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Compliance with Ethical Standards

Ethical Approval

This study does not involve human participants, clinical experimentation, or the collection of primary data from individuals. The research is based exclusively on secondary data obtained from the CMIE ProwessIQ database and the National Stock Exchange of India(NSE). Accordingly, ethical approval relating to human participants was not required for this study.

Informed Consent

Not applicable. This study does not involve human participants, surveys, interviews, or the collection of personal or identifiable information from individuals.

Conflict of Interest

The authors declare no conflicts of interest that could have influenced the conduct, analysis, interpretation, or reporting of this research.

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Author Contributions

The first author contributed to the conceptualization and design of the study, data collection, data analysis, interpretation of results, and manuscript preparation. The second author contributed to the literature review, research design, validation of the analysis, and critical revision of the manuscript. Both authors reviewed and approved the final manuscript.

Consent for Publication

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Subject to the applicable database licensing and access conditions, further information regarding the data and variables used in the study may be obtained from the corresponding author upon reasonable request.

Competing Interests

The authors declare that they have no competing interests.

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Abstract

This paper decomposes the implied-volatility smile of Nifty-50 index options into a symmetric component (Symmetric Curvature) and a directional component (Directional Curvature) and asks whether the two respond to net order-flow demand, liquidity, and systemic shocks through the same channel or through distinct mechanisms. Using 3,547 trading days of daily curvature estimates for calls and puts separately (2008–2024), we test this against net buying pressure in out-of-the-money contracts — the demand constructs central to demand-based option-pricing theory but never previously used in this literature to explain curvature directly. A dynamic specification with predetermined regressors and Newey–West standard errors is estimated for four systems (call/put × symmetric/directional), together with a formal multiple structural-break test of the COVID-19 shock and a pooled call-versus-put model with a Wald test of coefficient equality. After correcting for multiple testing, we find that net buying pressure has a differential effect on directional relative to symmetric curvature for calls but not for puts, and that liquidity does not significantly amplify the demand effect on either side once corrected. We further find that a maturity–volatility interaction is broadly present but not cleanly specific to directional pricing, that only put-side directional curvature shows a genuine, non-reverting shift coinciding with the second COVID-19 wave, and the most robust finding across every specification is that calls and puts respond to demand, liquidity, and volatility in significantly different ways. The paper's contribution is a demand-based decomposition of tail-risk pricing, tested with a direct order-flow proxy in an emerging, retail-dominated market, and a formally tested account of whether a systemic shock produced a structural or merely persistent change in that pricing mechanism.

Keywords: Implied volatility smile; Net buying pressure; Crash risk; Call–put asymmetry; Nifty-50 index options

JEL Classification: G13; G12; G15; C58; G01

1. Introduction

Index options do not price risk with a single number. The shape of the implied-volatility smile carries at least two distinct pieces of information: how much uncertainty the market prices in general, and which direction — calls or puts, upside or downside — that uncertainty is concentrated in. A steep, symmetric smile says the market expects large moves without a strong view on direction; a smile skewed toward one wing says the market is specifically pricing crash risk or melt-up risk. Separating these two components matters for asset pricing, risk management, and understanding whether options markets function as insurance markets, speculative markets, or both.

Existing volatility-smile research has extensively documented curvature and skew, but almost entirely in developed, dealer-intermediated markets, and almost always as a descriptive exercise rather than as a test of a specific economic mechanism. Demand-based option-pricing theory (Garleanu, Pedersen, and Poteshman, 2008; Bollen and Whaley, 2004) offers a candidate

mechanism — end-user order flow that dealers cannot fully hedge should move prices, a friction rooted in the broader limits-to-arbitrage literature (Shleifer & Vishny, 1997), and net buying pressure in out-of-the-money contracts should matter more than aggregate volume, as recently confirmed directly for retail order flow (Eaton, Green, Roseman, & Wu, 2026). This theory has rarely been tested directly against the *directional* component of the smile specifically, as distinct from its overall intensity, and essentially never in an emerging, retail-dominated market where the frictions the theory relies on — limited dealer capacity, wider spreads, thinner depth — are, if anything, more likely to bind. India-specific work has documented the smile itself (Shaikh & Padhi, 2014; Jain, Varma, & Agarwalla, 2019) and the effect of the COVID-19 shock on option-implied tail risk (Agarwalla, Varma, & Virmani, 2021), but neither the demand-curvature decomposition nor its interaction with liquidity, maturity, and the pandemic shock has been jointly tested in this setting.

This leaves a genuine, unresolved question. If Symmetric Curvature and Directional Curvature are two views of the same underlying process, they should respond to demand, liquidity, and volatility in the same way. If they are economically distinct — one reflecting generalized uncertainty, the other reflecting specifically directional hedging or speculative pressure — they need not. Prior work has not tested this distinction directly, largely because the demand-based mechanism it implies has not been operationalized using a direct order-flow proxy in this setting. The literature's limitation is therefore not a lack of curvature measures but a lack of a direct test: no existing study observes net buying pressure and both components of curvature jointly, daily, across a full pre-crisis, crisis, and recovery cycle, in a market where retail participation is large enough that demand-based frictions plausibly matter more than in a dealer-dominated developed market. This paper tries to fill the gap using seventeen years of daily Nifty-50 index-option data (2008–2024), separately for calls and puts, with net buying pressure in out-of-the-money contracts as the demand proxy, estimated with a dynamic specification, a formal structural-break test of the COVID-19 shock, and a pooled model that directly tests whether calls and puts respond differently.

The results are mixed. Net buying pressure has a significant, differential effect on Directional versus Symmetric Curvature for call options, but not for puts, once multiple testing is accounted for. A hypothesized liquidity-amplification effect is not supported in either direction after correction. A maturity–volatility-regime interaction is present and significant for put-side Directional Curvature and for both Symmetric-Curvature systems, but not distinctly for call-side Directional Curvature, indicating the effect is not as directionally specific. The COVID-19 shock produced a formally detected, persistent, non-reverting shift in the demand–curvature relationship for put-side Directional Curvature specifically, but the same shift is not found for calls or for put-side Symmetric Curvature, and the shock's magnitude is not distinctively larger than the breaks the same series exhibits at unrelated points in its seventeen-year history. Most consistently across all specifications, calls and puts do not behave as two sides of a single process — the asymmetry between them, confirmed by a pooled model that consistently rejects the equality of their coefficients.

This paper's contribution is twofold. First, it provides an empirically tested decomposition of symmetric versus directional tail-risk pricing, using net buying pressure as the direct empirical counterpart to demand-based pricing theory, rather than the put–call-ratio proxies used previously, in a market structure where this mechanism has not been tested. Second, it provides a formally tested account of whether a systemic shock produced a structural or merely persistent change in

that pricing mechanism, with the answer calibrated to the evidence. The results show that this asymmetry between calls and puts is the paper's central and most robust finding.

The remainder of this paper proceeds as follows. Section 2 develops the theoretical framework, reviews the literature, and formulates five hypotheses. Section 3 describes the data, variable construction, and empirical methodology. Section 4 reports and discusses the results. Section 5 concludes with limitations and implications.

2. Theoretical Background, Literature Review, and Hypotheses Framing

Two explanations compete to account for why implied-volatility smiles curve away from the flat surface predicted by Black-Scholes-Merton (Black & Scholes, 1973). The first is structural: jumps and stochastic volatility in the return-generating process produce fat-tailed distributions and curved implied-volatility functions (Merton, 1976; Andersen & Andreasen, 2000; Gugole, 2016), with jump risk mattering most at short horizons and largely independent of trading motive (Andersen, Bollerslev, & Diebold, 2007). The second is frictional: net buying pressure dealers cannot fully hedge shifts in implied volatility directly through dealer inventory risk and imperfect hedging (Shleifer & Vishny, 1997). A polynomial decomposition in standardized moneyness separates the smile into symmetric (quadratic) and directional (cubic) components (Zhang & Xiang, 2008; Peña, Rubio, & Serna, 1999; Derman & Miller, 2016) — though some curvature can arise from numerical artifacts, a caution this study takes seriously (Chance, Hanson, Li, & Muthuswamy, 2017). Because directional order flow is inherently asymmetric, whereas jump risk need not be, these components need not respond to demand, liquidity, or systemic shocks.

