volume-weighted average price of trades during the final thirty minutes of continuous trading. The National Stock Exchange of India (NSE) subsequently introduced a separate 15:15–15:35 closing auction for cash-market securities on which derivatives are available, with the historical CAS archive commencing on 3 August 2026 (National Stock Exchange of India [NSE], 2026a, 2026b; Securities and Exchange Board of India [SEBI], 2026). The reform therefore replaced a continuous-trading-based closing rule with a discrete auction for a large and economically important group of Indian equities.

The Indian setting is useful for studying closing-market design for three reasons. First, CAS was introduced as a clearly dated regulatory change rather than as a gradual exchange practice. Second, Phase 1 treatment is concentrated in derivative-eligible securities, a group that is systematically more liquid, larger, and more institutionally followed than the ordinary equity universe. Third, the reform operates in a major emerging market where market microstructure research remains less extensive than in the United States and Western Europe. Recent Indian evidence continues to emphasize the importance of liquidity and regulatory design for price formation, reinforcing the value of studying institutional changes in the Indian market directly rather than extrapolating from developed-market settings (Agarwal & Pradhan, 2026).

Existing research offers competing predictions. Closing calls have been associated with lower execution costs, improved liquidity aggregation, and stronger price discovery in several markets (Chelley-Steeley, 2009; Kandel et al., 2012; Pagano & Schwartz, 2003). Other studies show that call auctions do not automatically improve price effectiveness and that participation conditions matter (Agarwalla et al., 2015; Han et al., 2022). More directly related to the present paper, U.S. evidence documents a temporary component in closing-auction price impact and rapid post-close reversal (Bogousslavsky & Muravyev, 2023; Jegadeesh & Wu, 2022). These findings suggest that price discovery and temporary price pressure can coexist.

This study provides early high-frequency evidence on India's new closing architecture using approximately 70.84 million one-minute observations from Dhan and official NSE auction records. The reform analysis fixes an ex ante launch cohort of 208 CAS stocks and compares changes in signed and absolute closing-mechanism returns with their own pre-reform history and with a contemporaneous benchmark of 497 non-CAS equities. Because matching and overlap diagnostics reveal inadequate common support, the benchmark is used only for comparative context rather than as a causal difference-in-differences control. For actual CAS stock-days, the analysis then tests whether auction-specific price movements persist to the next-session open using stock/date fixed effects and date-by-date cross-sectional regressions.

The findings are consistent with a hybrid interpretation. Closing movements for the CAS cohort increase after implementation, but the stronger evidence concerns persistence: stock-specific auction returns systematically reverse by the next open. The controlled average daily cross-sectional slope is -0.336, negative on 24 of 25 usable trading days, and remains close to -0.33 under multiple robustness checks. Reversal is strongest for the largest auction moves and becomes more negative when auction volume is

high relative to the preceding 15-minute trading window. At the same time, the aggregate daily mean reversal is statistically insignificant, indicating that the result is a cross-sectional stock-specific phenomenon rather than a broad market reversal.

The paper contributes in three ways. First, it provides early evidence on a major market-design reform in an emerging equity market. Second, it separates a change in closing-price formation from evidence on the persistence of stock-specific auction movements, avoiding the assumption that larger closing adjustments automatically imply improved price discovery. Third, it illustrates a conservative empirical strategy for regulatory event studies in which a superficially attractive control group is not treated as causal when common-support diagnostics fail. These features make the results relevant to exchanges, regulators, institutional investors, benchmark trackers, and derivatives-market participants.

The remainder of the paper proceeds as follows. Section 2 reviews the institutional design of CAS and the related literature and develops the hypotheses. Section 3 describes the data, sample construction, and empirical methodology. Section 4 reports the reform-level, reversal, and robustness results. Section 5 interprets the findings and discusses their implications, Section 6 sets out limitations and directions for future research, and Section 7 concludes.

2. Institutional Background and Related Literature

2.1 Closing auctions, liquidity aggregation, and market quality

Call auctions replace continuous matching with an interval during which orders are collected and subsequently cleared at a single price. Their potential advantage is that dispersed liquidity can be aggregated before execution. Pagano and Schwartz (2003) show that the introduction of a closing call at Euronext Paris reduced execution costs and improved price discovery. Chelley-Steeley (2009) reports improvements in market quality following the London Stock Exchange closing call, while Kandel et al. (2012) demonstrate that auction design affects volume, spreads, volatility, and the behavior of liquidity suppliers near the close.

