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Effectiveness of domain stabilization: A broader perspective

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ABSTRACT

This study evaluates the effectiveness of domain stabilization (DS) in mitigating the impact of truncation on model-free implied moment estimation in a new market context. Using refined daily data from the KOSPI200 options market, we address a research gap by linking implied moments to contemporaneous prices and market events. When DS is applied, implied moments more effectively explain contemporaneous underlying price levels and log returns. The in-sample return predictability and out-of-sample forecasting performance of implied moment estimates also improve with DS, albeit to a slightly lesser extent than observed in the U.S. market. Even in an emerging market, DS enhances the informational content of implied moment estimates, strengthening their explanatory power for underlying prices and returns as well as their predictive and forecasting capabilities.

1. Introduction

The option-implied risk-neutral density (RND) summarizes market expectations about the underlying asset's future price. However, despite its informational richness, a key limitation of the RND lies in its representation as a continuous function, which complicates its direct application in empirical analysis. Researchers, therefore, use the RND's moments as discrete summaries. These moments provide a parsimonious and interpretable representation of the RND, facilitating their use in a wide range of empirical studies that examine the informational content of options markets and their implications.

The development of the model-free implied moment estimators by Bakshi et al. (2003, BKM) has been a key driver behind the widespread use of the moments of the RND as variables in empirical research. The estimators compute volatility, skewness, and kurtosis from out-of-the-money (OTM) prices without strong model assumptions. By parsimoniously capturing the fundamental characteristics of the RND and ensuring robustness against model misspecifications, the BKM estimators have become a cornerstone of the literature. Investor demand for higher moments (Buckle et al., 2016), informative OTM prices (Hu et al., 2022; Jiang & Zhou, 2024; Lee et al., 2021), and the asymmetric and non-normal price effects (Cheema et al., 2023; Han et al., 2022; Jin et al., 2020; Zhang et al., 2023) all promote these estimators. These factors matter for BKM estimators because they shape the implied-volatility surface (Chen et al., 2022). Recent studies use these estimators to proxy the option-implied risk about the underlying price (Sautner et al., 2023; Zhan et al., 2022), the price of the insurance against left-tail events (Ilhan et al., 2021), and the moments themselves (Ai et al., 2022; Augustin & Izhakian, 2020; Chabi-yo & Loudis, 2020; Wang et al., 2024).

However, despite their theoretical robustness and empirical convenience, the BKM estimators face challenges in satisfying their

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assumptions due to the inherent incompleteness of real-world options markets. While the estimators require OTM option prices that cover a continuous set of strike prices spanning the positive real line, such a set is unavailable in virtually every options market. The study of Jiang and Tian (2005) (hereafter, JT) highlights this issue and breaks it down into two distinct phenomena. First, options price quotes are available only for a discontinuous set of strikes. Second, a large portion of the deep out-of-the-money (DOTM) region in the strike price domain lacks observable option prices or has prices removed during filtering, a problem termed "truncation" by JT. Truncation presents a particularly challenging problem for at least two reasons. First, extrapolation requires stronger assumptions than interpolation. Second, as demonstrated by Lee et al. (2025a), truncation not only distorts implied moment estimates but also introduces biases that are systematically interrelated with the underlying price and implied moments in a complex manner.

Literature on model-free implied moment estimation proposes at least two model-free approaches to address truncation. First, JT suggests obtaining missing DOTM prices by extending the implied volatility curve with flat lines attached at both ends. We refer to this method as "flat extrapolation." Second, Dennis and Mayhew (2002) propose making the two ends of the integration domain equally distant from the underlying price by further discarding available OTM price observations for implied skewness estimation. This method is referred to as "domain symmetrization" in this study. Despite their popularity, both methods have well-documented drawbacks. Pan et al. (2022, 2024) argue that flat extrapolation can distort the implied tail density, complicating both implied moment estimation and its interpretation. Lee and Ryu (2024a) demonstrate that implied skewness and kurtosis estimators remain sensitive to truncation, even when flat extrapolation is applied. Shelton et al. (2021) show that domain symmetrization does not always reduce truncation error and may result in biased and inconsistent implied skewness estimation. Lee et al. (2025b) also demonstrate that the relationship between estimation bias and domain symmetry is unclear.

To provide an alternative truncation treatment method, the recent study by Lee et al. (2025c) (hereafter, LRY) proposes domain stabilization (DS) to mitigate the impact of truncation on estimation. DS stabilizes truncation to reduce estimation noise and improve the information in implied moment dynamics. LRY demonstrates that, when applied to S&P500 index options data, DS significantly enhances the in-sample predictive accuracy and out-of-sample forecasting performance of implied moment estimates for underlying log returns. Their test results indicate that, when DS is applied with an appropriate intensity level, implied moment estimates outperform those derived using alternative truncation treatment methods in both in-sample and out-of-sample tests. These findings highlight the potential of DS as a valuable tool for improving the information content of implied moment estimates.

Based on these findings, we test DS in the Korean Composite Stock Price Index 200 (KOSPI200) options market. We broaden our methodology to evaluate DS more comprehensively in an emerging options market. From a market environment perspective, we focus on one of the leading emerging markets, the Korean market. This ensures that the market is qualitatively distinct from the U.S. market while maintaining active trading in options with informative prices (Kim et al., 2025). Methodologically, we go beyond testing the in-sample and out-of-sample return predictive and forecasting performance by also examining the contemporaneous relationship between the underlying price and implied moment estimates. To provide a comprehensive analysis, we investigate this contemporaneous relationship at both the levels and first-order differences, offering deeper insights into the effectiveness of DS.

Our empirical findings demonstrate that DS is an effective truncation treatment method for the KOSPI200 options market, consistent with the results reported by LRY for the S&P500 index options market. DS enhances the contemporaneous explanatory power of implied moment estimates for the underlying asset, both at the levels and first-order differences, while also improving the in-sample return predictive accuracy and out-of-sample forecasting performance of implied moment estimates. Although the enhancement generally becomes more pronounced as the intensity level of DS increases, it diminishes when DS is applied too intensively. The optimal improvement is observed when the intensity level is between 50 % and 75 %. Despite these enhancements, the in-sample predictive and out-of-sample forecasting abilities of implied moment estimates remain weaker in the KOSPI200 options market compared to the S&P500 options market, even after applying DS. This disparity may be attributed to differences in the participation rates of retail investors between the two markets.

The main implication of this study is that DS can be considered a valid truncation treatment method for implied moment estimation in a broader and more general context than previously examined in LRY. From the perspective of market diversity, this study demonstrates that DS is effective not only in the U.S. market but also in the Korean market, a leading emerging market. From an informational standpoint, this study shows that DS not only enhances the return predictive and forecasting performance of implied moment estimates but also clarifies the concurrent relationship between the underlying price and implied moments. This empirical evidence highlights the potential of DS as a valuable tool and encourages future empirical research to adopt DS to maximize the informational content of implied moment estimates.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical and empirical background, and Section 3 details the data sources, filtration criteria, and descriptive statistics for the KOSPI200 options market dataset. Section 4 outlines the methodology for implied moment estimation, and Section 5 presents the empirical results. Section 6 concludes with a discussion of the findings and their implications.

2. Research background

BKM proposes a model-free implied moment estimation approach, restructuring the volatility, skewness, and kurtosis of the implied RND as functions of the fair values of volatility, cubic, and quartic contracts, denoted as V, W, and X, respectively. These contracts are named based on their payoff functions, which correspond to R^2, R^3, and R^4, where R represents the underlying asset's holding period log return until maturity. At time t, BKM's implied moment estimators for maturity τ are defined as follows:

$$\mathrm{VOL}(t,\tau) = \left[e^{r\tau}V(t,\tau) - \mu^2(t,\tau)\right]^{1/2} \tag{1}$$

$$\mathrm{SKEW}(t,\tau) = \frac{e^{r\tau}W(t,\tau) - 3\mu(t,\tau)e^{r\tau}V(t,\tau) + 2\mu^3(t,\tau)}{\left[e^{r\tau}V(t,\tau) - \mu^2(t,\tau)\right]^{3/2}} \tag{2}$$

$$\mathrm{KURT}(t,\tau) = \frac{e^{r\tau}X(t,\tau) - 4\mu(t,\tau)e^{r\tau}W(t,\tau) + 6e^{r\tau}\mu^2(t,\tau)V(t,\tau) - 3\mu^4(t,\tau)}{\left[e^{r\tau}V(t,\tau) - \mu^2(t,\tau)\right]^2} \tag{3}$$

where r denotes the risk-free rate and $\mu(t,\tau)$ represents the underlying asset's expected holding period risk-neutral log return. BKM demonstrates that the fair values V, W, and X can be derived from a continuum of OTM option prices as follows:

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2\left(1 - \ln\left[\frac{K}{S(t)}\right]\right)}{K^2} C(t,\tau;K)dK + \int_0^{S(t)} \frac{2\left(1 + \ln\left[\frac{S(t)}{K}\right]\right)}{K^2} P(t,\tau;K)dK \tag{4}$$

$$W(t,\tau) = \int_{S(t)}^{\infty} \frac{6\ln\left[\frac{K}{S(t)}\right] - 3\left(\ln\left[\frac{K}{S(t)}\right]\right)^2}{K^2} C(t,\tau;K)dK - \int_0^{S(t)} \frac{6\ln\left[\frac{S(t)}{K}\right] + 3\left(\ln\left[\frac{S(t)}{K}\right]\right)^2}{K^2} P(t,\tau;K)dK \tag{5}$$

$$X(t,\tau) = \int_{S(t)}^{\infty} \frac{12\left(\ln\left[\frac{K}{S(t)}\right]\right)^2 - 4\left(\ln\left[\frac{K}{S(t)}\right]\right)^3}{K^2} C(t,\tau;K)dK + \int_0^{S(t)} \frac{12\left(\ln\left[\frac{S(t)}{K}\right]\right)^2 + 4\left(\ln\left[\frac{S(t)}{K}\right]\right)^3}{K^2} P(t,\tau;K)dK \tag{6}$$

where $S(t)$ represents the underlying price at time t, and $C(t,\tau;K)$ and $P(t,\tau;K)$ denote the OTM call and put option prices for strike K, respectively. The fair value of $\mu(t,\tau)$ is approximated as:

$$\mu(t,\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V(t,\tau) - \frac{e^{r\tau}}{6}W(t,\tau) - \frac{e^{r\tau}}{2}X(t,\tau) \tag{7}$$

When truncation occurs, the observed OTM prices span a strike price domain of finite width, expressed as $[K_{\min}(t,\tau), K_{\max}(t,\tau)]$, where $K_{\min}(t,\tau)$ and $K_{\max}(t,\tau)$ represent the minimum and maximum strike prices of the integration domain, respectively. Because the integration domain has finite, non-zero endpoints, estimating the fair values of the implied moments under truncation implicitly assumes that OTM option prices are zero outside the observed strike range. LRY demonstrates that this assumption is equivalent to truncating the implied RND itself, such that the risk-neutral probability is zero for the subset of strike prices outside the observed domain. Given this relationship, if implied moments are estimated using daily observations with varying levels of truncation, the moments are effectively derived from daily implied RNDs that are truncated randomly. Therefore, proceeding with implied moment estimation under such truncation implies reliance on time-varying assumptions about the shape of implied RND, undermining the consistency and suitability of the estimation approach. LRY addresses this concern through DS, whose detailed implementation procedure is explained in Section 4.

3. Data

We employ data from the KOSPI200 options market, globally recognized as one of the most liquid derivatives markets. The index derivatives market is a cornerstone of Korea's financial system because of its high trading volume and distinctive market structure (Ahn et al., 2008; Chung et al., 2016; Park & Ryu, 2019, 2021; Yu et al., 2024). The market attracts a diverse range of participants, with retail investors playing a particularly significant role, introducing distinct trading dynamics compared to institution-dominated markets (Ryu, 2011; Ryu & Yang, 2019). Due to the active participation of retail traders, the market exhibits high volatility and unique trading dynamics influenced by behavioral biases and informational asymmetries, characteristics often observed in emerging markets (Ryu & Yang, 2020; Ryu et al., 2022a, 2022b; Song et al., 2016). At the same time, the market's high trading activity and the availability of granular tick-by-tick transaction data support rigorous empirical analysis (Yang et al., 2019).