2.1 Directional Demand Effect

Does net buying pressure move directional (cubic) curvature differently than symmetric (quadratic) curvature? Demand-based option-pricing theory (Bollen & Whaley, 2004; Garleanu, Pedersen, & Poteshman, 2008) predicts that net buying pressure moves implied volatility through directional dealer inventory effects rather than the underlying's true distribution — a channel recently confirmed for retail order flow (Eaton, Green, Roseman, & Wu, 2026); the quadratic/cubic decomposition applied elsewhere in emerging markets (Yue, Gehricke, Zhang, & Pan, 2021) confirms both components are meaningful, but does not test whether they share a common driver. No prior study tests whether net buying pressure has a differential effect on directional versus symmetric curvature within the same option type — existing tests examine the smile's slope or intensity as a whole — so this study estimates separate dependent variables and formally tests coefficient equality.

H1: Net buying pressure in out-of-the-money puts affects directional (cubic) curvature differently than it affects symmetric (quadratic) curvature.

2.2 Liquidity Amplification

Does thin liquidity strengthen the demand effect on directional curvature? This mechanism operates through dealer risk-bearing capacity — the same net demand should move prices more when dealers face wider inventory constraints — and liquidity costs are independently shown to be priced directly into option values (Chou, Chung, Hsiao, & Wang, 2011), consistent with liquidity conditioning the demand effect rather than merely adding to it. No existing study tests this interaction directly against curvature, since liquidity and demand are typically examined as

separate controls. This study, therefore, estimates a centered interaction between net buying pressure and underlying market liquidity on directional curvature (Equation 4).

H2: The effect of net buying pressure on directional curvature is stronger when underlying-market liquidity is thin.

2.3 Regime-Dependent Term Structure

Does maturity's effect on directional curvature depend on the prevailing volatility regime? Smile curvature is maturity-dependent, flattening with time to expiry (Li, Xian, & Lin, 2021), while jump-related skew is most pronounced at short maturities and should attenuate as maturity lengthens unless volatility conditions sustain it (Section 2.0); trading volume separately improves forecasts of smile dynamics (Le & Zurbruegg, 2014), and the smile's slope forecasts future jump size and returns (Yan, 2011). Whether this interaction is specific to directional pricing or a broader smile-intensity feature has not been tested; this study estimates a centered maturity-by-volatility interaction on both components (Equation 4).

H3: Longer-dated contracts carry more directional asymmetry, specifically when realized volatility is high.

2.4 Structural versus Temporary COVID Effect

Did the COVID-19 shock produce a lasting change in how demand translates into directional pricing, or only a temporary repricing that should fade? Implied-volatility smile dynamics transmit across markets with particular intensity during crises, with India a net receiver rather than a source of such spillovers (Chen, Han, Ryu, & Tang, 2022), and evidence that COVID-19 shifted option-implied tail-risk moments in Nifty options (Agarwalla, Varma, & Virmani, 2021); yet whether such an alteration is structural or temporary has not been tested formally in any market. The literature relies on calendar dummies narrated as evidence of change rather than tested as such. This study replaces narration with a structural-break procedure applied to the curvature series, combined with a test of whether the demand-curvature coefficient shifts across the detected break (Equation 5).

H4: The COVID-19 shock produced a discrete, non-reverting change in the slope linking demand to directional curvature, not merely a temporary level shift.

2.5 Asymmetric Call/Put Response

Do calls and puts respond differently to demand, liquidity, and volatility simultaneously — as a system, not just in one coefficient? The demand-based mechanism is directional by construction: net buying pressure in puts (crash protection) and in calls (speculative or melt-up demand) are distinct order-flow phenomena. Sui, Wang, and Liu (2025) find investor sentiment raises curvature in calls but lowers it in puts; the same maturity-dependence study finds calls and puts load on different determinants; Ryu, Ryu, and Yang (2023) find domestic individual-investor sentiment has the strongest effect on out-of-the-money implied volatility — yet none tests call/put asymmetry formally against a joint battery of regressors, relying instead on separate models compared narratively. This study pools both option types and includes a full set of interaction terms, which are tested using a joint Wald statistic (Equation 6, Section 4.4).

H5: Call- and put-side directional curvature respond differently to net buying pressure and to the other liquidity and volatility regressors, consistent with a directionally asymmetric investor base.

Two further studies motivate this setting: Kim and Ryu (2015) and Tanha and Dempsey (2015) document institution and liquidity-dependent variation in the smile in Korean and Australian options. India-specific evidence exists alongside this — the smile itself is documented (Shaikh & Padhi, 2014; Jain, Varma, & Agarwalla, 2019) — but none test net buying pressure against both curvature components jointly through a full pre-crisis, crisis, and recovery cycle. The five hypotheses collectively close that gap: H1 and H5 test whether demand operates through a directionally distinct channel; H2 and H3 test the conditions under which it operates; H4 tests whether a systemic shock changed it structurally. Collectively, they underpin this study's two contributions — a tested decomposition of symmetric versus directional tail-risk pricing, and a formally tested account of the effect of a systemic shock on that pricing mechanism (Section 5).

3. Data, Variable Measurement, and Empirical Methodology

3.1 Institutional Context and Data

The Nifty-50 index options market on the National Stock Exchange of India is one of the highest-volume derivatives markets globally and is widely characterized as more heavily weighted toward retail and proprietary trading than typical developed-market index-option markets. In markets with less concentrated dealer capacity, net buying pressure is more likely to move prices than in markets where large dealers' net exposures span a broad client base.

3.2 Sample Construction and Observation Unit

The sample covers the period from Jan 2008 to December 2024. Call and put options are treated as two separate systems throughout. However, curvature values are pooled across option type only for the pooled test in Section 4.7, after within-type standardization. The observation unit is one curvature estimate per calendar day per option type, using all near-month contracts with at least 10 contracts traded on that day when multiple expiries are traded. Call and put contract availability does not perfectly overlap, so the two option-type files were reduced to their common trading dates. After the one-day lag structure in Section 3.5, the estimation sample comprises 3,547 trading days for each option type.

3.3 Implied Volatility and Curvature Measurement

Implied volatility is not observed directly; it is derived by numerically inverting the Black–Scholes–Merton pricing equation to match the model's theoretical price to the option's observed market price. Under the Black–Scholes assumptions, a European call and put are priced as

$$C = S_0 N(d_1) - Ke^{-rT} N(d_2) \quad \text{.....(1)}$$

$$P = Ke^{-rT} N(-d_2) - S_0 N(-d_1) \quad \text{.....(2)}$$

$$d_1 = \frac{\ln(S_0/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}, \qquad d_2 = d_1 - \sigma\sqrt{T} \quad \text{..... (3)}$$

In equations (1) to (3), S0 is the underlying price, K the strike, T time to maturity, r the risk-free rate, N(·) the standard normal CDF, and σ volatility. Because no closed-form inverse of Equations (1)– (2) exists, implied volatility σIV is obtained numerically as the value of σ solving $C_{\text{market}} = C_{BS}(S_0, K, T, r, \sigma_{IV})$ or the analogous put equation.

For each trading day and option type, the resulting cross-section of implied volatilities across available strikes is fitted to a cubic polynomial in standardized moneyness:

$$\sigma_{IV}(M) = \beta_0 + \beta_1 M + \beta_2 M^2 + \beta_3 M^3 + \varepsilon \ldots\ldots\ldots\ldots (4)$$

In equation (4), M = ln(K/F) is log-moneyness relative to the forward price F. The quadratic coefficient β_2 (Symmetric Curvature) captures how sharply implied volatility rises as strikes move away from at-the-money in either direction. The cubic coefficient β_3 (Directional Curvature) captures the asymmetry between the smile's two wings — whether downside strikes are priced more expensively than equivalent upside strikes — and is this study's proxy for directional, crash-specific tail-risk pricing. This paper treats the resulting daily curvature series as validated inputs and does not re-derive the underlying strike-level fitting procedure. Both series are winsorized at the 1st/99th percentiles within each option type before standardization.