These results do not imply that every auction design necessarily improves price formation. Han et al. (2022), studying the Shanghai Stock Exchange, find improved closing-price continuity but no prominent improvement in price effectiveness. In India, Agarwalla et al. (2015) report limited participation and little improvement in intraday price discovery following the reintroduction of an opening call auction. The implication is that the market-quality consequences of auctions depend on institutional design, participation, and the depth of liquidity surrounding the clearing event.

2.2 Temporary price pressure and post-auction reversal

Liquidity concentration can improve execution while still allowing temporary pressure to enter the clearing price. When auction demand is concentrated relative to available liquidity, liquidity suppliers may require compensation for absorbing inventory, causing part of the observed price movement to reverse once ordinary trading resumes. This distinction is particularly important at the close because the resulting price is used for valuation and settlement even though the liquidity imbalance that produced it may be short-lived.

Jegadeesh and Wu (2022) document a transitory component in closing-auction price impact on Nasdaq and the NYSE. Bogousslavsky and Muravyev (2023) similarly show that closing-auction price deviations reverse quickly on average and connect the phenomenon to trading at the close. Following this literature, post-auction resilience is informative about persistence: movements that survive the

resumption of ordinary trading are more consistent with durable information incorporation, whereas systematic opposite-signed returns indicate a temporary component (Bogousslavsky & Muravyev, 2023; Jegadeesh & Wu, 2022). The two mechanisms are not mutually exclusive because an auction may improve common price discovery while producing transitory cross-sectional dislocations in securities facing concentrated participation.

2.3 Emerging-market and Indian context

Emerging markets provide a particularly useful setting for examining liquidity-sensitive market design because trading depth, institutional participation, and regulatory structures can differ materially from those of developed markets. Indian evidence shows that stock liquidity is closely connected to market structure and regulatory features. Agarwal and Pradhan (2026), for example, document significant relationships between free float, liquidity, and price discounts in India and describe market microstructure in emerging markets as an area in which evidence remains relatively sparse.

The present reform differs from earlier Indian call-auction settings because it concerns the official close rather than the open and is initially concentrated in derivative-eligible securities. End-of-day demand may include benchmark rebalancing, institutional execution, and settlement-related trading that has no close counterpart at the market open. This institutional setting makes it important to study both whether the closing mechanism changes the distribution of end-of-day price movements and whether the stock-specific component of those movements persists.

2.4 India's Closing Auction Session

Under NSE's Phase 1 design, CAS applies to cash-market stocks on which derivative contracts are available. Continuous trading used to construct the auction reference price runs through 15:15. NSE computes that reference price from the volume-weighted average of trades between 15:00 and 15:15, after which the separate CAS begins at 15:15 and continues to 15:35. Order entry occurs within the auction, with a system-driven random closure during the final two minutes and order matching completed before 15:35 (NSE, 2026a).

The auction price is constrained by a $\pm 3\%$ band around the reference price. The equilibrium price is selected using maximum executable volume, minimum order imbalance, and proximity to the reference price as sequential criteria. Non-CAS securities continue under the ordinary cash-market closing mechanism. Because eligibility is tied to derivative availability, treatment is structurally associated with liquidity, capitalization, and investor attention. This feature is central to the empirical design because it makes a simple treated-versus-untreated causal comparison difficult to defend.

2.5 Hypotheses

Prior evidence shows that closing auctions can materially alter closing-price formation, although the direction and market-quality implications vary across institutional settings. The first hypothesis is therefore deliberately non-directional.

H1: The introduction of CAS is associated with a change in the distribution of closing-mechanism returns.

Evidence from U.S. closing auctions indicates that part of the auction price impact may be temporary and subsequently reverse.

H2: Closing-auction price movements contain a temporary component that is reflected in subsequent price reversal.

The literature also indicates that auction outcomes depend on liquidity provision, trading concentration, and surrounding market conditions rather than auction design alone.

H3: The magnitude and persistence of closing-auction price movements vary with auction participation and pre-close trading conditions.

3. Data and Methodology

3.1 Data sources and sample construction

The study combines three data sources. Dhan's historical market-data API provides one-minute open, high, low, close, and volume observations. Official NSE CAS files provide stock-date reference prices, final auction prices, final auction volume, and auction value. Dhan's detailed instrument master and NSE derivative-underlying identifiers are used to construct a security-ID crosswalk, avoiding reliance on company-name text during the merge.

The intraday download covers 708 securities and approximately 70.84 million one-minute observations. Data-quality checks identified zero-volume carry-forward vendor bars after the ordinary market close on several early post-reform dates. All bars after 15:29 are therefore excluded from continuous-market measurement. Official NSE auction prices and reference prices are used directly rather than reconstructed from vendor OHLCV data.