The empirical dataset comprises every on-exchange transaction in KOSPI200 options from January 2015 through December 2023, together with time-stamped levels of the underlying index, all supplied by the Korea Exchange. Because each tick record reports the exact execution price and time, using transaction prices rather than quoted bids and asks eliminates the need for midpoint approximations or extensive quote filters, while providing more accurate, higher-resolution price information. To convert this tick stream into a daily panel for model-free moment estimation, we keep only trades executed during the final 60 s of regular trading. Restricting the sample to that interval achieves two goals. First, it pairs every retained option price with the closing level of the underlying index, ensuring a consistent time stamp across spot and options markets. Second, it aligns prices across strikes so that the implied volatility surface is constructed from near-simultaneous transactions.

We approximate the risk-free and dividend rates for each maturity by linearly interpolating the rates of adjacent maturities on the zero-coupon and futures-implied dividend curves. To approximate zero-coupon curves, we use the daily Korea Interbank Offered Rate (KORIBOR) data provided by the Bank of Korea. We collect daily closing prices of KOSPI200 futures from the Korea Exchange to estimate daily futures-implied continuously compounded dividend rate curves. After retrieving all the necessary datasets, we apply a series of data filtering criteria to ensure that the empirical analysis is conducted using only relevant and reliable option price observations, as outlined below. First, we remove options that are not OTM. Second, observations are discarded if the corresponding transaction price is below 0.03.[1] Third, we exclude any observations with incomplete data entries. Finally, observations are discarded if they violate the no-arbitrage condition.[2]

Table 1 presents the summary statistics for the final dataset. Panel A reports the statistics for Black-Scholes d_1, used in this study to measure option moneyness as in LRY. d_1 is defined as

$$d_1[S(t), K, \sigma, r, \tau] = \frac{ln[S(t)/K] + [r + \sigma^2/2]\tau}{\sigma\sqrt{\tau}} \quad (8)$$

where σ is the volatility of the underlying returns. Descriptive statistics are separately reported for observations with 15–45 calendar days to expiration in Panel A because these options bracket the one-month target maturity used in our moment estimation procedure. Each trading day, we construct a synthetic one-month contract by linearly interpolating implied volatilities across the nearest shorter- and longer-dated maturities. Options that mature in 15–45 days influence the interpolation result most directly, and focusing on the 15- to 45-day range keeps the descriptive statistics aligned with the option set that drives the empirical analysis.

The table reveals four noteworthy findings. First, the magnitude of d_1, used in this study to measure option moneyness as in LRY, is greater for OTM puts than calls, suggesting that OTM puts are deeper out-of-the-money on average. The asymmetry implies that the wider portion of the integration domain for implied moment estimation is covered by OTM puts, which is equivalent to a stronger impact of truncation on OTM calls. This tendency is also reflected in the percentile values. Second, the implied volatility level is higher for OTM puts than for OTM calls. This difference explains why truncation has a more severe impact on OTM call observations. Given the monotonic relationship between implied volatility and option price for a fixed level of moneyness, lower implied volatility translates into lower option prices, which increases the likelihood of exclusion by the minimum price filter. Third, as a result of the first two features, the final sample contains more puts than calls as the minimum-price screen removes a disproportionate share of DOTM calls. Negative implied volatility skew, which is common in equity options markets (Mixon, 2009; Wu & Tian, 2024), makes OTM puts more expensive than equidistant OTM calls, so the minimum-price filter removes many calls but almost no puts. Fourth, compared to other observations, the observations with a time to maturity between 15 and 45 days do not exhibit significant differences. Therefore, although we focus on a single time to maturity of one month, it can be argued that the empirical results are representative of the entire KOSPI200 options market.

Fig. 1 illustrates the relationship between OTM moneyness and the implied volatility level across different sample subperiods. The figure reveals that, throughout the entire sample period, the implied volatility curve consistently exhibits a volatility smirk or skew, irrespective of the subperiod or the daily average implied volatility level. Building on evidence that links implied moments to the shape of the implied volatility curve (Zhang & Xiang, 2008), we expect the implied RND to be negatively skewed and leptokurtic, and Section 5 confirms this pattern.

4. Methodology

Our empirical analysis proceeds in three steps: (i) construct the implied volatility curve, (ii) estimate implied moments with and without DS, and (iii) run regressions comparing the information content of the two sets of moment estimates. We first extract daily one-month implied volatility curves from the final implied volatility surface, following prior work that fixes the maturity (Aspris et al., 2024; van Binsbergen et al., 2012). The selection of a one-month maturity is motivated by two factors: the liquidity of markets for nearby maturities and the feasibility of interpolating between maturities shorter and longer than the target maturity. To construct the surfaces, we apply bilinear approximation to minimize the impact of abnormal observations and ensure feasibility even when data are available for no more than two maturities. After extracting the implied volatility curve, we convert the implied volatility values into corresponding OTM option prices, further filtering out DOTM prices by reapplying a minimum price threshold of 0.03 to maintain consistency in data filtering. To minimize the effect of strike price discreteness, we set the strike price gap to 0.1, which is one twenty-fifth of the original gap.

After constructing a series of daily implied volatility curves for a fixed maturity, we proceed with DS as follows. First, we measure the locations of the minimum and maximum endpoints of daily implied volatility curves with respect to moneyness, which correspond to the endpoints of integration domains for implied moment estimators over the sample period. Following the approach of LRY, moneyness is expressed in terms of d_1, defined as in Equation (8). Using d_1 to measure moneyness is appropriate for two reasons when estimating implied moments with BKM estimators: (1) d_1 considers log moneyness, which is more directly related to the log return density than alternative measures such as percentage moneyness, and (2) d_1 is standardized in terms of return volatility, aligning it

[1] This threshold is based on the "three-minimum-price-change" rule used by LRY. In their S&P500 sample, the tick size is 0.25, and because they work with bid-ask midpoints, the smallest possible price change is half a tick, 0.125 points, and multiplying that minimum change by three produces their 0.375-point filter. For KOSPI200 options, the tick is 0.01 points, and we rely on transaction prices, so the minimum price change equals the tick itself, and three such increments amount to 0.03, which becomes our threshold.

[2] To check no-arbitrage conditions, we enforce the standard static no-arbitrage conditions by requiring that option prices must be at least as large as the intrinsic value and no greater than the underlying index level.

Table 1
Sample summary statistics.

Panel A. Black-Scholes d_1				
	Maturity between 15 and 45 days		Other maturities	
	Puts	Calls	Puts	Calls
Mean	1.376	−1.130	1.405	−1.178
Std. dev.	0.676	0.671	0.621	0.611
Minimum	0.025	−2.693	0.008	−2.736
25th pct.	0.846	−1.675	0.959	−1.642
Median	1.409	−1.125	1.425	−1.187
75th pct.	1.907	−0.571	1.877	−0.726
Maximum	3.083	0.110	3.244	0.267
# of obs.	32,564	21,775	21,461	16,075

Panel B. Black-Scholes implied volatility				
	Maturity between 15 and 45 days		Other maturities	
	Puts	Calls	Puts	Calls
Mean	0.229	0.153	0.233	0.155
Std. dev.	0.105	0.064	0.119	0.065
Minimum	0.079	0.046	0.051	0.043
25th pct.	0.159	0.118	0.160	0.119
Median	0.202	0.138	0.200	0.137
75th pct.	0.264	0.169	0.262	0.167
Maximum	0.968	0.728	1.165	0.624
# of obs.	32,564	21,775	21,461	16,075

Notes: This table presents summary statistics for the KOSPI200 options dataset used in this study. After data filtration, the daily sample of option prices comprises 91,875 observations. The following criteria are applied to exclude inappropriate observations: (1) the option is not out-of-the-money; (2) the closing price is below 0.03; (3) any corresponding data entries are missing; and (4) the no-arbitrage condition is violated. Panels A and B report the summary statistics for Black-Scholes d_1 and implied volatility, respectively.

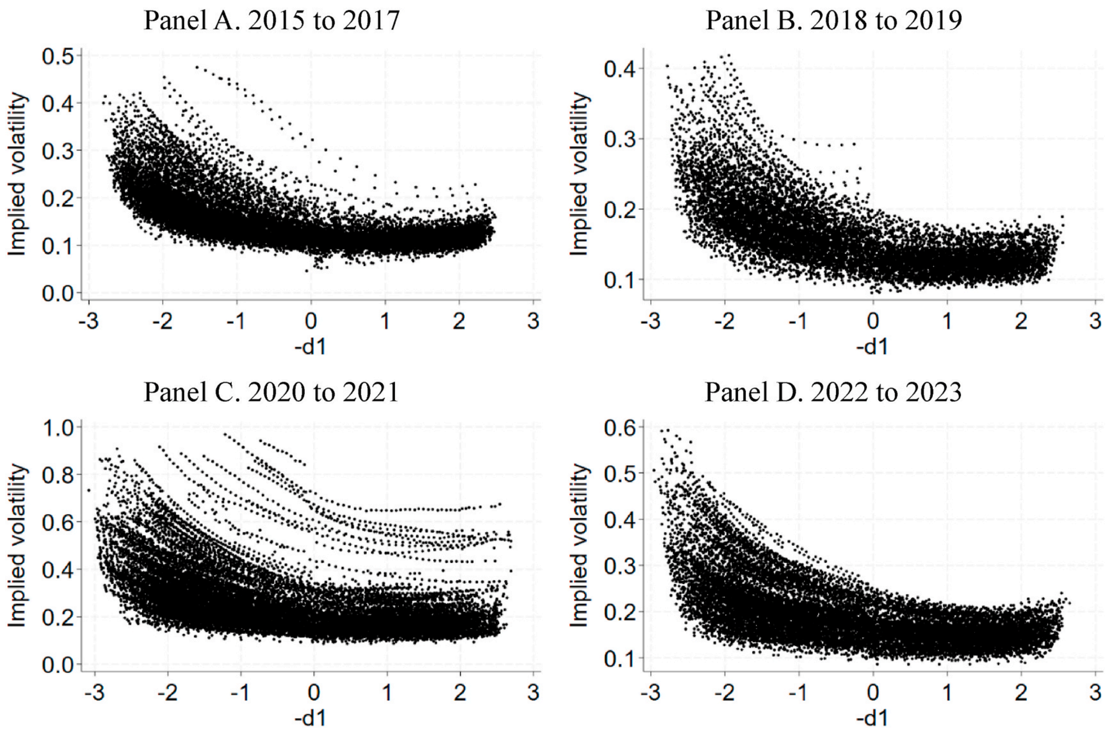

Fig. 1. Black-Scholes implied volatility by moneyness and time period
Notes: This figure illustrates the level of Black-Scholes implied volatility for out-of-the-money options, categorized by moneyness and time period. To enhance the clarity of the implied volatility curve, we focus exclusively on options with a time to maturity between 15 and 45 calendar days. Moneyness is measured using Black-Scholes d_1, which has been sign-switched to adhere to the convention of displaying puts on the left and calls on the right.

with the definition of higher moments in BKM.

Next, we determine the percentiles of the minimum and maximum endpoints, considering the extent to which OTM price observations will be further discarded. Once the percentiles are chosen, we apply DS by discarding observations whose strike prices fall outside these percentile values. Specifically, for an intensity level of i percent, we discard an OTM put price observation if the corresponding d_1 exceeds the i^{th} percentile of daily maximum endpoint observations. We exclude an OTM call price observation if the corresponding d_1 is more negative than the $(100-i)^{\text{th}}$ percentile of daily minimum endpoint observations. When the daily implied volatility curve does not span the range between the lower and upper endpoint percentiles, we extend the curve to those percentiles by flat extrapolation. After these treatments, we obtain a series of implied volatility curves with consistent endpoint locations across the sample period.

After applying DS at various intensity levels, we estimate implied volatility, skewness, and kurtosis using the BKM estimators and conduct a set of regression analyses to investigate whether DS enhances the information content of implied moment estimates. The regression analysis begins by examining the concurrent explanatory power of implied moment estimates for the underlying price. Because both underlying prices and implied moments reflect expectations about future price dynamics, we expect a strong contemporaneous relation between them, as the stock and options markets at least partly share information. This idea is supported by the literature, which shows that moments, including higher ones, are priced factors (Dittmar, 2002; Mitton & Vorkink, 2007).