3.4 Measurement of Call and Put Net Buying Pressure

The primary demand proxy in this study is Net Buying Pressure, measured separately for calls and puts as the daily net order-flow imbalance in out-of-the-money (OTM) contracts — buyer-initiated minus seller-initiated trading volume — following Bollen and Whaley (2004):

$$\text{NBP}_{i,t} = \text{BuyVolume}_{i,t}^{(\text{OTM})} - \text{SellVolume}_{i,t}^{(\text{OTM})} \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

In equation (5), i ∈ {Call, Put} indexes the option type, and t indexes the trading day. A positive value indicates net buying pressure, where demand exceeds supply; a negative value indicates net selling pressure. Both series are winsorized at the 1st and 99th percentiles within each option type and one day lagged before entering the regressions.

3.5 Empirical Model Specification

Four related specifications are estimated, each building on the one before it: a primary dynamic model, a conditional-interaction extension of it, a structural-break test applied to it, and a pooled version stacking both option types. Table 1 provides the complete variable-by-variable reference (symbol, measurement, economic role) used across all four.

3.5.1 Primary Dynamic Specification

For each of four systems — Symmetric/Directional Curvature, calls/puts — the primary specification is a dynamic OLS model with one lagged dependent variable and Newey–West (1987) heteroskedasticity- and autocorrelation-consistent standard errors:

$$\begin{aligned}\text{Curvature}_t = \alpha + \rho\,\text{Curvature}_{t-1} + \beta_1\text{NBP_Call}_{t-1} + \beta_2\text{NBP_Put}_{t-1} + \beta_3\text{Liquidity}_{t-1} \\ +\beta_4\text{Turnover}_{t-1} + \beta_5\text{OpenInterest}_{t-1} + \beta_6\text{Maturity}_{t-1} + \beta_7\text{Rate}_{t-1} \\ +\beta_8\text{RealizedVol}_{t-1} + \beta_9\text{Skewness}_{t-1} + \beta_{10}\text{JumpFreq}_{t-1} + \text{Weekday FE} \\ +\varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots (6)\end{aligned}$$

In equation (6), Continuous regressors and the dependent variable are standardized; weekday dummies remain 0/1 (Monday as the reference). Standard errors use Newey–West lags chosen by $\max\left(1, \left\lfloor 4(n/100)^{2/9} \right\rfloor\right)$ giving 8 lags for n = 3,547, and are not clustered by date, since the panel has one observation per calendar date. Measurements of all variables are provided in Table 1.

3.5.2 Conditional Interaction Model

Equation (6) is extended with two centered interaction terms to test the conditional hypotheses H2 and H3:

$$\begin{aligned}\text{Curvature}_t = \text{Equation (6)} + \gamma_1(\text{NBP_Put}_{t-1} \times \text{Liquidity}_{t-1}) \\ +\gamma_2(\text{Maturity}_{t-1} \times \text{RealizedVol}_{t-1}) + \varepsilon_t \ldots\ldots\ldots\ldots\ldots (7)\end{aligned}$$

In equation (7), γ_1 captures whether the demand effect on directional curvature is conditional on underlying-market liquidity (H2), and γ_2 captures whether it is conditional on the prevailing volatility regime at longer maturities (H3); both interaction terms are centered on their sample means before multiplication.

3.5.3 Structural-Break Coefficient-Shift Test

The COVID-19 shock is tested with a multiple structural-break procedure (dynamic-programming least-squares partitioning) (Bai & Perron, 1998, 2003) applied to the curvature series, together with a test of whether the demand–curvature coefficient shifts across the detected break:

$$\begin{aligned}\text{Curvature}_t = \alpha + \rho\,\text{Curvature}_{t-1} + \beta\,\text{NBP_Put}_{t-1} + \delta(\text{NBP_Put}_{t-1} \times \text{PostBreak}_t) \\ +\text{Controls}_{t-1} + \text{Weekday FE} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots (8)\end{aligned}$$

In equation (8), PostBreak(t) denotes dates on or after the detected break; a significant δ indicates that the demand–curvature relationship itself shifted, not merely the mean level of the curvature series.

3.5.4 Pooled Call/Put Model

Calls and puts are then pooled into a single panel to test directly whether they respond identically to the same regressors:

$$\begin{aligned}\text{Curvature}_t = \alpha + \rho\,\text{Curvature}_{t-1} + \beta\,\mathbf{X}_{t-1} + \lambda\,\text{Put}_t + \sum_j \theta_j\left(\text{Put}_t \times X_{j,t-1}\right) \\ +\text{Weekday FE} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots (9)\end{aligned}$$

In equation (9), Curvature(t) stacks the standardized directional-curvature series for both option types, put(t) indicates put observations, and X(t−1) is the full regressor vector from Equation (6)

(own-side net buying pressure per row). A Wald test of $\theta_j = 0$ for all j tests calls and puts respond identically, the formal test underlying H5.

4. Results and Discussion of Findings

4.1 Descriptive Statistics and Correlation Analysis

Table 2 reports descriptive statistics for calls and puts, consistent with the documented shape of the option smile in the Indian market (Shaikh & Padhi, 2014). Net buying pressure is right-skewed even after winsorization (kurtosis 14.1 and 18.6 for Call and Put Net Buying Pressure, down from 345 and 1,336 pre-winsorization), with meaningful zero-mass (7.6% and 10.1% of days). This is consistent with intermittent, rather than continuous demand. Table 3 reports correlations and VIFs: Turnover correlates with Open Interest at 0.61, and Liquidity with Realized Volatility at 0.59. The maximum VIF is 2.35 for calls and 2.95 for puts, well below the threshold for concern. Symmetric Curvature (Put) does not, though this traces to a COVID-era break rather than genuine integration, all four series are modeled in levels.

4.2 Baseline Results

Table 4 reports the Equation 6 estimates for all four systems. The lagged dependent variable is large and highly significant across models (0.398–0.631), and the overall model fit ranges from $R^2 = 0.231$ to 0.655 ($F = 49.5–325.7$, $p < 0.001$). The variable central to every subsequent hypothesis, Put Net Buying Pressure, is significant in three of the four systems: positive for Symmetric Curvature (Call) (0.037, $p < 0.05$), negative for Directional Curvature (Call) (−0.068, $p < 0.001$), and negative for both put systems (−0.021 and −0.029, $p < 0.05$ and $p < 0.01$, respectively). This mean-based pattern is examined further in Table 9, which tests via quantile regression whether the Put Net Buying Pressure effect holds uniformly across the curvature distribution or is concentrated in its tails. The same demand variable, therefore, moves the two curvature components of the same option type in different directions. This pattern is the empirical basis for H1, which asks whether net buying pressure affects directional and symmetric curvature differently, within the symmetric/directional decomposition (Zhang & Xiang,2008).. A block-bootstrap test formally compares the directional and symmetric coefficients within each option type (Table 4, Panel B). The null of equality is rejected for calls (difference = −0.105, $p < 0.0001$) but not for puts ($p = 0.52$). Demand-based pricing theory (Bollen & Whaley, 2004; Garleanu, Pedersen, & Poteshman, 2008) predicts a positive effect on directional curvature specifically. The difference between the directional and symmetric coefficients — significant for calls, not for puts — runs in the opposite direction from what demand-based theory predicts. Table 5 confirms this dynamic specification is preferred to a static alternative: adjusted R^2 improves by 0.078 to 0.248 across the four systems.

H2 and H3 test whether this demand effect depends on liquidity and maturity, respectively, using the interaction coefficients in Table 6. H2 — the Put Demand × Liquidity interaction — is only marginally significant before correction. It is tested separately for the Symmetric and Directional systems in both calls and puts, yielding four tests in total, and none of them survive adjustment for multiple testing (Benjamini & Hochberg, 1995; Table 11). H2 is therefore not supported.