The treatment sample is defined ex ante as the 208 stocks participating in CAS on 3 August 2026. Fixing this launch cohort prevents later eligibility changes from altering the reform sample. Three additional securities entered CAS after launch, so the set of securities observed in the official auction archive is not identical to the fixed 208-stock launch cohort. The official archive contains 5,429 stock-date rows across 26 CAS dates, of which 5,428 map to the 708-security research universe. Reform comparisons therefore retain the original 208-stock cohort, whereas auction-mechanism analysis follows actual stock-date participation in the official archive.

The initial benchmark consists of the 500 highest-liquidity ordinary equities ranked using six-month pre-CAS median traded value. The three securities that subsequently entered CAS are removed from the benchmark for the entire sample, leaving 497 securities. This keeps the benchmark free of later CAS participation. The benchmark is fixed and contemporaneous, but it is not interpreted as a causal counterfactual.

Item	Value	Interpretation
Original CAS launch cohort	208	Stocks eligible for CAS on 3 August 2026
Initial non-CAS benchmark	500	Highest-liquidity ordinary equities before contamination removal
Later CAS entrants removed	3	Subsequently appeared in official NSE CAS archive
Clean non-CAS benchmark	497	Fixed contemporaneous benchmark
Actual CAS auction stock-	5,428	Matched official NSE auction

Item	Value	Interpretation
days		observations
Launch-cohort closing sample	56,368	Valid pre/post closing-mechanism observations
Auction reversal sample	5,218	Observations with exact next-session 09:15 open
CAS trading dates	26	3 August–7 September 2026

Table 1. Sample construction and analytical coverage

Note. Benchmark selection uses six-month pre-CAS median traded value. Launch-cohort identity is fixed on 3 August 2026; actual auction participation is stock-date specific.

3.2 Comparable closing outcomes

The closing mechanism itself changes after the reform, so the analysis anchors both regimes at 15:14, the last one-minute bar before the transition to CAS. For pre-CAS launch-cohort observations and for non-CAS securities, the endpoint is the 15:29 continuous-market close. For actual CAS stock-dates after 3 August, the endpoint is the official NSE final auction price. This construction compares price adjustment over a common economic interval while respecting the different closing mechanisms.

Signed closing returns capture directional movement, while absolute closing returns capture the magnitude of end-of-day adjustment. Reform-level inference is performed on daily cross-sectional means and medians rather than on individual stock-days. This avoids treating hundreds of securities exposed to the same market date as independent reform events. Pre/post changes are estimated with Newey–West heteroskedasticity-and-autocorrelation-consistent standard errors (Newey & West, 1987).

The primary pre-reform window is six months. Three- and twelve-month windows are used as robustness checks. The primary overnight-reversal measure requires the exact next-session 09:15 opening price. All 210 missing next opens among actual CAS observations occur on 7 September 2026, the final auction date in the sample. The usable reversal panel therefore ends on 4 September and contains 5,218 stock-days across 25 trading dates.

3.3 Benchmark comparison and rejected causal design

A causal difference-in-differences design was considered but rejected after explicit overlap diagnostics. This decision is important because CAS eligibility is tied to derivative availability and therefore to observable characteristics that differ sharply from the ordinary equity universe. Treating the non-CAS sample as an untreated causal counterfactual would require credible pre-treatment comparability that the data do not provide.

Treatment-control comparability was examined using pre-treatment characteristics following propensity-score logic (Rosenbaum & Rubin, 1983) and overlap weighting (Li et al., 2018). Global optimal one-to-one matching on liquidity, return volatility, intraday range, pre-period return, and price failed to balance the samples. In the six-month window, the post-match standardized mean difference for liquidity remained above 2.3. Common-support and overlap-weighting diagnostics were also inadequate: only 144 treated and 43 control securities remained within common support, and the maximum weighted standardized mean difference remained approximately 0.29.

Table 2. Diagnostics supporting rejection of a causal difference-in-differences design

Diagnostic	Result	Interpretation
Global optimal one-to-one matching: liquidity balance	Post-match SMD > 2.3	Substantial residual imbalance
Common-support restriction	144 treated; 43 controls retained	Large loss of overlap and representativeness
Overlap weighting	Maximum weighted SMD $\approx$ 0.29	Balance remains inadequate for a strong causal design

Note. SMD = standardized mean difference. These diagnostics were used to assess whether the non-CAS sample could support a causal comparison; they are not treatment-effect estimates.

Accordingly, the CAS-minus-benchmark statistic is described only as a comparative differential change. It shows whether the change observed among CAS stocks differs from contemporaneous behavior in a broad non-CAS group, but it is not interpreted as a causal treatment effect.