We test the concurrent relationship in two ways. First, we evaluate the explanatory power of implied moment levels for the underlying price level using the following model:

$$ln[S(t)] = \alpha + \beta_0 \cdot VOL(t) + \beta_1 \cdot SKEW(t) + \beta_2 \cdot KURT(t) + \varepsilon(t) \tag{9}$$

where $ln[S(t)]$ is the natural logarithm of the underlying KOSPI200 level on day t, $VOL(t)$, $SKEW(t)$, and $KURT(t)$ denote the levels of implied volatility, skewness, and kurtosis estimates on day t, respectively. Next, we investigate the explanatory power of the first-order differences of implied moments for the underlying log returns with the following model:

$$\Delta ln[S(t)] = \alpha + \beta_0 \cdot \Delta VOL(t) + \beta_1 \cdot \Delta SKEW(t) + \beta_2 \cdot \Delta KURT(t) + \varepsilon(t) \tag{10}$$

where Δ is the first-order difference operator.

We then investigate whether DS enhances the predictive and forecasting performance of implied moment estimates. Evidence of informed OTM trading (Kang et al., 2022; Lin et al., 2018) suggests that implied moments can predict returns (Conrad et al., 2013; Kumar, 2009). If the predictive and forecasting abilities are distorted by the noise introduced by time-varying truncation, these abilities should improve when DS is applied, as shown by LRY. To evaluate this, we conduct in-sample return predictability and out-of-sample return forecasting ability tests using the following model:

$$\Delta ln\ [S(t)] = \alpha + \beta_0 \cdot \Delta ln\ [S(t-1)] + \gamma_0 \cdot \Delta VOL(t-1) + \gamma_1 \cdot \Delta SKEW(t-1) + \gamma_2 \cdot \Delta KURT(t-1) + \varepsilon(t) \tag{11}$$

Through this set of empirical analyses, we comprehensively evaluate the explanatory, predictive, and forecasting performance of implied moments for underlying returns, providing a more diverse perspective on the effectiveness of DS. A list of variable definitions is provided in Table 2.

5. Empirical results

5.1. Degree of truncation and moment estimates

Before evaluating the effectiveness of DS, we first examine the basic properties of implied moment estimates to understand the primary characteristics of the estimation results. Table 3 presents the summary statistics of implied moment estimates, with DS not applied during their collection. The table reveals that the implied RND is generally negatively skewed and leptokurtic, consistent with findings from several previous studies. The KOSPI200 return distribution is likewise negatively skewed and leptokurtic (Lee & Ryu, 2024b; Song et al., 2018), shaping the implied RND moments. Hence, the statistics suggest that the implied moment estimates reflect the shape of the realized density. However, it is noteworthy that the kurtosis of the underlying log return distribution is significantly higher than the implied kurtosis on average, a difference that may be attributed to truncation.

We further investigate the implied moment estimation results by examining their time-series dynamics. Fig. 2 illustrates the dynamics of daily implied moment estimates over the sample period. Panel A presents the implied volatility estimate dynamics, which demonstrates a time trend without significant noise. The clear dynamics suggest that the implied volatility estimates are not

Table 2
Variable descriptions.

Symbol	Definition	Source/Notes
S	KOSPI200 spot level	Korea Exchange
VOL	Option-implied volatility	Korea Exchange; Bakshi et al. (2003) estimator
SKEW	Option-implied skewness	Same as above
KURT	Option-implied kurtosis	Same as above

Notes: This table lists the key variables used in the empirical analysis and their sources.

Table 3
Underlying price and implied moment estimates.

	Panel A. Levels				Panel B. Daily first-order differences			
	ln(S)	*VOL*	*SKEW*	*KURT*	$\Delta ln(S) \bullet 10^2$	ΔVOL	$\Delta SKEW$	$\Delta KURT$
Mean	5.694	0.164	−0.988	5.081	0.022	0.000	0.000	0.000
Std. dev.	0.159	0.062	0.414	1.857	1.209	0.016	0.245	1.350
Minimum	5.363	0.092	−2.945	1.373	−12.175	−0.127	−1.124	−7.465
25th pct.	5.559	0.126	−1.205	3.884	−0.571	−0.006	−0.144	−0.724
Median	5.685	0.146	−0.943	4.665	0.059	0.000	0.005	−0.033
75th pct.	5.789	0.182	−0.710	5.697	0.627	0.005	0.005	0.703
Maximum	6.087	0.615	0.304	10.098	5.527	0.230	0.146	6.471
# of obs.	1703	1703	1703	1703	1702	1702	1702	1702

Notes: This table presents summary statistics for the daily closing underlying log prices and implied moment estimates, calculated without applying domain stabilization. To estimate the implied moments, we approximate option prices for a one-month time to maturity based on daily implied volatility surfaces. Panels A and B report the summary statistics for the levels and first-order differences, respectively.

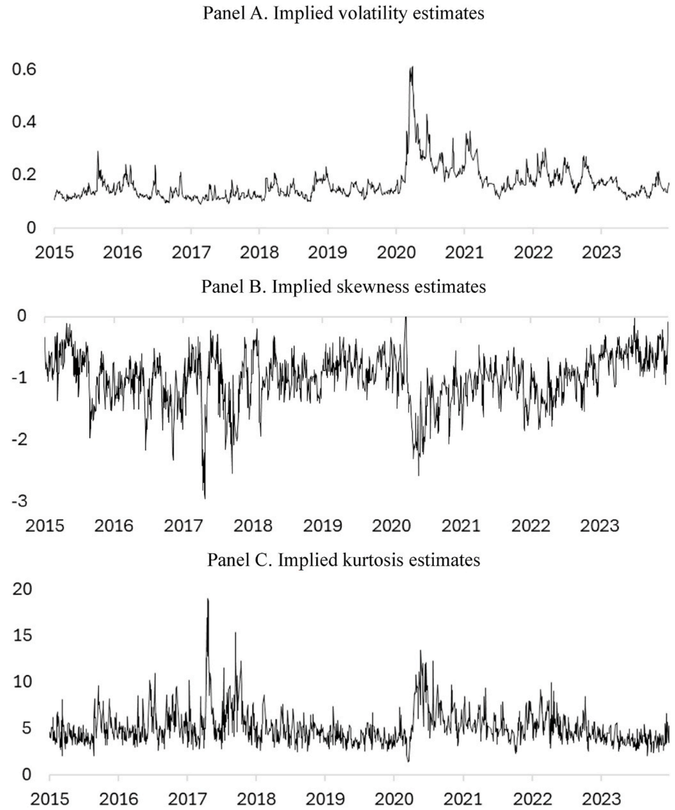

Fig. 2. Dynamics of implied moment estimates.
Notes: This figure depicts the daily dynamics of implied moment estimates, calculated using the BKM estimators, for a fixed one-month time to maturity. We do not consider any truncation error correction method for implied moment estimation. Panels A, B, and C depict the dynamics of implied volatility, skewness, and kurtosis estimates, respectively.

significantly affected by noise factors such as truncation. By comparison, Panels B and C, which depict the implied skewness and kurtosis estimate dynamics, respectively, reveal that the estimate dynamics are heavily affected by noisy fluctuations. These fluctuations are likely attributable to variations in the degree of truncation, implying that applying DS could be effective.

To evaluate the consistency of daily integration domains, it is essential to examine how their shape varies over time. Fig. 3 illustrates the dynamics of the integration domain's shape, measured in various ways, throughout the sample period. Panels A and B show that when the width of the integration domain is measured in nominal price terms, it begins to expand notably from 2020, coinciding with the onset of the COVID-19 period. This widening is primarily attributed to an increase in implied volatility, as evidenced in Panel A of Fig. 2. In contrast, Panel C of Fig. 3, which examines the integration domain in terms of d_1, shows that the noisy fluctuations are more pronounced, indicating that these fluctuations are a key factor driving the variability in the integration domain. This, in turn, may contribute to the noisy dynamics observed in the implied higher moment estimates, as noted by LRY. We conclude

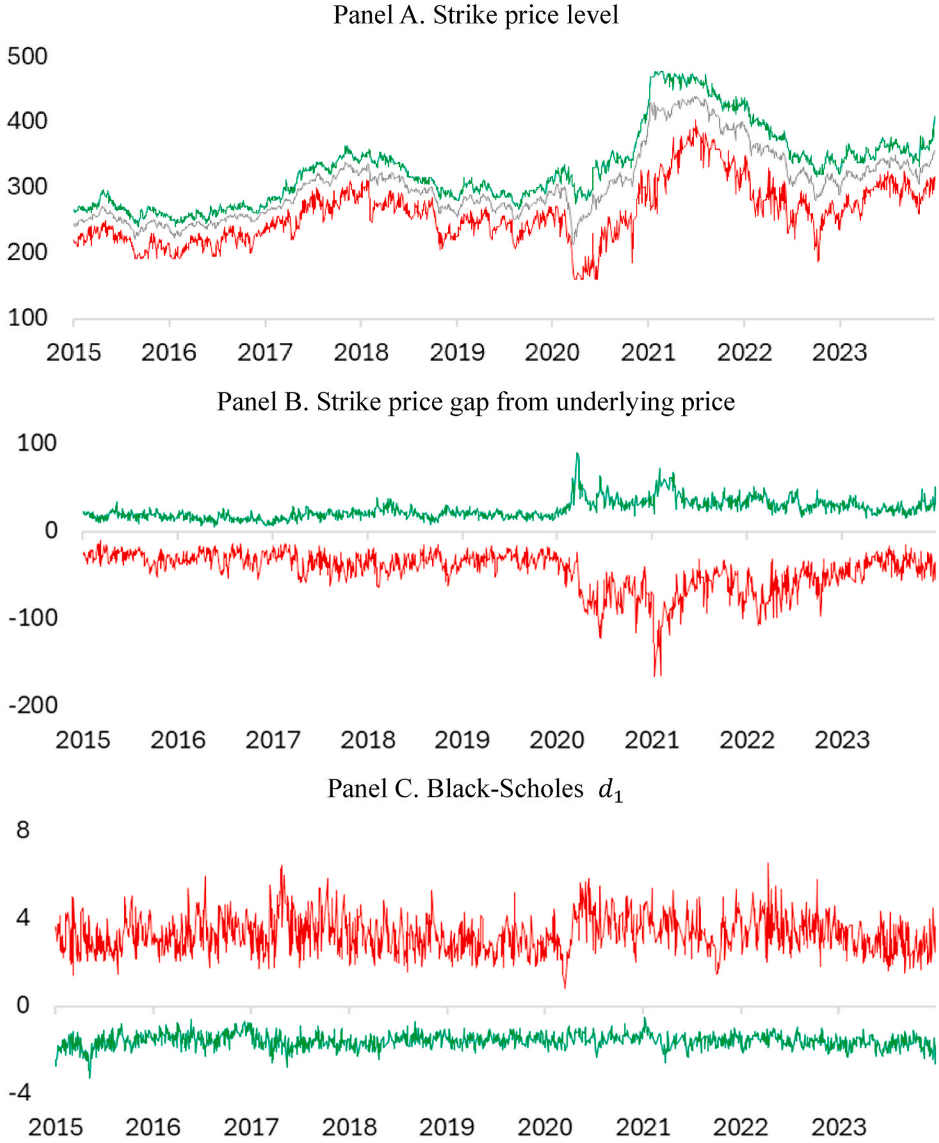

Fig. 3. Dynamics of the integration domain
Notes: This figure illustrates the time-series dynamics of the integration domain after data filtering. The minimum and maximum endpoints of the integration domain are defined as $K_{\min}$ and $K_{\max}$ in Panel A, $K_{\min} - S$ and $K_{\max} - S$ in Panel B, and $d_1(K_{\min})$ and $d_1(K_{\max})$ in Panel C. Here, $K_{\min}$ and $K_{\max}$ represent the minimum and maximum strike prices of the integration domain, S is the underlying price, and d_1 refers to the Black-Scholes d_1.

that the dynamics in the shape of the integration domains are noisy and may require treatment to improve stability. Motivated by this finding, we proceed to apply DS and explore its consequences.