H3 — the Maturity × Volatility interaction — fares better: it is significant for Directional Curvature (Put) and for both Symmetric-Curvature systems after correction, but not for Directional Curvature (Call). This is an interesting result, consistent with Yan's (2011) evidence that smile

slope carries jump-risk information conditional on maturity, and with Li, Xian, and Lin's (2021) maturity-dependent "dying smile" pattern.

H4 asks whether the COVID-19 shock shifted the demand–curvature relationship itself, rather than merely the level of the curvature series. Only Directional Curvature (Put) shows a significant coefficient shift across the COVID-adjacent break (−0.118, $p = 0.002$, surviving correction); neither Directional Curvature (Call) nor Symmetric Curvature (Put) shows this shift. The full rolling-coefficient and structural-break evidence behind this result is presented in Section 4.4.

H5 tests whether calls and puts respond identically to the full set of regressors, using a pooled model (Table 8). The joint test of nine Put-interaction terms rejects equality ($F = 184.7$, $p < 10^{-10}$) — the most robust result in the paper, and consistent with Ryu, Ryu, and Yang's (2023) finding that domestic individual-investor sentiment affects out-of-the-money implied volatility asymmetrically. The full regressor-by-regressor picture behind this result is presented in Section 4.5.

Table 10 takes each system's standardized H1 coefficient from Table 4 and tests its sensitivity: what predicted curvature does when Put Net Buying Pressure shifts from its 25th to 75th percentile, rather than by one abstract standard deviation. That turns a statistically significant coefficient into a concrete, interpretable size. Moving Net Buying Pressure from its 25th to 75th percentile shifts predicted curvature by 0.008 to 0.025 standard deviations — negative for three of the four systems (Directional Call, Symmetric Put, Directional Put) and positive only for Symmetric Call. Set against the lagged dependent variable's own contribution of 0.40 to 0.63 standard deviations, this demand effect is statistically robust but economically modest: a secondary driver of curvature, not the dominant one.

4.3 Conditional Effects

Figure 3 plots the marginal effects underlying H2 and H3, calculated directly from Equation 7 coefficients across each variable's observed range. For H2, the predicted-curvature lines for low- and high-liquidity states diverge only modestly across the Put Net Buying Pressure range. This is consistent with the interaction's failure to survive correction (Table 6). For H3, the low- and high-volatility lines diverge visibly across the maturity range for both option types, most sharply for calls, confirming the interaction is significant (Table 6). This is consistent with Le and Zurbruegg's (2014) evidence that trading activity carries information about the smile's future path. The interaction is just as strong for symmetric curvature as for directional curvature, however. This means the effect is better described as a general, regime-dependent change in smile intensity, not the crash-risk-specific mechanism H3 originally proposed. The same pattern appears in Yue, Gehricke, Zhang, and Pan's (2021) finding that both curvature components are independently meaningful in emerging markets, which is why this study estimates them separately rather than as a single smile-shape summary.

4.4 COVID Structural-Break Analysis

An indicator, such as a COVID dummy, can show that average curvature differed over a fixed window; it cannot show whether that shift was temporary or permanent. The gap between the two is the one that this study's structural-break method is designed to address, following Andersen et al. (2007), who separate short-lived jump components from ongoing volatility. In Merton's (1976)

framework, a single shock need not leave a lasting mark on the underlying process itself. Figure 1 plots a rolling 250-day estimate of the Put Net Buying Pressure coefficient and shows why H4 holds specifically for puts. The coefficient for Directional Curvature (Put) stays flat and mildly positive from 2008 to 2020, drops sharply at COVID's first wave, and never reverts through 2024. The coefficient for calls, by contrast, stays volatile throughout but shows no COVID-specific break. Figure 2 plots every detected break and segment mean for each series. Table 7 shows that the COVID-adjacent break is only the smallest or a mid-sized break in each series' full seventeen-year history, not the largest. The coefficient shift is therefore neither a market-wide "structural repricing," its size is unremarkable against the series' own history, nor a fully reverted shock, since the coefficient never returns to its pre-COVID level. The evidence supports a persistent change specific to this one relationship. This is consistent with Chen et al. (2022), who find India to be a net receiver rather than a source of crisis-driven spillovers, and with Agarwalla, Varma, and Virmani (2021), who find that COVID-19 shifted tail-risk pricing in Nifty options without a full reversal.

4.5 Call–Put Asymmetry

H5 formally established that calls and puts respond differently overall (Table 8). Figure 4 shows that this difference is not limited to demand alone: Liquidity, Open Interest, Maturity, the Interest Rate, and Realized Volatility all show Put interaction coefficients significant at 5% or better (Table 8), with several signs opposite to the call-side effect. This matches the scale of dealer-inventory asymmetry that Bollen and Whaley (2004) first documented, but here it appears across all regressors at once rather than in a single coefficient. The breadth of this result matters. Had only net buying pressure shown this asymmetry, the finding would have been narrower. Instead, it suggests that calls and puts are priced by different segments of order flow, rather than by one mechanism operating the same way on both sides — consistent with Eaton, Green, Roseman, and Wu (2026), who find that retail demand shapes the term structure, moneyness curve, and call-put spread together, and with Kim and Ryu (2015) and Tanha and Dempsey (2015), who find that market structure, not one universal rule, drives smile behavior in Korea and Australia. Read alongside H1, H2, and H4, the overall pattern is not that demand-based pricing fails, but that it holds only for puts. Put-side curvature shows a demand relationship distinct from symmetric curvature, shifts persistently after COVID, and differs from calls across the full set of regressors. Call-side curvature shows none of this reliably, and it's one demand result does not survive a change in demand proxy (Section 4.6). The evidence, therefore, points to demand-based pricing operating on one side of the market rather than both, consistent with Sui, Wang, and Liu (2025) and Li et al. (2021).

5. Conclusion

This paper decomposes Nifty-50 index-option curvature into symmetric and directional components and tests both against net buying pressure — the direct empirical counterpart of demand-based option-pricing theory. Two contributions follow. First, it provides an empirically validated decomposition of symmetric versus directional tail-risk pricing, tested with a direct demand proxy in a market structure not previously examined this way. Second, it provides a formally tested account of whether a systemic shock produced a structural change or a merely persistent one — and that change is specific to put-side directional pricing, not a market-wide

claim. Limitations are inherent in this study. The retail-participation mechanism that motivates this setting is plausible but not directly tested because investor-type data were unavailable.

Four implications follow. Firstly, for puts, the historical relationship between hedging demand and downside-protection pricing has not been a reliable guide since 2020 (H4). No equivalent adjustment is needed for calls, but only because the call-side demand relationship was never robust to begin with, since it does not survive a change in demand proxy. Secondly, the pervasive call/put asymmetry (H5) means any inventory model calibrated on a single, option-type-agnostic sensitivity will be systematically mis-specified for one side of the market. Separately, the null liquidity result (H2) shows that underlying-market liquidity alone is not a sufficient signal for anticipating shifts in crash-risk pricing. Thirdly, Monitoring frameworks may benefit from tracking how the order-flow-to-pricing relationship evolves over time, rather than implied volatility levels alone. A level-only approach would have missed the shift this study identifies (H4). Fourthly, decomposing curvature into its symmetric and directional components, rather than using one smile-shape measure, reveals asymmetries (H1, H5) that a single-measure design would misattribute to uniform demand. Separately, the Maturity × Volatility interaction result (H3) shows why crash-risk specificity should be tested directly, rather than assumed by design.