3.4 Auction return and reversal models

For each actual CAS stock-date, the official auction return is defined as:

$$AuctionReturn_{it} = \ln(FinalAuctionPrice_{it} / ReferencePrice_{it})$$

The next-open return is measured from the official auction close to the exact 09:15 opening price on the following trading day:

$$NextOpenReturn_{it+1} = \ln(Open09:15_{it+1} / FinalAuctionPrice_{it})$$

The primary panel specification relates the next-open return to the auction return while controlling for stock and date fixed effects and observable pre-close and auction conditions. The model is:

$$NextOpenReturn_{it+1} = \alpha_i + \delta_t + \beta AuctionReturn_{it} + \gamma'X_{it} + \varepsilon_{it}$$

where α_i denotes stock fixed effects, δ_t denotes date fixed effects, and X_{it} contains the 15:00–15:14 pre-close return, pre-close realized volatility, pre-close volume share, log auction value, and log auction intensity. Auction intensity is defined as auction volume divided by trading volume during the 15:00–15:14 pre-close window and enters as $\log(1 + \text{intensity})$.

Standard errors are two-way clustered by stock and date following Cameron et al. (2011). Because the number of post-reform dates is much smaller than the number of securities, inference uses a conservative t-reference based on the smaller cluster dimension.

3.5 Daily cross-sectional inference and mechanism analysis

With only 25 post-reform dates containing usable next opens, the panel estimates are supplemented by a Fama–MacBeth-style daily cross-sectional procedure (Fama & MacBeth, 1973). The controlled reversal regression is estimated separately on each auction date. The resulting daily auction-return slopes are then treated as a time series, and the mean slope is tested using HAC standard errors. This approach makes the trading date the inferential unit and provides a direct check that the panel finding is not driven by treating thousands of stock-days as independent observations.

A separate mechanism model uses the absolute auction return as the dependent variable. Explanatory variables are log auction intensity, log auction value, pre-close realized volatility, absolute pre-close return, and pre-close volume share. The aim is not to identify a causal structural mechanism, but to

examine whether unusually large auction adjustments are systematically associated with concentrated participation and market conditions immediately preceding the auction.

Robustness checks vary the pre-period, winsorize relevant return variables at the 1st and 99th percentiles by capping rather than deleting observations, exclude the first five CAS trading days, remove the top 1% of auction values, remove the top 1% of absolute auction returns, and permit the first available opening bar within five minutes of 09:15.

4. Empirical Results

4.1 Closing-price formation after CAS

Table 3. Primary six-month pre/post closing-price results

Outcome	CAS pre (%)	CAS post (%)	CAS Δ	CAS p	Bench. Δ	Bench. p	Comp. Δ	Comp. p
Mean signed closing return	0.010	0.125	0.115	0.0002	-0.008	0.8088	0.123	0.0136
Mean absolute closing return	0.234	0.341	0.107	0.0232	-0.061	0.0021	0.168	0.0002
Median signed closing return	0.006	0.101	0.095	<0.0001	0.005	0.8250	0.090	0.0041
Median absolute closing return	0.178	0.283	0.105	0.0071	-0.048	<0.0001	0.153	<0.0001

Note. Return levels are percentages; Δ values are percentage-point changes. HAC inference uses daily cross-sectional aggregates. Comparative change is CAS minus benchmark and is not a causal DiD estimate.

The launch cohort's mean signed closing return rises from 0.010% in the six-month pre-period to 0.125% after implementation, an increase of 0.115 percentage points ($p = 0.0002$). Mean absolute closing movement rises from 0.234% to 0.341%, an increase of 0.107 percentage points ($p = 0.0232$). Median signed and absolute movements show the same pattern.

The benchmark differs. Its mean signed closing return changes by only -0.008 percentage points and is statistically insignificant, while mean absolute movement declines by 0.061 percentage points ($p = 0.0021$). The CAS-minus-benchmark comparative changes are positive for all four outcomes. For mean signed returns the differential change is 0.123 percentage points ($p = 0.0136$); for mean absolute movement it is 0.168 percentage points ($p = 0.0002$). These contrasts do not establish causality, but they

indicate that the post-CAS increase in end-of-day movement is not mirrored by the contemporaneous benchmark.