5.2. Stabilizing integration domain

Fig. 4 illustrates the shape of the integration domain, measured in terms of d_1, after applying DS at intensity levels of 0 %, 50 %, and 100 %. Panel A shows that with a 0 % intensity level, DS stabilizes the integration domain without discarding observations, but relies entirely on flat extrapolation up to the sample maximum put and minimum call d_1. While this no-exclusion approach avoids data loss, the assumption of a flat implied-volatility curve, which is significantly different from actual observations in options markets, may introduce substantial bias into the implied-moment estimates. As demonstrated by Lee and Ryu (2024a), this type of estimation bias differs fundamentally from truncation errors, and the interplay between these two types of biases may complicate the structure of implied moment estimation errors. By contrast, Panel C of Fig. 4 reveals that when the DS intensity level is set at 100 %, the effects of DS differ significantly from those observed in Panel A. At this maximum intensity, DS avoids flat extrapolation entirely and stabilizes the integration domain solely by discarding additional observations. While this approach simplifies the structure of estimation bias, the

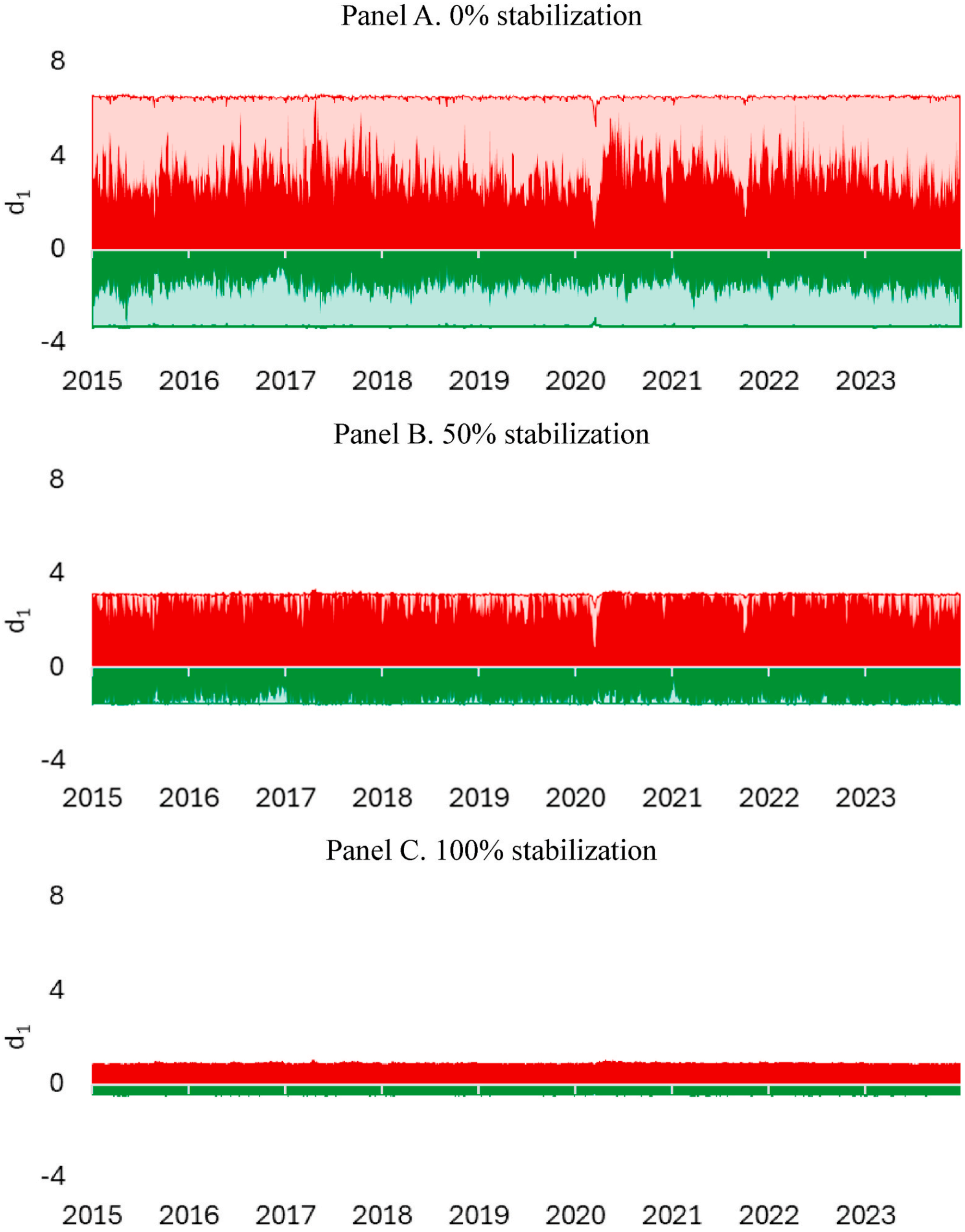

Fig. 4. Integration domain after domain stabilization
Notes: This figure depicts the dynamics of the integration domain endpoints following the implementation of domain stabilization at varying intensity levels. Under n percent stabilization, OTM option price observations are excluded if their d_1 values fall below the n^{th} percentile of the daily minimum d_1 values or exceed the $(100-n)^{th}$ percentile of the daily maximum d_1 values. Dark-shaded areas represent portions of the integration domain with observed OTM option prices, while light-shaded areas indicate regions with extrapolated prices. Panels A, B, and C depict the cases for 0 %, 50 %, and 100 % stabilization, respectively.

extreme truncation introduced by DS leads to severe information loss. Panels A and C highlight the trade-off involved in selecting the DS intensity level. Setting the intensity at a medium level, as shown in Panel B, where the intensity level is set at 50 %, may provide a reasonable balance between simplifying estimation bias and minimizing information loss.

Exploring how DS alters the time-series dynamics of implied moment estimates is valuable for a deeper understanding of its consequences. Fig. 5 illustrates the time-series dynamics of implied moment estimates for DS intensity levels of 0 %, 50 %, and 100 %. The figure reveals two noteworthy findings. First, DS does not significantly impact the implied volatility estimates. Even when the intensity level is set at 100 %, the pattern of the implied volatility dynamics remains largely unchanged, although the overall level of

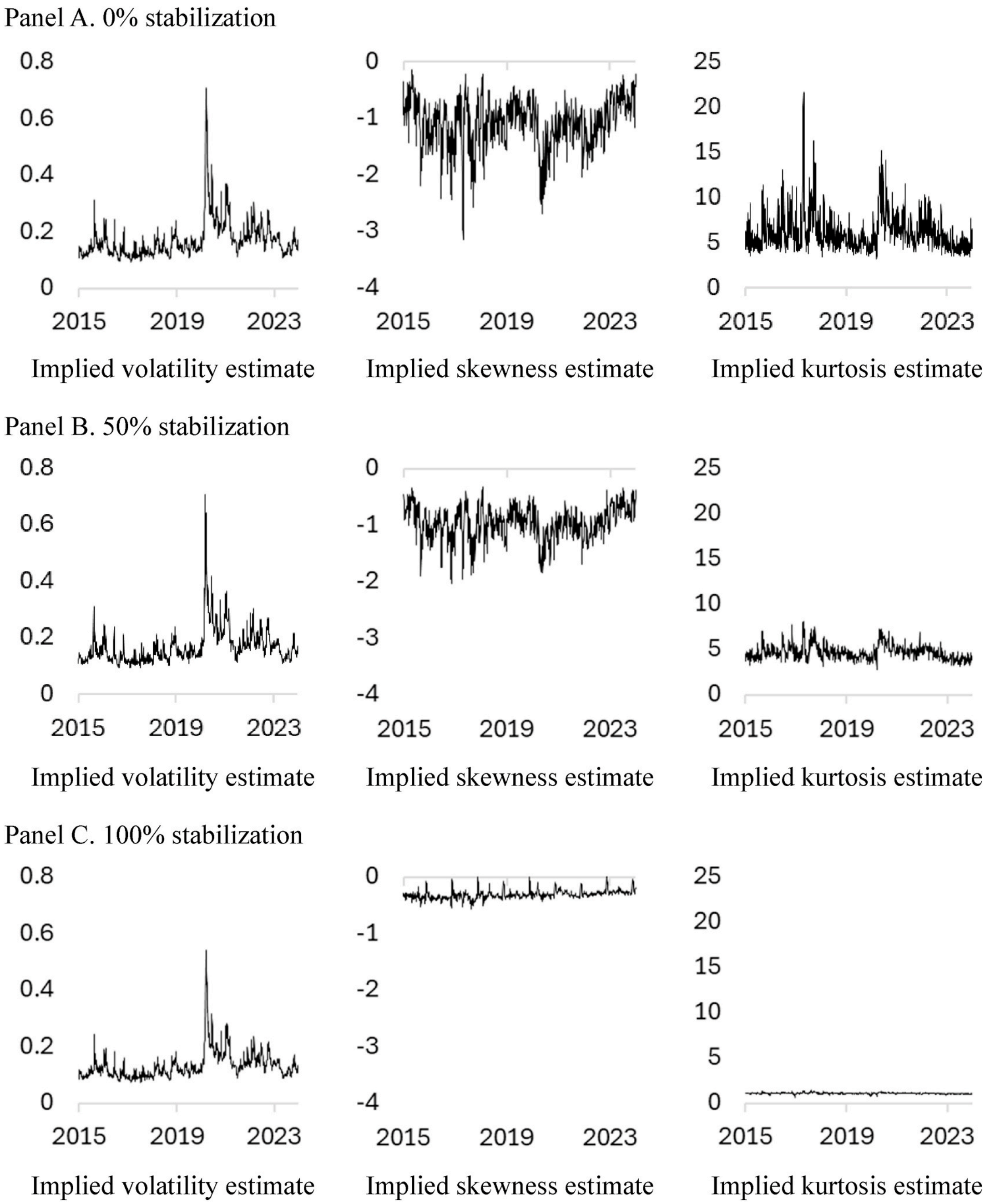

Fig. 5. Dynamics of implied moment estimates after domain stabilization.
Notes: This figure shows the dynamics of implied moment estimates after applying domain stabilization at different intensity levels. Panels A, B, and C depict the cases for 0 %, 50 %, and 100 % stabilization, respectively.

the estimates decreases to some degree. As suggested by LRY, this negligible impact can be attributed to the property of the BKM implied volatility estimator, which does not heavily rely on DOTM observations and is, therefore, less affected by truncation. Second, DS substantially alters implied skewness and kurtosis estimates. The magnitude of the higher moment estimates decreases significantly, while the noisy component becomes less pronounced, particularly for the implied kurtosis estimates. These changes likely reflect the trade-off highlighted in Fig. 4, which suggests that while extensive truncation may effectively reduce noise, it can also obscure true dynamics in implied moments, especially for higher moments.

The notable features in Fig. 5 can be further validated by examining the changes in the statistical properties of implied moment estimates as DS intensity levels vary. Table 4 presents the summary statistics of implied moment estimates for DS intensity levels of 0 %, 25 %, 50 %, 75 %, and 100 %. Consistent with Fig. 5, the table shows that DS substantially alters the statistical properties of implied

Table 4
Moment estimates after domain stabilization.