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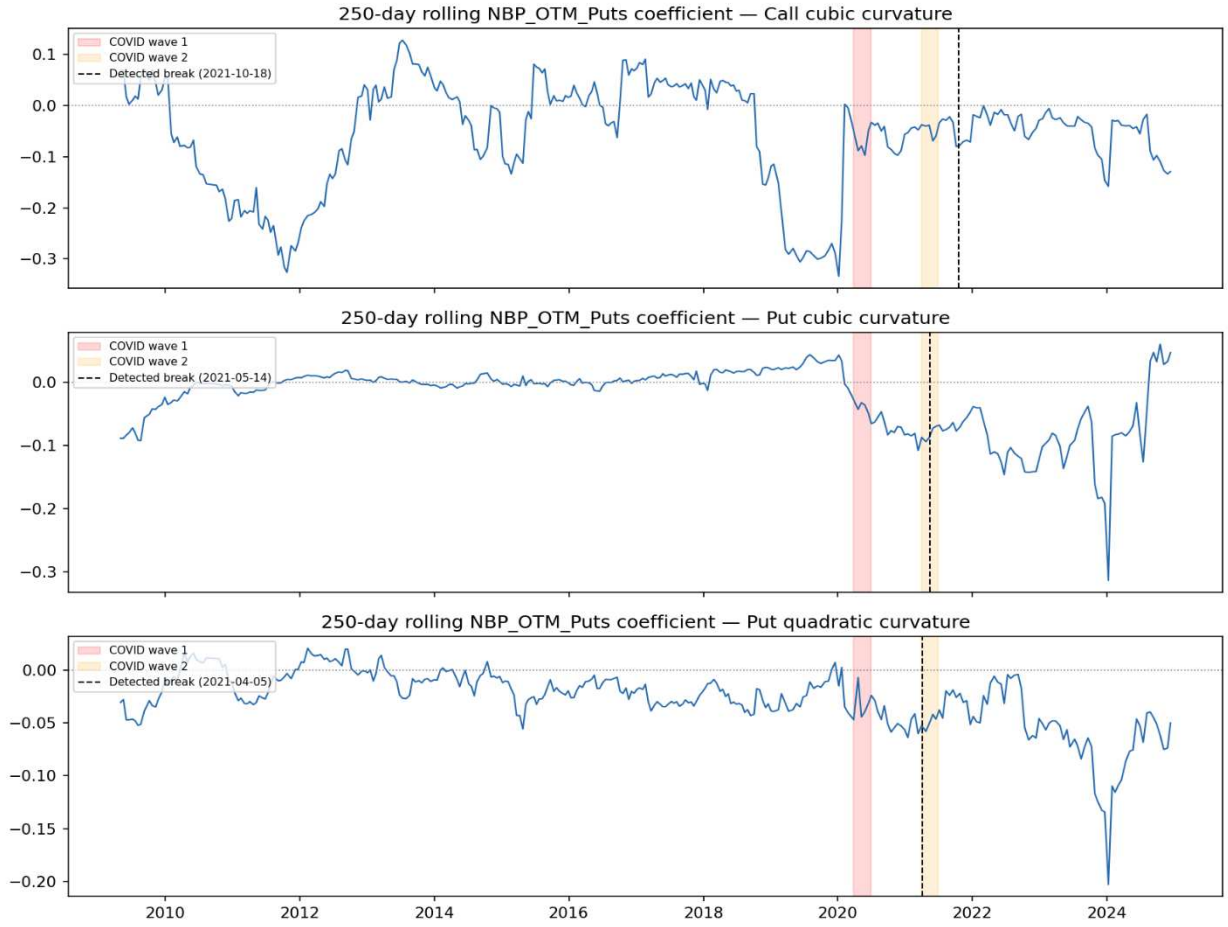
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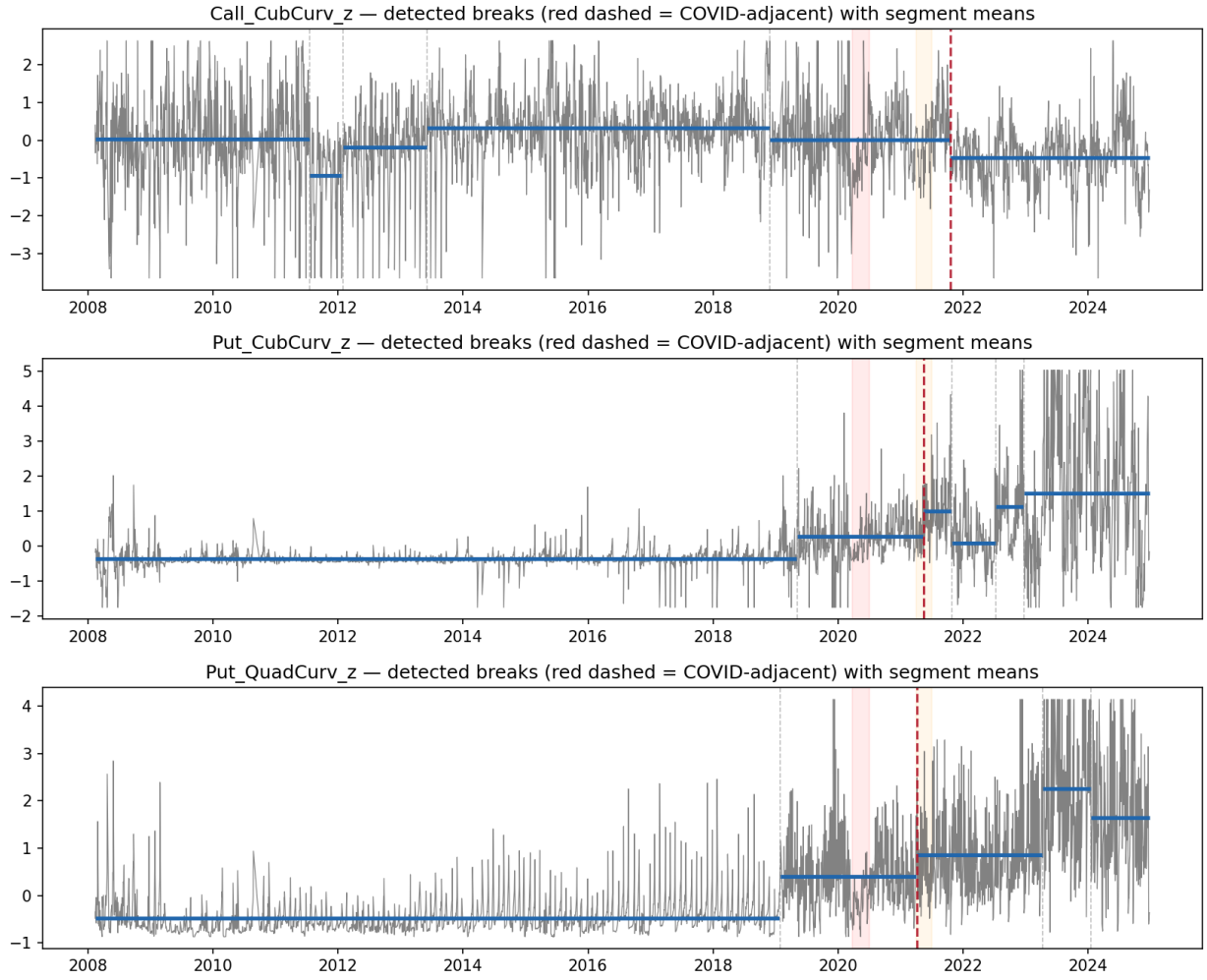
Appendix

Figure 1. 250-day rolling Put Net Buying Pressure coefficient across all three curvature systems, with COVID wave windows and detected structural breaks marked.