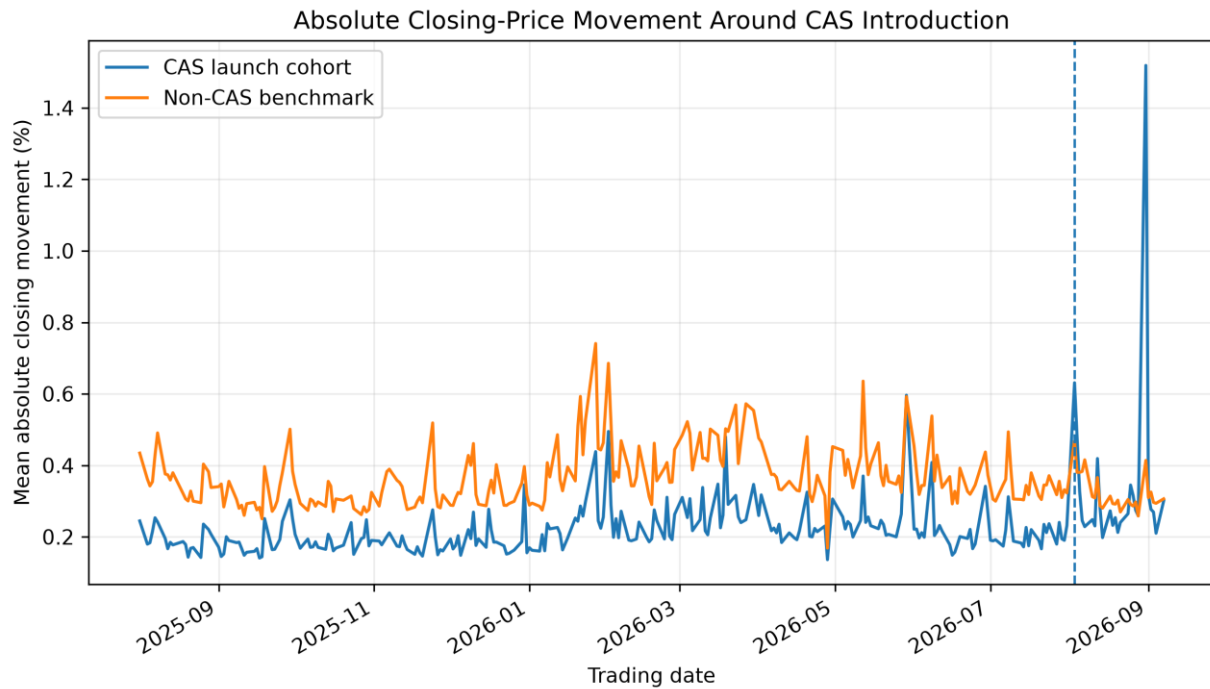


Figure 1. Daily mean absolute closing movement around CAS introduction

Note. The vertical line marks 3 August 2026. The figure is descriptive; formal inference uses the six-month pre-period.

4.2 Robustness across pre-periods

The reform pattern is stable under alternative pre-period definitions. With three months of pre-CAS data, mean signed closing return for CAS stocks rises by 0.092 percentage points ($p = 0.004$) and mean absolute movement rises by 0.115 percentage points ($p = 0.016$). Under the twelve-month window, the corresponding increases are 0.120 and 0.125 percentage points. CAS-minus-benchmark comparative changes remain positive and statistically significant across the three-, six-, and twelve-month windows. Across alternative pre-period definitions, CAS is associated with a material change in closing-price formation. This result should not be interpreted as direct evidence that price discovery improved. A larger closing adjustment can reflect faster incorporation of information, temporary liquidity pressure, or a combination of the two. The persistence analysis therefore provides the more discriminating evidence.

4.3 Auction moves and next-open reversal

Table 4. Price-pressure and auction-magnitude regressions

Variable	R1	R2	R3	M1
Auction return	-0.4444*** (0.0453)	-0.4574*** (0.0398)	-0.3905*** (0.0417)	
Pre-close return		0.1360*** (0.0349)	0.1149*** (0.0339)	
Pre-close		-0.0754	-0.0731	0.1991***

Variable	R1	R2	R3	M1
realized volatility		(0.0808)	(0.0794)	(0.0406)
Pre-close volume share		-0.0011 (0.0024)	-0.0013 (0.0024)	0.0041** (0.0017)
Log auction value		0.0004 (0.0003)	0.0004 (0.0003)	0.0014*** (0.0005)
Log auction intensity		-0.0012** (0.0005)	-0.0011* (0.0005)	0.0041*** (0.0005)
Auction return × intensity			-0.0838*** (0.0264)	
Absolute pre-close return				0.0477 (0.0298)

Note. R1–R3 dependent variable: next-open log return; M1 dependent variable: absolute auction log return. R1–R3 include stock and date fixed effects. Parentheses report two-way stock/date clustered standard errors. *** $p < .01$, ** $p < .05$, * $p < .10$.