Panel A. Volatility										
	Level					First-order difference				
Intensity	0 %	25 %	50 %	75 %	100 %	0 %	25 %	50 %	75 %	100 %
Mean	0.167	0.166	0.164	0.162	0.130	0.000	0.000	0.000	0.000	0.000
Std. dev.	0.065	0.065	0.064	0.063	0.048	0.018	0.018	0.017	0.017	0.013
Minimum	0.093	0.093	0.092	0.092	0.073	−0.133	−0.138	−0.139	−0.138	−0.101
25th pct.	0.128	0.127	0.126	0.124	0.100	−0.006	−0.006	−0.006	−0.006	−0.005
Median	0.148	0.147	0.146	0.145	0.117	0.000	0.000	0.000	0.000	0.000
75th pct.	0.183	0.182	0.181	0.179	0.144	0.005	0.005	0.005	0.005	0.004
Maximum	0.710	0.709	0.707	0.701	0.541	0.314	0.313	0.312	0.309	0.233
# of obs.	1703	1703	1703	1703	1703	1702	1702	1702	1702	1702
Panel B. Skewness										
	Level					First-order difference				
Intensity	0 %	25 %	50 %	75 %	100 %	0 %	25 %	50 %	75 %	100 %
Mean	−1.072	−1.018	−0.958	−0.879	−0.307	0.000	0.000	0.000	0.000	0.000
Std. dev.	0.430	0.337	0.288	0.240	0.073	0.217	0.161	0.134	0.110	0.041
Minimum	−3.146	−2.234	−2.035	−1.810	−0.556	−1.223	−0.937	−0.768	−0.606	−0.209
25th pct.	−1.300	−1.216	−1.123	−1.015	−0.349	−0.114	−0.091	−0.072	−0.057	−0.018
Median	−1.018	−0.982	−0.927	−0.852	−0.314	0.004	0.005	0.006	0.004	−0.001
75th pct.	−0.770	−0.779	−0.755	−0.714	−0.275	0.125	0.097	0.076	0.058	0.015
Maximum	−0.134	−0.271	−0.308	−0.332	0.047	1.016	0.723	0.693	0.658	0.410
# of obs.	1703	1703	1703	1703	1703	1702	1702	1702	1702	1702
Panel C. Kurtosis										
	Level					First-order difference				
Intensity	0 %	25 %	50 %	75 %	100 %	0 %	25 %	50 %	75 %	100 %
Mean	6.089	5.289	4.710	4.043	1.095	0.000	0.000	0.000	0.000	0.000
Std. dev.	2.053	1.115	0.792	0.547	0.072	1.273	0.635	0.425	0.276	0.045
Minimum	3.125	2.985	2.796	2.510	0.674	−8.581	−2.851	−1.661	−1.396	−0.281
25th pct.	4.750	4.485	4.144	3.663	1.058	−0.652	−0.392	−0.239	−0.141	−0.022
Median	5.599	5.107	4.602	3.954	1.092	−0.037	−0.008	−0.003	0.000	0.000
75th pct.	6.748	5.817	5.123	4.308	1.126	0.617	0.385	0.236	0.140	0.022
Maximum	21.672	10.362	8.091	6.440	1.443	6.381	3.205	2.186	1.435	0.217
# of obs.	1703	1703	1703	1703	1703	1702	1702	1702	1702	1702

Notes: This table provides summary statistics for the implied moment estimates after applying domain stabilization at different intensity levels. 0 %, 25 %, 50 %, 75 %, and 100 % indicate the intensity levels. Panels A, B, and C report the summary statistics for implied volatility, skewness, and kurtosis estimates, respectively.

higher moments, while it affects implied volatility only modestly, except when the intensity level is 100 %. The table also shows that DS substantially influences the distribution of both the levels and first-order differences of implied skewness and kurtosis, including the higher moments of these distributions. Notably, intensive DS tends to make the distribution of higher moment estimates less skewed and less leptokurtic, provided the intensity level is below 100 %. This tendency implies that DS can help mitigate the impact of outliers in implied moment estimates, although excessive truncation may lead to unintended consequences.

The changes in statistical properties due to DS can also be examined by analyzing the correlations across implied moment estimates and the underlying price, as demonstrated in LRY. Table 5 presents the correlation coefficient estimates between the underlying log price and the implied moment estimates, with and without DS applied, and for intensity levels of 0 %, 25 %, 50 %, 75 %, and 100 %. The table shows that DS significantly impacts the correlations between the underlying log price and the implied moment estimates, both in terms of levels and first-order differences. The correlation between the underlying log price and the implied higher-moment estimates becomes more pronounced as DS is applied and the intensity level increases, except when the intensity level is set to 100 %. A similar pattern is observed in the correlations of first-order differences, suggesting that the dynamics of implied higher moments become more closely linked to underlying log returns as DS is applied more intensively.

The empirical results thus far demonstrate that DS and its intensity level significantly influence the dynamics and statistical properties of implied moment estimates, suggesting that the choice of intensity level is a critical factor when applying DS. To gain deeper insights into selecting the optimal intensity level, we investigate how effectively DS enhances the informativeness of implied moment estimates under various intensity levels. Specifically, we first examine the concurrent explanatory power of the estimates for underlying log returns, followed by a series of in-sample and out-of-sample tests to evaluate their predictive and forecasting performance.

5.3. *Contemporaneous relationship*

Table 6 presents the regression results for the model specified in Equation (9), which tests the contemporaneous explanatory power

Table 5
Correlations among underlying log prices and implied moment estimates.

Panel A. No stabilization

	Level					First-order difference			
	ln(*S*)	*VOL*	*SKEW*	*KURT*		Δ*ln*(*S*)	Δ*VOL*	Δ*SKEW*	Δ*KURT*
ln(*S*)	1.00				Δ*ln*(*S*)	1.00			
VOL	0.05**	1.00			Δ*VOL*	−0.63***	1.00		
SKEW	0.04*	−0.33***	1.00		Δ*SKEW*	0.10***	−0.25***	1.00	
KURT	0.03	0.18***	−0.86***	1.00	Δ*KURT*	0.00	0.14***	−0.86***	1.00

Panel B. 0 % stabilization

	Level					First-order difference			
	ln(*S*)	*VOL*	*SKEW*	*KURT*		Δ*ln*(*S*)	Δ*VOL*	Δ*SKEW*	Δ*KURT*
ln(*S*)	1.00				Δ*ln*(*S*)	1.00			
VOL	0.04*	1.00			Δ*VOL*	−0.64***	1.00		
SKEW	0.07***	−0.39***	1.00		Δ*SKEW*	0.20***	−0.29***	1.00	
KURT	−0.01	0.20***	−0.88***	1.00	Δ*KURT*	−0.04*	0.12***	−0.88***	1.00

Panel C. 25 % stabilization

	Level					First-order difference			
	ln(*S*)	*VOL*	*SKEW*	*KURT*		Δ*ln*(*S*)	Δ*VOL*	Δ*SKEW*	Δ*KURT*
ln(*S*)	1.00				Δ*ln*(*S*)	1.00			
VOL	0.04*	1.00			Δ*VOL*	−0.64***	1.00		
SKEW	0.09***	−0.40***	1.00		Δ*SKEW*	0.27***	−0.33***	1.00	
KURT	−0.02	0.24***	−0.88***	1.00	Δ*KURT*	−0.12***	0.17***	−0.87***	1.00

Panel D. 50 % stabilization

	Level					First-order difference			
	ln(*S*)	*VOL*	*SKEW*	*KURT*		Δ*ln*(*S*)	Δ*VOL*	Δ*SKEW*	Δ*KURT*
ln(*S*)	1.00				Δ*ln*(*S*)	1.00			
VOL	0.04*	1.00			Δ*VOL*	−0.64***	1.00		
SKEW	0.11***	−0.41***	1.00		Δ*SKEW*	0.30***	−0.34***	1.00	
KURT	−0.03	0.25***	−0.87***	1.00	Δ*KURT*	−0.15***	0.18***	−0.85***	1.00

Panel E. 75 % stabilization

	Level					First-order difference			
	ln(*S*)	*VOL*	*SKEW*	*KURT*		Δ*ln*(*S*)	Δ*VOL*	Δ*SKEW*	Δ*KURT*
ln(*S*)	1.00				Δ*ln*(*S*)	1.00			
VOL	0.04*	1.00			Δ*VOL*	−0.64***	1.00		
SKEW	0.12***	−0.40***	1.00		Δ*SKEW*	0.32***	−0.35***	1.00	
KURT	−0.04*	0.25***	−0.86***	1.00	Δ*KURT*	−0.17***	0.18***	−0.82***	1.00

Panel F. 100 % stabilization

	Level					First-order difference			
	ln(*S*)	*VOL*	*SKEW*	*KURT*		Δ*ln*(*S*)	Δ*VOL*	Δ*SKEW*	Δ*KURT*
ln(*S*)	1.00				Δ*ln*(*S*)	1.00			
VOL	0.05**	1.00			Δ*VOL*	−0.65***	1.00		
SKEW	0.29***	0.15***	1.00		Δ*SKEW*	0.11***	−0.08***	1.00	
KURT	−0.05**	0.02	−0.60***	1.00	Δ*KURT*	−0.08***	0.01	−0.57***	1.00

Notes: This table presents the estimated Pearson correlation coefficients among the log price, implied volatility, implied skewness, and implied kurtosis, which are denoted as ln(*S*), *VOL*, *SKEW*, and *KURT*, respectively. Panels A–F report the correlation coefficient estimates for the cases of no stabilization, 0 %, 25 %, 50 %, 75 %, and 100 % stabilization, respectively. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

of implied moment estimate levels on the underlying log price level. Since we employ Newey-West standard errors to address residual autocorrelation and heteroskedasticity, issues identified through Breusch-Godfrey and Breusch-Pagan tests conducted during OLS estimation, it is inappropriate to rely solely on R^2 for comparing goodness-of-fit across models. To enhance robustness in evaluating model fit, we additionally calculate Akaike Information Criterion (AIC) values. The results reveal two noteworthy findings. First, the explanatory power of the model, as measured by the goodness-of-fit using AIC, increases as DS is applied and the intensity level rises. Second, the statistical significance of the coefficient estimate, measured by *t*-statistics, increases monotonically with higher DS intensity for the implied skewness estimate, though this pattern is not observed for the other moments. The increase in the explanatory power suggests that DS enhances the explanatory power of implied moment estimates primarily through the implied skewness estimate. Overall, the regression results indicate that the levels of implied moment estimates explain the underlying price level more

Table 6
Explanatory power of implied moments for underlying log price: Levels.

		No	0 %	25 %	50 %	75 %	100 %
VOL(t)		0.294	0.324	0.360	0.361	0.360	−0.042
		(0.91)	(1.03)	(1.17)	(1.17)	(1.43)	(-0.13)
SKEW(t)		0.134***	0.151***	0.229***	0.255***	0.287***	0.869***
		(2.63)	(2.80)	(3.33)	(3.40)	(4.20)	(4.81)
KURT(t)		0.027***	0.025***	0.054***	0.068***	0.085***	0.422***
		(2.87)	(2.61)	(2.98)	(2.89)	(3.27)	(2.88)
Intercept		5.641***	5.650***	5.583***	5.559***	5.542***	5.505***
		(125.27)	(122.01)	(94.09)	(80.61)	(82.40)	(44.47)
# of obs.		1703	1703	1703	1703	1703	1703
Unadjusted R^2		0.031	0.033	0.044	0.045	0.047	0.104
AIC	Value	−1470.2	−1474.3	−1494.2	−1496.0	−1499.0	−1604.6
	Diff.	0.0	−4.1	−24.0	−25.8	−28.8	−134.4
BG		1672.9***	1679.1***	1675.0***	1675.4***	1675.3***	1640.5***
BP		25.3***	9.9***	8.9***	7.3***	5.5**	43.5***

Notes: This table presents the regression results of the underlying log price on the levels of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $lnS(t)$, represents the natural logarithm of the underlying index on day *t*. $VOL(t)$, $SKEW(t)$, and $KURT(t)$ denote the daily levels of implied volatility, skewness, and kurtosis estimates on day *t*, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of nine selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. *t*-statistics are presented in parentheses. *** and ** indicate statistical significance at the 1 % and 5 % levels, respectively.

effectively when DS is applied and the intensity level increases.

Table 7 summarizes the regression results for the model specified in Equation (10), which tests the contemporaneous explanatory power of the first-order differences of implied moment estimates on the underlying log returns. The results highlight two noteworthy findings. First, while DS improves the model's explanatory power, the degree of improvement plateaus when the DS intensity level exceeds 25 %. This finding suggests that the optimal DS intensity level may vary depending on the estimation objective and market conditions, and it does not necessarily need to be set at 100 %, consistent with the findings of LRY. Second, in contrast to the relationships observed for levels, the first-order differences of the implied volatility estimate show a stronger and more significant relationship with log returns compared to higher-moment estimates. This can be attributed to the asymmetric volatility phenomenon documented in several prior studies (Bekaert & Wu, 2000; Engle & Mistry, 2014). The enhancement in the explanatory power of implied moment estimates is evident in both levels and first-order differences. However, the magnitude and consistency of this

Table 7
Explanatory power of implied moments for underlying log price: First-order differences.