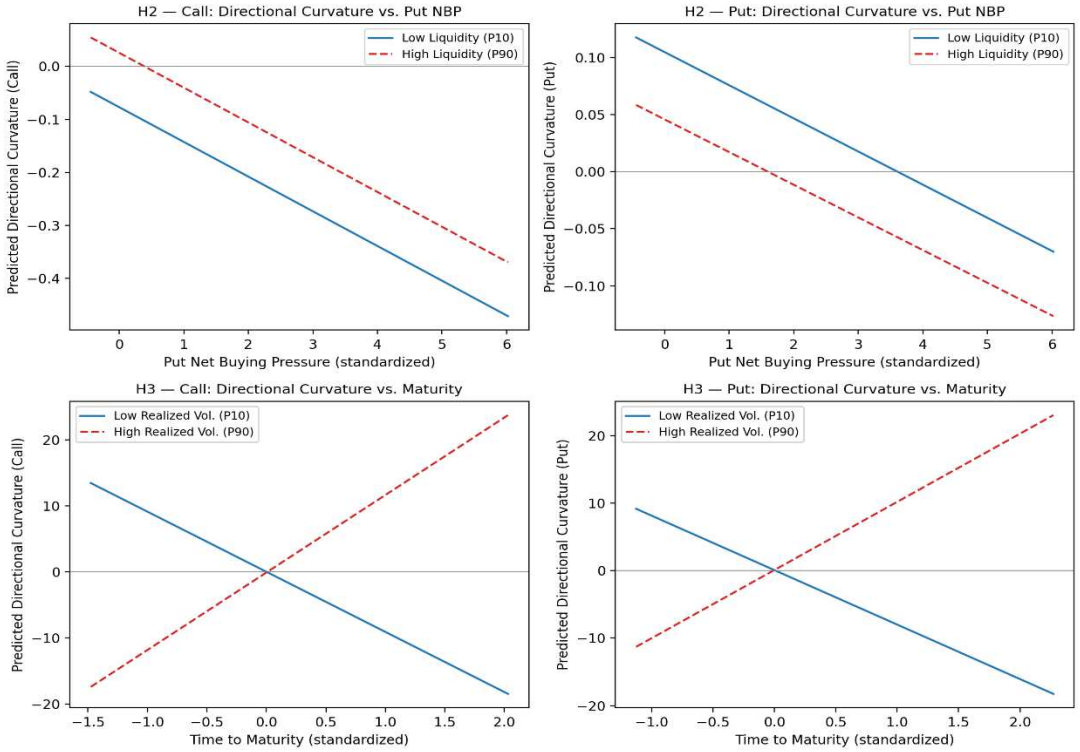
Source: Authors' calculations

Figure 2: Figure 2. Detected structural breaks and segment means across all three curvature systems, with the COVID-adjacent break marked separately.



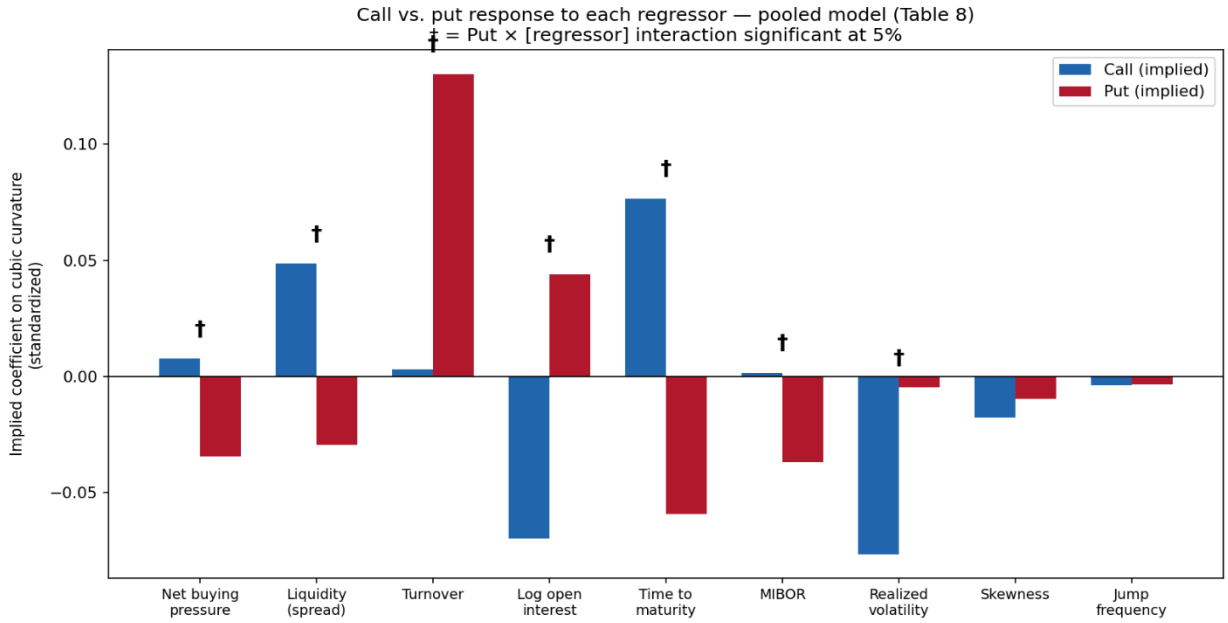
Source: Authors' calculations

Figure 3. Marginal Effects on Directional Curvature for H2 and H3



Source: Authors' calculations

Figure 4. Implied call vs. put coefficients on Directional Curvature across all nine pooled-model regressors.



Source: Authors' calculations

Table 1. Variable Definitions and Measurement

Variable	Symbol	Measurement
Symmetric Curvature (Call / Put)	Q_C, Q_P	Quadratic coefficient (β_2) from a cubic polynomial fit of implied volatility on standardized log-moneyness, estimated daily per option type; standardized (z-scored) within option type.
Directional Curvature (Call / Put)	D_C, D_P	Cubic coefficient (β_3) from the same polynomial fit; standardized (z-scored) within option type.
Call Net Buying Pressure	NBP_C	Net buying pressure in out-of-the-money call contracts; one-day lagged
Put Net Buying Pressure	NBP_P	Net buying pressure in out-of-the-money put contracts, one-day lagged
Put-Call Ratio	PCR	Ratio of put to call trading activity; one-day lagged
Liquidity (Bid-Ask Spread)	LIQ	Bid-ask spread on the underlying Nifty-50 index/futures market; one-day lagged
Turnover Ratio	TURN	Daily trading volume scaled by open interest; winsorized, one-day lagged
Open Interest	OI	Log of open interest, option-type-specific; one-day lagged.
Time to Maturity	TTM	Contract time-to-expiry in years, option-type-specific; one-day lagged.
Interest Rate (MIBOR)	RATE	Mumbai Interbank Offer Rate; one-day lagged.
Realized Volatility	RV	30-day annualized realized volatility of Nifty-50 spot returns; one-day lagged
Realized Skewness	SKEW	21-day realized skewness of Nifty-50 spot returns; one-day lagged.
Jump Frequency	JUMP	Proportion of days within a rolling window where the Nifty-50 return exceeds a three-standard-deviation threshold; one-day lagged.
COVID Peak Dummy	COVID_PEAK	Equals 1 for trading days falling in either of two pandemic-wave windows: 25 March–30 June 2020 (first wave) or 1 April–30 June 2021 (second wave); equals 0 for all other days.
Post-COVID Dummy	POST_COVID	1 for all dates from 1 Jul 2020 onward not in a peak window; 0 otherwise
Weekday Dummies (Tue-Fri)	—	0/1 indicators for Tuesday through Friday; Monday is the reference category
Lagged Curvature	Curvature(t-1)	One-day lag of the dependent variable (own system)
Put Demand x Liquidity	NBP_P x LIQ	Product of mean-centered Put Net Buying Pressure and mean-centered Liquidity, both one-day lagged
Maturity x Volatility	TTM x RV	Product of mean-centered Time to Maturity and mean-centered Realized Volatility, both one-day lagged
Post-Break Indicator	PostBreak	1 for dates on or after the detected COVID-adjacent structural break, 0 before
Put Indicator	PUT	1 for put-side observations, 0 for call-side, in the pooled panel