The central reversal coefficient is strongly negative. In the parsimonious stock/date fixed-effects model, the coefficient on auction return is -0.4444 (clustered SE = 0.0453). Adding pre-close conditions, auction value, and auction intensity produces a coefficient of -0.4574 (SE = 0.0398). In elasticity-like terms for small log returns, a 1% larger stock-specific auction move is associated with an approximately 0.46% movement in the opposite direction by the next opening, conditional on the model. This should not be read as a mechanical statement that 46% of every individual auction move reverses.

The coefficient remains close to -0.45 after winsorization. The stability of the estimate under capping of extreme observations reduces the likelihood that a handful of unusually large returns account for the finding. The panel evidence is therefore consistent with a substantial temporary component in stock-specific auction price impact.

Auction intensity strengthens the interpretation. In the interaction model, the auction-return coefficient remains negative (-0.3905), while the auction return × log auction intensity coefficient is -0.0838 (SE = 0.0264). The marginal reversal slope therefore becomes more negative as auction volume rises relative to the preceding 15-minute trading window. The interaction coefficient is a change in the reversal slope per one-unit increase in log intensity; it should not be interpreted as an 8.4% reversal rate.

The auction-magnitude model provides complementary evidence. Larger absolute auction returns are positively associated with auction intensity, auction value, pre-close realized volatility, and pre-close volume share. Absolute pre-close return is not statistically significant. Participation and surrounding trading conditions therefore matter for auction-move magnitude, although not every proposed pre-close channel is statistically relevant.

4.4 Daily cross-sectional evidence and magnitude sorting

Table 5. Daily cross-sectional reversal and robustness

Specification	Dates	Mean β	Median β	Negative days	HAC SE	p-value
Aggregate	25	-0.103	—	—	0.202	0.6165

Specification	Dates	Mean β	Median β	Negative days	HAC SE	p-value
daily mean regression						
Baseline daily cross-sectional	25	-0.325	-0.319	96.0%	0.044	<0.0001
Controlled daily cross-sectional	25	-0.336	-0.356	96.0%	0.043	<0.0001
Largest 20% auction moves	25	-0.344	-0.304	100.0%	0.029	<0.0001
Alternative opening-price rule	25	-0.336	-0.356	96.0%	0.043	<0.0001
Exclude first five CAS days	20	-0.315	-0.333	95.0%	0.051	<0.0001
Exclude top 1% auction value	25	-0.335	-0.356	96.0%	0.043	<0.0001
Exclude top 1% auction moves	25	-0.334	-0.339	96.0%	0.043	<0.0001

Note. Each daily beta is estimated cross-sectionally on one trading date. Mean-beta inference uses HAC standard errors over the time series of daily slopes. The aggregate daily mean regression is a separate robustness check, not a Fama–MacBeth slope.

The daily cross-sectional estimates demonstrate that the panel result is not an artifact of treating thousands of stock-days as independent. The controlled daily slope averages -0.336, has a median of -0.356, and is negative on 24 of 25 dates. The baseline daily cross-sectional estimate is similar (-0.325). The consistency of the sign across dates is important because the available post-reform time span is short even though the stock-day panel is large.

The aggregate date-level mean regression produces a much smaller and statistically insignificant coefficient (-0.103, HAC SE = 0.202, $p = 0.6165$). This contrast indicates that the main finding concerns relative stock-specific dislocations within each trading day rather than a broad market-wide CAS reversal. Common market news that moves many securities in the same direction is therefore not the primary source of the estimated cross-sectional effect.

Magnitude sorting reinforces this conclusion. The directional next-open reversal share increases from 35.8% in the smallest auction-move quintile to 65.8% in the largest. Restricting the daily cross-sectional regression to the largest 20% of auction moves yields a mean slope of -0.344, negative on all 25 dates.

The reversal relationship is therefore strongest precisely where temporary liquidity pressure would be expected to be most visible.