		No	0 %	25 %	50 %	75 %	100 %
ΔVOL(t)		−0.472***	−0.408***	−0.410***	−0.415***	−0.423***	−0.600***
		(-19.20)	(-16.88)	(-16.39)	(-16.35)	(-16.43)	(-19.06)
ΔSKEW(t)		0.003	0.015***	0.018***	0.018***	0.018***	0.009
		(0.90)	(3.96)	(3.52)	(3.13)	(2.65)	(0.70)
ΔKURT(t)		0.001**	0.002***	0.004***	0.004**	0.003	−0.016**
		(2.54)	(4.31)	(3.28)	(2.37)	(1.31)	(-2.11)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.99)	(0.99)	(0.99)	(0.99)	(1.00)	(1.00)
# of obs.		1702	1702	1702	1702	1702	1702
Unadjusted R^2		0.410	0.422	0.423	0.423	0.423	0.423
AIC	Value	−11090.4	−11126.4	−11129.0	−11128.7	−11129.0	−11127.9
	Diff.	0.0	−36.0	−38.6	−38.3	−38.6	−37.4
BG		10.9*	11.4**	11.1**	11.2**	11.4**	11.2**
BP		1.1	0.8	0.5	0.8	1.1	12.0***

Notes: This table presents the regression results of the underlying log return on the first-order differences of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $\Delta lnS(t)$, represents the log return of the underlying index on day *t*. $\Delta VOL(t)$, $\Delta SKEW(t)$, and $\Delta KURT(t)$ denote the daily first-order differences of implied volatility, skewness, and kurtosis estimates on day *t*, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of nine selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

enhancement are less pronounced for first-order differences compared to levels.

5.4. In-sample and out-of-sample return prediction

Table 8 presents the in-sample test results for the model specified by Equation (11), which evaluates the predictive accuracy of implied moment dynamics on underlying log returns. The results reveal three noteworthy findings. First, the predictive ability of the model is enhanced by DS when the intensity level is appropriately chosen. Specifically, the goodness-of-fit, measured by the AIC value, improves when DS is applied at intermediate intensity levels. In contrast, AIC tends to increase when the intensity level is either too low (0 % or 25 %) or too high (100 %). Second, when DS enhances the predictive ability of implied moment estimates, the coefficient estimate for implied kurtosis is statistically significant at the 10 % level, whereas the estimates for implied volatility, implied skewness, and lagged returns are statistically insignificant. This finding contrasts with LRY, which demonstrates the statistical significance of implied skewness estimates only. This difference suggests that the overall price levels of DOTM options, relative to near-the-money options, contain distinct information in the KOSPI200 options market. This insight contributes to the existing literature, which primarily focuses on the differences between OTM put and call markets in Korea (Ryu et al., 2021; Ryu & Yang, 2018; Ryu & Yu, 2021). Third, although an enhanced predictive ability is observed when DS is applied at an appropriate intensity level, the degree of enhancement, as well as the explanatory power, remains modest compared to LRY, which examines the S&P500 index market. The results in Table 8 suggest that both the increases in R^2 and decreases in AIC are relatively minor. Overall, the regression results indicate that DS moderately enhances the in-sample predictive power of implied moment estimates for underlying returns, particularly when the intensity level is chosen appropriately. However, the observed enhancement is less significant compared to the findings from LRY. We further investigate the reason for the less significant information content of implied moment estimates and the impact of DS in the KOSPI200 options market in Sections 5.5 and 5.6.

We evaluate the out-of-sample forecasting performance of implied moment estimates on underlying log returns using the model specified in Equation (11). To assess the magnitude of improvement in out-of-sample return forecasting ability, we calculate the R_{OS}^2 statistic, as proposed by Campbell and Thompson (2008), which is defined as follows:

$$R_{OS}^2 = 1 - \left[\sum_{t=1}^{T} (r_t - \hat{r}_t)^2\right] \Big/ \left[\sum_{t=1}^{T} (r_t - \overline{r}_t)^2\right] \tag{12}$$

where T is the number of samples in the out-of-sample forecast period, $\hat{r}_t$ is the fitted value derived from a predictive regression estimated through the rolling window ending at time $t-1$, and $\overline{r}_t$ is the benchmark return for the rolling window, defined as the historical average return. A positive R_{OS}^2 value indicates that the predictive regression produces a lower mean-squared prediction error than the benchmark return. We evaluate the model using sixteen rolling window lengths, ranging from five to eighty months, with five-month intervals.

Table 8
In-sample return predictive ability of implied moments.

		No	0 %	25 %	50 %	75 %	100 %
ΔlnS(t-1)		0.021	0.007	0.003	0.003	0.003	−0.002
		(0.61)	(0.23)	(0.10)	(0.11)	(0.10)	(-0.05)
ΔVOL(t-1)		−0.014	−0.033	−0.030	−0.029	−0.029	−0.038
		(-0.36)	(-0.76)	(-0.65)	(-0.64)	(-0.65)	(-0.70)
ΔSKEW(t-1)		−0.007*	−0.006	−0.002	0.000	0.002	−0.007
		(-1.76)	(-1.51)	(-0.33)	(0.08)	(0.33)	(-0.87)
ΔKURT(t-1)		−0.001	−0.001	0.001	0.002*	0.004*	0.010
		(-1.49)	(-1.18)	(1.12)	(1.84)	(1.86)	(0.98)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.74)	(0.76)	(0.76)	(0.76)	(0.76)	(0.76)
# of obs.		1701	1701	1701	1701	1701	1701
Unadjusted R^2		0.006	0.004	0.006	0.007	0.007	0.004
AIC	Value	−10193.9	−10189.9	−10193.4	−10195.6	−10195.4	−10190.5
	Diff.	0.0	4.0	0.5	−1.7	−1.5	3.4
BG		11.3**	14.9***	12.4**	12.3**	12.2**	19.0***
BP		37.5***	60.0***	52.3***	61.0***	75.8***	70.8***

Notes: This table presents the regression results of the underlying log return on the first-order differences of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $\Delta lnS(t)$, represents the log return of the underlying index on day t. The lagged log-return, $\Delta lnS(t-1)$, is included as an independent variable to control for return reversals. $\Delta VOL(t-1)$, $\Delta SKEW(t-1)$, and $\Delta KURT(t-1)$ denote the lagged daily first-order differences of implied volatility, skewness, and kurtosis estimates, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of nine selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 9 summarizes the out-of-sample test results, revealing three notable features. First, when DS is not applied, incorporating implied moments does not enhance out-of-sample return forecasting, regardless of the rolling window length. The first column of R^2_{OS} statistics indicates that the values are consistently negative when DS is not applied. As noted in the interpretation of Table 8, this result may be attributed to the dominance of retail investors in the KOSPI200 options market. Second, when DS is applied with an appropriate intensity level and rolling window length, out-of-sample forecasting performance improves with the inclusion of implied moments. The second to fourth R^2_{OS} columns demonstrate that the statistic becomes positive in most cases when the rolling window length is set to 75 or 80 months. This result implies that DS can make the originally uninformative implied moment estimates informative. Third, even when DS does not significantly enhance forecasting performance, it still improves the forecasting ability of implied moment estimates under suboptimal intensity levels. Table 9 shows that, when the intensity level is set to 0 % or 100 %, R^2_{OS} values still exceed the maximum R^2_{OS} observed in the no-stabilization case when the rolling window length is 70 months or longer. This increase in R^2_{OS} suggests that the lack of informativeness in implied moment estimates is primarily due to the limited information content of the moments themselves, which DS can enhance under various circumstances. In summary, the results suggest that both the return predictive accuracy and out-of-sample forecasting performance of implied moment estimates are enhanced when DS is employed at an appropriate intensity level.

Our results show that, with an adequately chosen intensity level, DS improves the explanatory, predictive, and forecasting power of implied moments for underlying log returns. These findings also highlight a strong association between implied moments and both the level and dynamics of the underlying price, an association that becomes more apparent when DS is applied. Although the results are somewhat less pronounced compared to those reported in LRY, this difference can, at least partially, be attributed to the higher rate of retail trader participation in the KOSPI200 options market. Based on this reasoning, we argue that this study provides evidence that DS consistently enriches the information content of implied moment estimates across multiple markets.

5.5. Subperiods and volatility regimes

We next divide the data into calendar subperiods and volatility states to learn whether our findings are shaped by period-specific factors. The subperiods focus on two structural changes in the KOSPI200 index options market, namely the contract size adjustment and the later introduction of weekly options, so that we can isolate any influence these events may have on DS. The contract multiplier was reduced from KRW 500,000 to KRW 250,000 on March 27th, 2017, and the Korea Exchange began listing weekly options on September 23rd, 2019. The smaller contract likely widened retail participation, and the weekly listings concentrated trading near expiration, both of which could change quote availability and the noise in implied moment estimates. We therefore split the sample at these dates and repeat the analysis within each segment to see how these market-specific changes affect the performance of DS.

Table 10 presents the regression results for the contemporaneous explanatory power of implied moment estimate levels on the underlying log price level, as in Table 6, for each subperiod. This table demonstrates an interesting difference before and after the contract size change. Although Panel A shows that DS does not improve contemporaneous explanatory power in the period before the contract size reduction, Panels B and C show that the procedure becomes effective once market participation broadens. This pattern

Table 9
Out-of-sample return forecasting ability of implied moments after stabilization.

Rolling window length	R^2_{OS} (%)					
	No	0 %	25 %	50 %	75 %	100 %
5 months	−9.79	−13.96	−13.40	−13.12	−13.51	−13.06
10 months	−4.77	−7.66	−7.86	−7.76	−7.96	−6.58
15 months	−3.97	−6.07	−5.94	−5.75	−5.87	−4.69
20 months	−2.36	−4.21	−4.12	−4.01	−4.11	−3.17
25 months	−1.93	−3.40	−3.09	−2.98	−3.08	−2.65
30 months	−1.98	−2.80	−2.37	−2.23	−2.33	−1.95
35 months	−1.64	−2.12	−1.74	−1.61	−1.74	−1.62
40 months	−1.53	−1.91	−1.62	−1.52	−1.66	−1.51
45 months	−1.27	−1.59	−1.33	−1.20	−1.26	−1.27
50 months	−0.93	−1.29	−1.05	−0.88	−0.91	−1.05
55 months	−1.01	−1.35	−1.10	−0.87	−0.86	−1.03
60 months	−0.86	−1.00	−0.53	−0.36	−0.40	−0.71
65 months	−1.33	−1.16	−0.45	−0.25	−0.31	−0.57
70 months	−1.00	−0.66	−0.28	−0.21	−0.25	−0.38
75 months	−1.15	−0.56	−0.21	0.11	0.05	−0.53
80 months	−2.29	−0.84	0.07	0.45	0.59	−0.14

Notes: This table presents the results of the out-of-sample return forecasting ability test at intensity levels of 0, 25, 50, 75, and 100 percent. Following Campbell and Thompson (2008), we report the R^2_{OS} statistic, which is defined as $R^2_{OS} = 1 - \left[\sum_{t=1}^{T}(r_t - \widehat{r}_t)^2\right] / \left[\sum_{t=1}^{T}(r_t - \overline{r}_t)^2\right]$, where $\widehat{r}_t$ is the fitted value derived from a predictive regression estimated through the rolling window that ends at time $t-1$, and $\overline{r}_t$ is the benchmark value for the rolling window. Benchmark value is defined as the historical mean log return. A positive value of R^2_{OS} indicates that the predictive regression produces a lower mean squared prediction error than the benchmark value.

Table 10
Explanatory power of implied moments by subperiod: Log price levels.