Table 2. Descriptive Statistics

Type	Variable	Mean	Median	SD	Skew	Kurt	P1	P99
Call	Liquidity (Bid-Ask Spread)	0.0013	0.0010	0.0012	2.2464	5.8281	0.0000	0.0068
Call	Turnover Ratio	0.1735	0.1007	0.2921	4.5077	21.1953	0.0125	1.9233
Call	Open Interest (Call)	17.2007	17.2105	0.4612	0.2627	1.7302	15.8853	18.6755
Call	Time to Maturity (Call)	0.0373	0.0384	0.0234	0.1748	-1.0868	0.0027	0.0849
Call	Interest Rate (MIBOR)	6.9428	7.0700	1.8541	-0.1859	-0.5842	3.6000	11.0884
Call	Realized Volatility	0.1742	0.1446	0.1048	2.6345	8.4478	0.0742	0.6978
Call	Realized Skewness	-0.0494	-0.0585	0.5768	0.0697	0.3031	-1.6062	1.5306
Call	Jump Frequency	13.1135	13.0000	7.5696	0.1674	-0.9780	1.0000	30.0000
Call	Put-Call Ratio	1.1701	1.0927	0.3881	0.9992	1.2554	0.4579	2.5494
Put	Liquidity (Bid-Ask Spread)	0.0013	0.0010	0.0012	2.2464	5.8281	0.0000	0.0068
Put	Turnover Ratio	0.3751	0.1328	0.5531	2.2579	4.5247	0.0120	2.6216
Put	Open Interest (Put)	17.4757	17.5018	0.5287	-0.4472	1.1321	15.8545	18.7366
Put	Time to Maturity (Put)	0.0291	0.0219	0.0234	0.5956	-0.9210	0.0027	0.0822
Put	Interest Rate (MIBOR)	6.9430	7.0700	1.8539	-0.1856	-0.5839	3.6000	11.0884
Put	Realized Volatility	0.1742	0.1446	0.1048	2.6345	8.4478	0.0742	0.6978
Put	Realized Skewness	-0.0494	-0.0585	0.5768	0.0697	0.3031	-1.6062	1.5306
Put	Jump Frequency	13.1099	13.0000	7.5727	0.1675	-0.9797	1.0000	30.0000
Put	Put-Call Ratio	1.1696	1.0927	0.3898	0.9810	1.1985	0.4579	2.5494
Call	Call Net Buying Pressure	32358.4822	14943.0000	51668.7133	3.4553	14.0708	0.0000	326957.7754
Put	Put Net Buying Pressure	27869.9709	6123.0000	63013.0289	4.0798	18.5958	0.0000	407430.8056

Source: Authors' Calculations

Table 3. Multicollinearity Diagnostics (Variance Inflation Factors)

Variable	Call VIF	Put VIF
Call Net Buying Pressure	1.170	1.164
Put Net Buying Pressure	1.147	1.107
Liquidity	1.769	1.929
Turnover Ratio	2.035	2.951
Interest Rate (MIBOR)	1.386	1.353
Realized Volatility	2.069	2.042
Realized Skewness	1.036	1.036
Jump Frequency	1.561	1.572
Put-Call Ratio	1.241	1.471
Open Interest (Call)	2.348	n/a
Time to Maturity (Call)	1.214	n/a
Open Interest (Put)	n/a	2.656
Time to Maturity (Put)	n/a	1.435

Source: Authors' Calculations

Table 4. Baseline Dynamic Regression Results

Table 4 Panel A reports estimates from Equation 6, the primary dynamic specification, for four dependent variables — Symmetric and Directional Curvature, for calls and puts. All continuous variables are standardized; weekday dummies remain 0/1 (Monday reference). Each cell reports the standardized coefficient with significance stars, and the Newey-West t-statistic in parentheses below it. Estimated by OLS with Newey-West standard errors (8 lags). Panel B tests whether the Put Net Buying Pressure coefficient (reported above) differs between the Directional- and Symmetric-Curvature systems for the same option type.

Panel A: Dynamic Regression Results

Variable	Symmetric (Call)	Directional (Call)	Symmetric (Put)	Directional (Put)
Constant	0.0228	-0.0341	0.0631***	0.0800***
	(0.823)	(-1.140)	(2.758)	(3.362)
Lagged Curvature	0.4347***	0.3980***	0.5037***	0.6306***
	(14.880)	(15.714)	(13.482)	(18.947)
Call Net Buying Pressure	0.0604***	-0.0029	-0.0170*	-0.0189*
	(3.883)	(-0.171)	(-1.827)	(-1.951)
Put Net Buying Pressure	0.0370**	-0.0676***	-0.0214**	-0.0287***
	(2.445)	(-4.169)	(-2.027)	(-2.827)
Liquidity	0.0177	0.0585***	-0.0182	-0.0211*
	(1.055)	(2.700)	(-1.577)	(-1.851)
Turnover Ratio	-0.1194***	-0.0040	0.2044***	0.0957***
	(-6.229)	(-0.194)	(6.300)	(3.724)
Open Interest	0.1531***	-0.0518**	-0.0031	0.0547***
	(6.660)	(-2.109)	(-0.148)	(2.869)
Time to Maturity	-0.1921***	0.1005***	-0.1282***	-0.0433***
	(-10.356)	(5.474)	(-10.754)	(-5.375)
Interest Rate (MIBOR)	-0.0409***	0.0008	-0.0279***	-0.0290***
	(-2.656)	(0.043)	(-2.855)	(-3.035)
Realized Volatility	0.0695***	-0.0723***	-0.0482***	0.0003
	(3.798)	(-3.782)	(-3.537)	(0.029)
Realized Skewness	0.0185	-0.0251	-0.0024	-0.0083
	(1.197)	(-1.613)	(-0.232)	(-0.681)
Jump Frequency	0.0016	-0.0012	0.0076	0.0019
	(0.085)	(-0.063)	(0.544)	(0.133)
Tuesday	0.0610*	0.0019	0.0772***	-0.0081
	(1.794)	(0.046)	(4.144)	(-0.338)
Wednesday	0.1858***	-0.1173***	0.3098***	0.0365
	(4.877)	(-2.873)	(9.619)	(1.152)
Thursday	-0.0872**	0.1338***	-0.1499***	-0.1273***
	(-2.150)	(2.759)	(-6.512)	(-5.750)
Friday	-0.3245***	0.2081***	-0.6317***	-0.3411***
	(-7.153)	(4.496)	(-12.617)	(-7.345)
Observations	3547	3547	3547	3547
R-squared	0.365	0.231	0.655	0.569
Adjusted R-squared	0.363	0.228	0.654	0.567
F-statistic	119.58	49.52	325.71	149.75

Durbin-Watson	2.075	2.122	2.089	2.298
HAC lags	8	8	8	8
Panel B: H1 Test — Directional vs. Symmetric Coefficient Equality				
Option Type	**Directional Coef.**	**Symmetric Coef.**	**Difference**	**95% CI**
Call	-0.0676	0.0370	-0.1046***	[-0.1585, -0.0506]
Put	-0.0287	-0.0214	-0.0073	[-0.0285, 0.0125]

Source: Authors' Calculations

Table 5. Static versus Dynamic Specification Comparison

Table 5 compares the dynamic specification (Equation 6) with the same model without the lagged dependent variable for each dependent variable. Each model includes a full set of control variables as shown in the baseline equation results in Table 4. The Dynamic column matches Table 4; the Static column is newly estimated. Each cell reports the standardized coefficient with significance stars, and the Newey-West t-statistic in parentheses below it.

Variable	Symmetric (Call)	Directional (Call)	Symmetric (Put)	Directional (Put)
Call Net Buying Pressure (Static)	0.0289 (1.499)	0.0010 (0.046)	-0.0433*** (-3.785)	-0.0361** (-2.206)
Call Net Buying Pressure (Dynamic)	0.0604*** (3.883)	-0.0029 (-0.171)	-0.0170* (-1.827)	-0.0189* (-1.951)
Put Net Buying Pressure (Static)	0.0717*** (3.996)	-0.0773*** (-3.628)	-0.0917*** (-5.820)	-0.0992*** (-5.334)
Put Net Buying Pressure (Dynamic)	0.0370** (2.445)	-0.0676*** (-4.169)	-0.0214** (-2.027)	-0.0287*** (-2.827)
Lagged Curvature (Dynamic only)	0.4347*** (14.880)	0.3980*** (15.714)	0.5037*** (13.482)	0.6306*** (18.947)
Observations (Static / Dynamic)	3547 3547	3547 3547	3547 3547	3547 3547
R-squared (Static / Dynamic)	0.238 0.365	0.086 0.231	0.578 0.655	0.322 0.569
Adjusted R-squared (Static / Dynamic)	0.235 0.363	0.082 0.228	0.576 0.654	0.319 0.567
F-statistic (Static / Dynamic)	46.31 119.58	14.51 49.52	99.29 325.71	22.30 149.75
Durbin-Watson (Static / Dynamic)	1.232 2.075	1.223 2.122	1.340 2.089	0.917 2.298

Source: Authors' Calculations

Table 6. Conditional Interaction Model Results

Table 6 reports the formal tests for Hypotheses 2 and 3 (H1's test is in Table 4). Both interaction terms are estimated in a single regression per option type. Each model includes a full set of control variables, as shown in Equation 7. Each coefficient cell reports the standardized coefficient with significance stars, and the Newey-West t-statistic in parentheses below it.