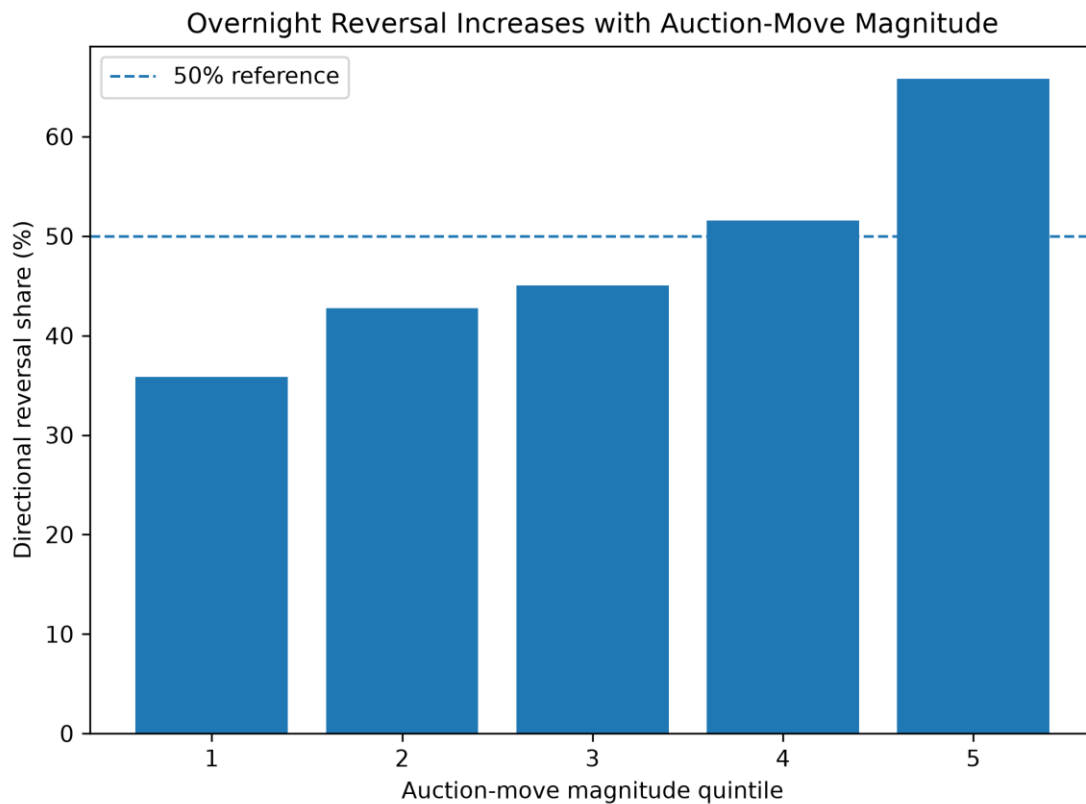


Figure 2. Directional next-open reversal by auction-move magnitude quintile

4.5 Robustness

The reversal result survives several checks aimed at early-sample sensitivity and extreme observations. Allowing the first available opening price within five minutes of 09:15 leaves the controlled mean daily slope at -0.336. Excluding the first five CAS trading days, when participants may still have been adapting to the new mechanism, produces a mean slope of -0.315 and a negative coefficient on 95% of the remaining dates.

Removing observations above the 99th percentile of auction value leaves the mean slope at -0.335. Removing observations above the 99th percentile of absolute auction returns produces -0.334. These trimming exercises differ from the winsorization check, which caps rather than deletes extreme values. The similarity across specifications suggests that the central reversal result is not driven by the implementation week or by a small number of extreme auction observations.

5. Discussion and Implications

5.1 Hypothesis assessment and relation to prior evidence

The evidence supports a hybrid interpretation rather than a binary judgment about the success or failure of CAS. The reform materially changes end-of-day price formation: signed and absolute closing movements increase for the launch cohort relative to its pre-reform history, while the broad non-CAS benchmark does not show the same pattern. Yet the stock-specific component of large auction

adjustments is not fully persistent. A substantial opposite-signed next-open movement appears across most trading days and is strongest for large auction moves and high auction intensity.

Against the stated hypotheses, the evidence is differentiated rather than uniform. H1 is supported in its non-directional form because the distribution of closing-mechanism returns changes materially after CAS. H2 receives strong support at the stock-specific level because auction returns are followed by systematic opposite-signed next-open movements, but the insignificant aggregate daily mean regression cautions against interpreting this as a market-wide reversal. H3 is partially supported: auction intensity, auction value, pre-close volatility, and pre-close volume concentration are associated with auction-move magnitude or persistence, while some proposed pre-close channels are not statistically significant.

This combination is consistent with the broader closing-auction literature. Evidence from Paris and London shows that closing calls can improve liquidity aggregation and price discovery (Chelley-Steeley, 2009; Pagano & Schwartz, 2003), while Kandel et al. (2012) show that auction design affects liquidity-supplier behavior around the close. At the same time, Jegadeesh and Wu (2022) and Bogousslavsky and Muravyev (2023) document temporary closing-auction price impact and subsequent reversal. The Indian results therefore fit a framework in which an auction can improve the coordination of closing liquidity while still generating transitory cross-sectional price pressure when participation is concentrated.