Panel A. Subperiod #1: Before contract size change							
		No	0 %	25 %	50 %	75 %	100 %
VOL(*t*)		−1.015***	−0.957***	−1.019***	−1.069***	−1.119***	−1.506***
		(-8.67)	(-7.22)	(-7.09)	(-7.14)	(-7.32)	(-10.97)
SKEW(*t*)		0.036**	0.041**	0.050*	0.050	0.046	−0.016
		(2.13)	(2.10)	(1.88)	(1.61)	(1.31)	(-0.35)
KURT(*t*)		0.027***	0.011***	0.019***	0.024**	0.029*	0.034
		(3.33)	(3.06)	(2.60)	(2.21)	(1.80)	(0.61)
Intercept		5.638***	5.629***	5.610***	5.601***	5.598***	5.642***
		(318.96)	(289.52)	(209.70)	(166.36)	(133.21)	(105.50)
# of obs.		474	474	474	474	474	474
Unadjusted R^2		0.536	0.533	0.532	0.528	0.522	0.514
AIC	Value	−1916.1	−1912.7	−1911.6	−1907.8	−1902.0	−1893.6
	Diff.	0.0	3.4	4.5	8.3	14.1	22.5
BG		405.7***	406.2***	402.2***	403.2***	406.0***	413.7***
BP		2.8*	1.1	0.1	0.0	0.0	1.8
Panel B. Subperiod #2: After contract size change, before weekly options listing							
		No	0 %	25 %	50 %	75 %	100 %
VOL(*t*)		−1.414***	−1.415***	−1.138***	−1.119***	−1.161***	−1.739***
		(-4.63)	(-4.46)	(-3.44)	(-3.36)	(-3.46)	(-5.05)
SKEW(*t*)		−0.001	−0.005	0.070	0.094	0.107	0.192*
		(-0.04)	(-0.17)	(1.40)	(1.61)	(1.59)	(1.91)
KURT(*t*)		0.004	0.003	0.030**	0.046**	0.063**	0.249**
		(0.61)	(0.46)	(2.02)	(2.27)	(2.20)	(2.19)
Intercept		5.864***	5.863***	5.760***	5.715***	5.684***	5.666***
		(128.60)	(116.61)	(83.20)	(70.97)	(60.98)	(45.50)
# of obs.		493	493	493	493	493	493
Unadjusted R^2		0.251	0.254	0.290	0.303	0.308	0.305
AIC	Value	−1276.3	−1278.2	−1302.5	−1311.6	−1315.2	−1313.1
	Diff.	0.0	−1.9	−26.2	−35.3	−38.9	−36.8
BG		471.4***	470.9***	464.8***	463.5***	464.4***	464.2***
BP		7.5***	7.5***	1.6	0.8	0.7	6.1**
Panel C. Subperiod #3: After weekly options listing							
		No	0 %	25 %	50 %	75 %	100 %
VOL(*t*)		−0.885***	−0.788***	−0.779***	−0.794***	−0.818***	−1.128***
		(-5.80)	(-4.66)	(-4.60)	(-4.55)	(-4.51)	(-6.05)
SKEW(*t*)		−0.007	0.048	0.161*	0.193*	0.212*	0.127
		(-0.12)	(0.67)	(1.76)	(1.94)	(1.92)	(0.63)
KURT(*t*)		0.014	0.022	0.073***	0.103***	0.138***	0.531**
		(0.97)	(1.40)	(2.74)	(2.98)	(3.00)	(2.55)
Intercept		5.904***	5.885***	5.749***	5.673***	5.604***	5.447***
		(119.09)	(110.61)	(72.00)	(58.11)	(47.16)	(26.91)
# of obs.		737	737	737	737	737	737
Unadjusted R^2		0.189	0.190	0.229	0.234	0.231	0.205
AIC	Value	−892.5	−893.5	−929.8	−934.5	−931.4	−907.3
	Diff.	0.0	−1.0	−37.3	−42.0	−38.9	−14.8
BG		715.9***	715.4***	704.4***	704.3***	706.4***	709.8***
BP		0.3	0.3	0.0	0.1	0.0	0.6

Notes: This table presents the regression results of the underlying log price on the levels of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $lnS(t)$, represents the natural logarithm of the underlying index on day *t*. $VOL(t)$, $SKEW(t)$, and $KURT(t)$ denote the daily levels of implied volatility, skewness, and kurtosis estimates on day *t*, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of five for Panels A and B and six for Panel C, selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

suggests that a wider investor base may lead to more active and informed trading in OTM options, which makes truncation treatment more valuable for extracting information from these contracts. However, this interpretation should be made with caution, and the impact of truncation needs to be examined from several perspectives, as in the earlier sections.

Table 11 presents the regression results for the contemporaneous relationship between returns and the first differences of implied moments as in Table 7. The implications of the results are similar to those in Table 10. While Panel A reveals that DS does not improve contemporaneous explanatory power before the contract size reduction, Panels B and C show that explanatory power increases after the reduction. This increase, however, levels off when the intensity is stronger than about 50–75 percent, suggesting that a moderate balance between trimming and extrapolation remains optimal. Overall, this evidence confirms that domain stabilization meaningfully strengthens the contemporaneous link between implied moments and returns only after the investor composition broadens.

Table 12 reports the in-sample return predictability regressions and yields conclusions that differ from those in Tables 10 and 11.

Table 11

Explanatory power of implied moments for underlying log price: First-order differences, before and after contract size change.

Panel A. Subperiod #1: Before contract size change							
		No	0 %	25 %	50 %	75 %	100 %
ΔVOL(t)		−0.414***	−0.365***	−0.382***	−0.391***	−0.401***	−0.539***
		(-8.43)	(-6.90)	(-7.09)	(-7.34)	(-7.67)	(-8.81)
ΔSKEW(t)		0.004	0.010**	0.006	0.003	0.000	−0.008
		(1.41)	(2.00)	(0.99)	(0.52)	(0.00)	(-0.63)
ΔKURT(t)		0.002***	0.002***	0.002	0.001	−0.001	−0.022**
		(3.36)	(3.10)	(1.33)	(0.49)	(-0.35)	(-2.02)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.99)	(1.00)	(1.33)	(0.98)	(0.98)	(0.98)
# of obs.		473	473	473	473	473	473
Unadjusted R^2		0.406	0.397	0.381	0.380	0.381	0.392
AIC	Value	−3391.3	−3384.2	−3372.0	−3371.0	−3372.1	−3383.6
	Diff.	0.0	7.1	19.3	20.3	19.2	7.7
BG		10.4*	10.1*	9.8*	10.1*	10.7*	10.5*
BP		0.5	0.0	2.0	3.2*	3.6*	9.1***
Panel B. Subperiod #2: After contract size change, before weekly options listing							
		No	0 %	25 %	50 %	75 %	100 %
ΔVOL(t)		−0.424***	−0.357***	−0.353***	−0.357***	−0.366***	−0.569***
		(-6.10)	(-4.93)	(-4.80)	(-4.80)	(-4.81)	(-6.54)
ΔSKEW(t)		0.005	0.016**	0.023**	0.023**	0.022**	0.008
		(1.14)	(2.57)	(2.49)	(2.35)	(2.01)	(0.33)
ΔKURT(t)		0.001*	0.002***	0.004**	0.004*	0.003	−0.015
		(1.88)	(2.75)	(2.33)	(1.87)	(0.95)	(-1.01)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(-0.05)	(-0.04)	(-0.04)	(-0.04)	(-0.05)	(-0.05)
# of obs.		493	493	493	493	493	493
Unadjusted R^2		0.262	0.291	0.297	0.296	0.295	0.270
AIC	Value	−3339.2	−3358.7	−3362.8	−3362.5	−3361.6	−3344.0
	Diff.	0.0	−19.5	−23.6	−23.3	−22.4	−4.8
BG		2.7	1.4	1.5	1.6	1.9	3.2
BP		0.4	6.9***	13.2***	13.4***	12.7***	0.1
Panel C. Subperiod #3: After weekly options listing							
		No	0 %	25 %	50 %	75 %	100 %
ΔVOL(t)		−0.494***	−0.418***	−0.417***	−0.420***	−0.428***	−0.622***
		(-17.46)	(-14.94)	(-14.43)	(-14.13)	(-13.94)	(-16.95)
ΔSKEW(t)		0.001	0.022***	0.030***	0.032***	0.034***	0.032*
		(0.21)	(3.19)	(3.07)	(2.85)	(2.66)	(1.66)
ΔKURT(t)		0.001	0.003***	0.006**	0.007**	0.007	−0.013
		(1.02)	(2.94)	(2.53)	(2.00)	(1.50)	(-0.96)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.82)	(0.79)	(0.79)	(0.80)	(0.80)	(0.83)
# of obs.		737	737	737	737	737	737
Unadjusted R^2		0.454	0.471	0.476	0.477	0.478	0.475
AIC	Value	−4521.1	−4544.9	−4551.2	−4552.7	−4554.3	−4549.6
	Diff.	0.0	−23.8	−30.1	−31.6	−33.2	−28.5
BG		7.6	7.6	7.9	7.8	7.9	7.6
BP		0.3	1.9	1.1	1.3	1.5	9.4***

Notes: This table presents the regression results of the underlying log return on the first-order differences of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $\Delta lnS(t)$, represents the log return of the underlying index on day t. $\Delta VOL(t)$, $\Delta SKEW(t)$, and $\Delta KURT(t)$ denote the daily first-order differences of implied volatility, skewness, and kurtosis estimates on day t, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of five for Panels A and B and six for Panel C, selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 12
In-sample return predictive ability of implied moments.

Panel A. Subperiod #1: Before contract size change							
		No	0 %	25 %	50 %	75 %	100 %
ΔlnS(t-1)		−0.037	−0.036	−0.044	−0.043	−0.043	−0.047
		(-0.78)	(-0.77)	(-0.96)	(-0.92)	(-0.92)	(-0.99)
ΔVOL(t-1)		0.014	−0.019	−0.019	−0.019	−0.021	0.000
		(0.31)	(-0.76)	(-0.43)	(-0.44)	(-0.47)	(0.00)
ΔSKEW(t-1)		−0.002	−0.008**	−0.006	−0.005	−0.005	−0.012
		(-0.75)	(-2.06)	(-1.12)	(-0.86)	(-0.76)	(-1.01)
ΔKURT(t-1)		0.000	−0.001	0.000	0.001	0.001	−0.001
		(-0.09)	(-1.37)	(0.03)	(0.43)	(0.45)	(-0.05)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.79)	(0.79)	(0.79)	(0.79)	(0.78)	(0.81)
# of obs.		472	472	472	472	472	472
Unadjusted R^2		0.007	0.013	0.014	0.015	0.013	0.002
AIC	Value	−3138.9	−3141.3	−3142.2	−3142.6	−3141.7	−3138.6
	Diff.	0.0	−2.4	−3.3	−3.7	−2.8	0.3
BG		3.1	2.1	2.6	3.1	4.1	3.8
BP		2.0	0.9	0.4	0.0	0.0	1.9
Panel B. Subperiod #2: After contract size change, before weekly options listing							
		No	0 %	25 %	50 %	75 %	100 %
ΔlnS(t-1)		−0.031	−0.027	−0.034	−0.033	−0.030	−0.031
		(-0.71)	(-0.59)	(-0.71)	(-0.69)	(-0.64)	(-0.70)
ΔVOL(t-1)		−0.070	−0.049	−0.045	−0.052	−0.057	−0.093
		(-1.42)	(-1.02)	(-0.92)	(-1.05)	(-1.14)	(-1.43)
ΔSKEW(t-1)		−0.003	0.000	0.007	0.007	0.007	0.004
		(-0.86)	(0.05)	(1.03)	(0.91)	(0.91)	(0.33)
ΔKURT(t-1)		0.000	0.000	0.003*	0.003	0.005*	0.016
		(-0.08)	(0.67)	(1.77)	(1.64)	(1.75)	(1.53)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(-0.07)	(-0.06)	(-0.06)	(-0.05)	(-0.05)	(-0.06)
# of obs.		493	493	493	493	493	493
Unadjusted R^2		0.006	0.006	0.012	0.010	0.010	0.008
AIC	Value	−3183.2	−3182.9	−3186.1	−3185.1	−3185.0	−3184.3
	Diff.	0.0	0.3	−2.9	−1.9	−1.8	−1.1
BG		9.0	9.6*	10.4*	10.9*	10.8*	10.2*
BP		7.1***	2.8*	2.0	2.9*	2.8*	3.3*
Panel C. Subperiod #3: After weekly options listing							
		No	0 %	25 %	50 %	75 %	100 %
ΔlnS(t-1)		0.050	0.028	0.022	0.021	0.020	0.019
		(1.04)	(0.62)	(0.49)	(0.46)	(0.43)	(0.42)
ΔVOL(t-1)		−0.009	−0.032	−0.028	−0.025	−0.024	−0.032
		(-0.18)	(-0.57)	(-0.48)	(-0.44)	(-0.42)	(-0.45)
ΔSKEW(t-1)		−0.016*	−0.010	−0.003	0.002	0.004	−0.013
		(-1.84)	(-1.20)	(-0.29)	(0.20)	(0.44)	(-0.72)
ΔKURT(t-1)		−0.002*	−0.001	0.001	0.003	0.006	0.013
		(-1.87)	(-1.21)	(0.53)	(1.21)	(1.26)	(0.66)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.63)	(0.63)	(0.62)	(0.61)	(0.61)	(0.62)
# of obs.		736	736	736	736	736	736
Unadjusted R^2		0.015	0.005	0.006	0.008	0.008	0.006
AIC	Value	−4077.6	−4070.5	−4070.7	−4072.5	−4072.8	−4070.9
	Diff.	0.0	7.1	6.9	5.1	4.8	6.7
BG		6.4	12.8**	8.6	7.2	7.4	15.1***
BP		17.6***	35.2***	44.9***	45.2***	51.7***	41.9***

Notes: This table presents the regression results of the underlying log return on the first-order differences of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $\Delta lnS(t)$, represents the log return of the underlying index on day t. The lagged log-return, $\Delta lnS(t-1)$, is included as an independent variable to control for return reversals. $\Delta VOL(t-1)$, $\Delta SKEW(t-1)$, and $\Delta KURT(t-1)$ denote the lagged daily first-order differences of implied volatility, skewness, and kurtosis estimates, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of five for Panels A–B and six for Panel C selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Moderate domain stabilization lowers the AIC in the period before the contract size change, indicating stronger return predictability. However, the added fit declines after the size reduction, and it disappears after the introduction of weekly options. These results suggest that domain stabilization, although it strengthens contemporaneous relations in Tables 10 and 11, does not maintain its benefits for return forecasts in the later periods. One possible explanation is that broader retail participation and the growth of very short maturities allow option prices to adjust more quickly to new information, leaving little lead-lag pattern for DS to uncover.