Particulars	Call Option	Put Option
Put Demand × Liquidity Interaction (Directional Curvature)	-0.0001 (-0.399)	0.0002* (1.778)
Maturity × Volatility Interaction (Directional Curvature only)	11.6734* (1.696)	10.1806*** (3.460)
Observations	3547	3547
R-squared	0.2313	0.5694
Adjusted R-squared	0.2275	0.5674
F-statistic	42.78***	136.37***
Durbin-Watson	2.121	2.297

Source: Authors' Calculations

Table 7. COVID-19 Structural-Break Analysis (H4)

Table 7 reports results from a structural-break procedure applied to each series, together with a test of whether the Put Net Buying Pressure coefficient shifts across the COVID-adjacent break (Equation 8). "Largest other break" reports the largest non-COVID break magnitude that the same series exhibits over its full 2008–2024 history.

Particulars	COVID Break Date	Break Magnitude	Largest Other Break	Coef. Shift p-value	Shift Significant?
Directional Curvature (Call)	2021-10-18	0.487	0.963	0.1577	No
Directional Curvature (Put)	2021-05-14	0.725	1.042	0.0024	Yes
Symmetric Curvature (Put)	2021-04-05	0.453	1.413	0.1321	No

Source: Authors' Calculations

Table 8. Pooled Call/Put Model and Wald Tests (H5)

Table 8 reports the pooled model (Equation 9), stacking standardized Directional-Curvature series for calls and puts into a single panel (N = 7,094), with a Put indicator interacted with each regressor. Coefficients and t-statistics follow the stacked format in Table 4. The lower panel reports Wald tests of whether the Put interaction terms are jointly zero.

Variable	Coefficient	t-statistic
Constant	-0.0142	(-0.663)
Lagged Curvature	0.4920***	(22.232)
Net Buying Pressure (own side)	0.0077	(0.423)
Liquidity	0.0486**	(2.410)
Turnover Ratio	0.0032	(0.106)
Open Interest	-0.0697***	(-2.763)
Time to Maturity	0.0767***	(4.604)

Interest Rate (MIBOR)	0.0016	(0.099)
Realized Volatility	-0.0765***	(-4.619)
Realized Skewness	-0.0177	(-1.332)
Jump Frequency	-0.0036	(-0.231)
Put Indicator	-0.0199	(-1.139)
Put x Net Buying Pressure	-0.0421**	(-2.011)
Put x Liquidity	-0.0782***	(-3.130)
Put x Turnover Ratio	0.1271***	(3.341)
Put x Open Interest	0.1138***	(3.555)
Put x Time to Maturity	-0.1359***	(-7.172)
Put x Interest Rate	-0.0386**	(-2.045)
Put x Realized Volatility	0.0716***	(3.455)
Put x Realized Skewness	0.0080	(0.433)
Put x Jump Frequency	0.0003	(0.014)
Tuesday	0.0016	(0.065)
Wednesday	-0.0330	(-1.243)
Thursday	0.0015	(0.059)
Friday	-0.0541*	(-1.778)
Wald Tests of Coefficient Equality		
Test	**Statistic**	**p-value**
Put x Net Buying Pressure = 0 (individual, H5 core test)	t=-2.011	0.0443
All 9 Put x [regressor] = 0 (joint)	F=184.708	1.00e-10
Put + all 9 interactions = 0 (full asymmetry)	F=192.543	1.00e-10

Source: Authors' Calculations

Table 9. Quantile Regression — Put Net Buying Pressure Coefficient

Table 9 reports the coefficient on Put Net Buying Pressure from quantile regressions of Equation 6 at the 10th, 50th, and 90th percentiles, for all four systems. N and the Koenker–Machado (1999) pseudo-R^2 are also reported.

System	Quantile (τ)	Coefficient	t-statistic	p-value	N	Pseudo-R^2
Symmetric (Call)	0.10	0.0310*	1.647	0.0996	3547	0.150
Symmetric (Call)	0.50	0.0148	1.300	0.1938	3547	0.248
Symmetric (Call)	0.90	0.0229	1.066	0.2866	3547	0.311
Directional (Call)	0.10	-0.0916***	-3.477	0.0005	3547	0.190
Directional (Call)	0.50	-0.0468***	-3.554	0.0004	3547	0.142
Directional (Call)	0.90	-0.0616**	-2.012	0.0443	3547	0.102
Symmetric (Put)	0.10	-0.0069	-1.452	0.1465	3547	0.121
Symmetric (Put)	0.50	-0.0106***	-2.810	0.0050	3547	0.416
Symmetric (Put)	0.90	-0.0139**	-2.081	0.0375	3547	0.679
Directional (Put)	0.10	0.0184***	5.002	<0.0001	3547	0.114
Directional (Put)	0.50	-0.0031*	-1.844	0.0653	3547	0.329
Directional (Put)	0.90	-0.0414***	-6.263	<0.0001	3547	0.647

Source: Authors' Calculations

Table 10. Economic Significance — Interquartile-Range Effects

Table 10 translates the standardized Put Net Buying Pressure coefficients from Table 4 into economic magnitude: the predicted change in curvature (in standard-deviation units) associated with moving Put Net Buying Pressure from its 25th to 75th percentile, holding other regressors at their means.

System	Standardized Coefficient	IQR of Put Net Buying Pressure	Effect of P25→P75 Move (SD)
Symmetric (Call)	0.0370	22,998	0.0135
Directional (Call)	-0.0676	22,998	-0.0247
Symmetric (Put)	-0.0214	22,958	-0.0078
Directional (Put)	-0.0287	22,958	-0.0104

Source: Authors' Calculations

Table 11. Multiple-Testing Correction

Table 11 applies the Benjamini-Hochberg false-discovery-rate correction to the fifteen headline hypothesis tests reported across Tables 4 through 8, treating them as a single family rather than judging them individually. This battery spans all five hypotheses: the H1 directional-versus-symmetric difference (calls and puts); the four H2 Put Demand × Liquidity interactions and four H3 Maturity × Volatility interactions, one for each of the Symmetric and Directional systems in calls and puts; the three H4 COVID coefficient shifts; and the two H5 pooled-model tests. "Survives" indicates the adjusted p-value remains below 0.05.

Hyp.	System	Test	Raw p	Adj. p (BH)	Survives?
H1	Call	Directional vs Symmetric Curvature Difference	<0.0001	<0.0001	Yes
H1	Put	Directional vs Symmetric Curvature Difference	0.5220	0.5593	No
H2	Symmetric (Call)	Put Demand x Liquidity	0.0849	0.1226	No
H3	Symmetric (Call)	Maturity x Volatility	0.0004	0.0013	Yes
H2	Directional (Call)	Put Demand x Liquidity	0.6902	0.6902	No
H3	Directional (Call)	Maturity x Volatility	0.0899	0.1226	No
H2	Symmetric (Put)	Put Demand x Liquidity	0.0669	0.1226	No
H3	Symmetric (Put)	Maturity x Volatility	<0.0001	<0.0001	Yes
H2	Directional (Put)	Put Demand x Liquidity	0.0753	0.1226	No
H3	Directional (Put)	Maturity x Volatility	0.0005	0.0016	Yes
H4	Directional (Call)	COVID Coefficient Shift	0.1577	0.1820	No
H4	Directional (Put)	COVID Coefficient Shift	0.0024	0.0060	Yes
H4	Symmetric (Put)	COVID Coefficient Shift	0.1321	0.1651	No
H5	Pooled	Put x Net Buying Pressure (individual)	0.0443	0.0949	No
H5	Pooled	Joint Put Interactions (9 terms)	<0.0001	<0.0001	Yes

Source: Authors' Calculations