The distinction between aggregate and stock-specific reversal is particularly important. The insignificant aggregate daily mean regression does not support a claim that CAS systematically pushes the entire market away from fundamental value and then reverses the next morning. Instead, the daily cross-sectional evidence shows that stocks experiencing relatively larger auction moves tend to move in the opposite direction at the next open. This is a narrower and more defensible interpretation of temporary price pressure.

5.2 Regulatory and market implications

For exchanges and regulators, the relevant design objective is not to eliminate closing-price movement. Genuine information should be reflected in the official close. The more relevant question is whether the auction attracts sufficient two-sided liquidity to prevent concentrated demand from generating avoidable transitory dislocations. The negative interaction between auction return and auction intensity suggests that participation volume relative to immediately preceding trading conditions deserves attention when monitoring market quality.

For institutional investors and benchmark trackers, the findings indicate that execution at the auction close can carry meaningful short-horizon price impact in individual securities when participation is concentrated. This does not imply that investors should mechanically trade against auction movements; the study does not evaluate a tradable strategy after transaction costs, market impact, or overnight risk. It does imply that the auction close should be treated as a distinct microstructure state rather than as a mechanical continuation of pre-15:15 continuous trading.

The findings are also relevant to derivatives-market participants because the Phase 1 universe is defined by derivative eligibility and the official cash close can have settlement relevance. However, the present design does not isolate derivatives-expiry effects, trader identity, or directional order imbalance. Those mechanisms require a longer sample and richer order-level data. The current evidence should therefore be read as documenting persistence patterns and conditional associations rather than identifying the motives of auction participants.

5.3 Methodological implications

Methodologically, the study illustrates the value of resisting an attractive but unsupported causal design. The treated and non-treated universes differ sharply by construction because derivative eligibility is related to liquidity and size. Matching and overlap weighting did not produce adequate balance. Rather than report a causal DiD estimate despite failed diagnostics, the paper retains the benchmark as descriptive context and places stronger weight on within-auction persistence tests. This distinction reduces causal overstatement and makes the interpretation more consistent with the available data.

6. Limitations and Future Research

The principal limitation is the short post-reform horizon. The sample contains 26 CAS trading dates and only 25 dates with usable next-session opening prices. The daily cross-sectional consistency and robustness checks help address this constraint, but they cannot substitute for a longer period that includes additional market states, expiry cycles, and participant adaptation.

Second, the non-CAS benchmark is informative but not causal because treatment-control common support is inadequate. The results therefore establish a reform-associated change for the launch cohort and a strong stock-specific post-auction reversal pattern, but they do not identify a causal average treatment effect of CAS relative to an untreated counterfactual.

Third, one-minute OHLCV data cannot reconstruct the exchange's transaction-level reference-price calculation exactly, so official NSE reference and auction prices are used whenever the auction itself is measured. Fourth, the historical archive does not contain usable signed imbalance and equilibrium-quantity fields across the full sample. This prevents direct identification of whether the temporary component originates from buy-side or sell-side imbalances, dealer inventory constraints, benchmark execution, or other sources.

Future research can extend the present design in three directions. A longer post-CAS sample can trace whether reversal attenuates as participation deepens and traders adapt. Intraday next-day horizons can show how quickly the temporary component dissipates after the market reopens. Finally, expiry-day and liquidity heterogeneity can help determine whether temporary price pressure is especially pronounced when settlement demand or limited liquidity provision concentrates trading at the close.

7. Conclusion

India's new Closing Auction Session materially alters closing-price formation for derivative-eligible equities. In the primary six-month specification, signed and absolute closing movements rise for the CAS launch cohort, while the broad non-CAS benchmark does not display the same pattern. Because common-support diagnostics fail, these benchmark differences are treated as comparative rather than causal.

The stronger evidence concerns what happens after the auction. Stock-specific auction movements systematically reverse at the next open. The controlled mean daily reversal slope is -0.336, is negative on 24 of 25 trading dates, and remains close to -0.33 after alternative opening-price treatment, exclusion of the first implementation week, and trimming of extreme auction values and returns. The effect is also stronger for large auction moves and when auction intensity is high.

The hypothesis tests are therefore best read jointly: CAS changes closing-price formation, stock-specific auction moves contain a temporary component, and the strength of that component varies with auction

participation and surrounding trading conditions. The evidence is strongest for the stock-specific reversal channel and more qualified for the broader mechanism hypotheses.

Taken together, the evidence favors a mixed price-discovery and price-pressure interpretation. CAS appears to concentrate trading and materially reshape the close, yet unusually large stock-specific auction adjustments contain a temporary component that does not fully survive the next resumption of continuous trading. Continued observation as the mechanism matures will be important for determining whether deeper participation and liquidity provision reduce that temporary component.

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