Overall, the subperiod analysis indicates that the consequence of DS shifts with changes in market structure. Before the contract size change, DS enhances the return predictability of implied moments while offering little additional insight into their contemporaneous relation with the underlying. After the multiplier is halved, and more visibly after weekly options are introduced in 2019, stabilization instead strengthens the same-day explanatory power of the moments but no longer improves return predictability. These findings suggest that heavier retail trading and the rising share of short-maturity options compress the daily lead-lag between implied moments and returns, leaving little one-day-ahead information for our procedure to detect. Across all subperiods, trimming roughly 50–75 % continues to best balance noise reduction and information loss, indicating that DS remains effective even though the specific facet of price discovery it improves varies with market conditions.

Next, we explore how volatility affects the performance of DS by conducting a set of analyses for different volatility regimes. Using the sample median of implied volatility estimated without DS, 0.146, we split the data into high and low volatility regimes and estimate explanatory and predictive regressions for each group. Table 13 reports the contemporaneous regressions of implied moment levels on the log index level. The explanatory power increases after DS throughout the high volatility regime, but in the low volatility regime, such increases can be found only when the intensity level reaches its maximum. This pattern suggests that DS can reveal more information when market risk is elevated. One possible explanation is that investors trade OTM options more actively during turbulent periods to manage volatility exposure, which makes those prices more informative. As in the subperiod analysis, however, this

Table 13
Explanatory power of implied moments for the underlying log price in different volatility regimes: Levels.

Panel A. High volatility regime							
		No	0 %	25 %	50 %	75 %	100 %
VOL(*t*)		−0.226	−0.083	−0.049	−0.056	−0.076	−0.725***
		(-0.85)	(-0.36)	(-0.22)	(-0.26)	(-0.35)	(-2.77)
SKEW(*t*)		0.262***	0.316***	0.436***	0.472***	0.503***	0.984***
		(3.75)	(4.41)	(4.56)	(4.34)	(4.09)	(3.63)
KURT(*t*)		0.049***	0.049***	0.096***	0.116***	0.135***	0.360*
		(3.42)	(3.57)	(3.65)	(3.32)	(2.88)	(1.67)
Intercept		5.808***	5.815***	5.709***	5.674***	5.667***	5.747***
		(114.42)	(121.42)	(81.37)	(64.99)	(53.23)	(32.08)
# of obs.		852	852	852	852	852	852
Unadjusted R^2		0.095	0.130	0.147	0.146	0.143	0.141
AIC	Value	−605.4	−639.0	−656.2	−655.1	−652.3	−649.4
	Diff.	0.0	−33.6	−50.8	−49.7	−46.9	−44.0
BG		822.1***	820.0***	815.1***	816.0***	817.3***	818.0***
BP		0.5	0.5	0.3	0.5	0.7	10.0***
Panel B. Low volatility regime							
		No	0 %	25 %	50 %	75 %	100 %
VOL(*t*)		0.589	0.593	0.662	0.642	0.618	0.052
		(0.86)	(0.86)	(0.97)	(0.94)	(0.91)	(0.07)
SKEW(*t*)		0.122***	0.118***	0.168***	0.186***	0.210***	0.663***
		(3.18)	(2.85)	(3.26)	(3.33)	(3.40)	(4.12)
KURT(*t*)		0.025***	0.022***	0.043***	0.056***	0.075***	0.383***
		(3.53)	(3.01)	(3.10)	(3.06)	(3.04)	(3.08)
Intercept		5.569***	5.563***	5.506***	5.480***	5.451***	5.442***
		(64.00)	(61.12)	(53.77)	(50.07)	(46.29)	(35.69)
# of obs.		851	851	851	851	851	851
Unadjusted R^2		0.039	0.030	0.034	0.035	0.036	0.089
AIC	Value	−1108.8	−1100.4	−1104.3	−1104.9	−1106.1	−1154.5
	Diff.	0.0	8.4	4.5	3.9	2.7	−45.7
BG		820.3***	826.3***	825.5***	825.4***	825.2***	801.3***
BP		5.0**	1.3	2.1	1.7	1.2	24.3***

Notes: This table presents the regression results of the underlying log price on the levels of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $lnS(t)$, represents the natural logarithm of the underlying index on day *t*. $VOL(t)$, $SKEW(t)$, and $KURT(t)$ denote the daily levels of implied volatility, skewness, and kurtosis estimates on day *t*, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of six selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

interpretation remains tentative until the effectiveness of DS is tested with further specifications. Table 14 repeats the exercise with first differences and delivers a similar message that DS strengthens the contemporaneous link in high volatility markets and yields limited gains in calm markets unless intensity is set at its highest level.

Table 15 presents in-sample return predictability test results for the two volatility regimes, and their implications contrast with Table 14. DS is not found to contribute to better return predictability in the high volatility regime, while a modest contribution is observed when volatility is low. Again, the results suggest that the aspect of the relationship between implied moments and the underlying price that is improved by DS could be determined by specific market conditions. One explanation is that high volatility both enriches the information in option prices and speeds its incorporation into underlying prices, leaving little lead-lag structure for DS to uncover, consistent with our subperiod evidence.

The findings in this section show that the effectiveness of DS varies with market conditions. After structural reforms that widen participation and shorten option maturities, or when volatility is elevated, DS strengthens the contemporaneous link between implied moments and the underlying. In the earlier subperiod and calmer markets, the same procedure yields only small explanatory gains yet adds modest forecasting power. These patterns imply that DS refines empirical results by sharpening the information where implied moments are already informative, which is consistent with the findings of LRY.

5.6. Alternative truncation treatment methods

We next test whether the benefits of DS can be reproduced with other truncation treatment methods. Following LRY, we introduce domain reduction (DR) and domain symmetrization (DSym) as alternative methods. DR keeps the integration domain in its original shape but trims it uniformly until the average width of the remaining domain matches that produced by DS at the same intensity. DSym

Table 14

Explanatory power of implied moments for the underlying log price in different volatility regimes: First-order differences.

		No	0 %	25 %	50 %	75 %	100 %
Panel A. High volatility regime							
		No	0 %	25 %	50 %	75 %	100 %
ΔVOL(t)		−0.489***	−0.412***	−0.412***	−0.416***	−0.425***	−0.611***
		(-19.07)	(-15.29)	(-14.70)	(-14.56)	(-14.59)	(-18.57)
ΔSKEW(t)		−0.002	0.017***	0.022**	0.023**	0.022*	0.011
		(-0.33)	(2.53)	(2.26)	(2.03)	(1.78)	(0.59)
ΔKURT(t)		0.000	0.003***	0.004*	0.004	0.004	−0.022
		(0.45)	(2.44)	(1.83)	(1.33)	(0.81)	(-1.61)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(-0.34)	(-0.27)	(-0.25)	(-0.25)	(-0.26)	(-0.28)
# of obs.		852	852	852	852	852	852
Unadjusted R^2		0.467	0.477	0.480	0.480	0.481	0.483
AIC	Value	−5242.6	−5258.2	−5262.4	−5263.4	−5264.2	−5267.3
	Diff.	0.0	−15.6	−19.8	−20.8	−21.6	−24.7
BG		7.0	6.3	6.4	6.4	6.5	6.8
BP		2.2	1.8	1.3	1.5	2.0	9.8***
Panel B. Low volatility regime							
		No	0 %	25 %	50 %	75 %	100 %
ΔVOL(t)		−0.366***	−0.320***	−0.331***	−0.340***	−0.349***	−0.496***
		(-5.72)	(-5.02)	(-5.19)	(-5.37)	(-5.53)	(-6.85)
ΔSKEW(t)		0.007	0.014***	0.017***	0.016***	0.015***	0.011
		(3.07)	(4.50)	(3.83)	(3.31)	(2.72)	(0.85)
ΔKURT(t)		0.002***	0.003***	0.004***	0.004***	0.003	−0.010
		(4.49)	(4.92)	(3.82)	(2.72)	(1.41)	(-1.36)
Intercept		0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
		(2.90)	(2.99)	(2.94)	(2.92)	(2.91)	(2.84)
# of obs.		850	850	850	850	850	850
Unadjusted R^2		0.192	0.210	0.203	0.200	0.198	0.187
AIC	Value	−6039.4	−6058.0	−6051.2	−6047.6	−6045.7	−6034.0
	Diff.	0.0	−18.6	−11.8	−8.2	−6.3	5.4
BG		6.0	8.2*	6.8	6.5	10.7*	4.5
BP		34.1***	53.5***	52.4***	48.8***	3.6*	30.7***

Notes: This table presents the regression results of the underlying log return on the first-order differences of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $\Delta lnS(t)$, represents the log return of the underlying index on day t. $\Delta VOL(t)$, $\Delta SKEW(t)$, and $\Delta KURT(t)$ denote the daily first-order differences of implied volatility, skewness, and kurtosis estimates on day t, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of six selected according to the Newey-West rule of thumb. The difference in information criteria (Diff.) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 15
In-sample return predictive ability of implied moments in different volatility regimes.

Panel A. High volatility regime							
		No	0 %	25 %	50 %	75 %	100 %
ΔlnS(t-1)		0.040	0.022	0.015	0.015	0.014	0.012
		(0.93)	(0.52)	(0.36)	(0.36)	(0.34)	(0.30)
ΔVOL(t-1)		−0.017	−0.034	−0.025	−0.021	−0.019	−0.035
		(-0.37)	(-0.70)	(-0.51)	(-0.43)	(-0.40)	(-0.59)
ΔSKEW(t-1)		−0.014*	−0.008	0.002	0.007	0.011	0.003
		(-1.66)	(-1.11)	(0.28)	(0.95)	(1.32)	(0.19)
ΔKURT(t-1)		−0.002	−0.001	0.002	0.005**	0.008**	0.026
		(-1.54)	(-0.99)	(1.41)	(2.20)	(2.19)	(1.40)
Intercept		−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
		(-1.22)	(-1.19)	(-1.21)	(-1.22)	(-1.23)	(-1.21)
# of obs.		851	851	851	851	851	851
Unadjusted R^2		0.011	0.004	0.007	0.010	0.011	0.007
AIC	Value	−4707.7	−4702.1	−4704.7	−4707.3	−4707.7	−4704.1
	Diff.	0.0	5.6	3.0	0.4	0.0	3.6
BG		5.0	7.8	4.5	4.2	4.3	7.1
BP		17.7***	32.4***	29.1***	31.7***	37.5***	35.7***

Panel B. Low volatility regime							
		No	0 %	25 %	50 %	75 %	100 %
ΔlnS(t-1)		−0.004	0.000	−0.010	0.000	0.000	−0.001
		(-0.10)	(0.01)	(-0.03)	(-0.01)	(0.01)	(-0.04)
ΔVOL(t-1)		0.035	0.029	0.027	0.024	0.022	0.045
		(1.01)	(0.85)	(0.79)	(0.69)	(0.61)	(0.99)
ΔSKEW(t-1)		−0.002	−0.003	−0.002	−0.003	−0.003	−0.012
		(-0.99)	(-1.07)	(-0.56)	(-0.57)	(-0.59)	(-1.55)
ΔKURT(t-1)		0.000	0.000	0.000	0.001	0.001	−0.001
		(-0.47)	(-0.43)	(0.33)	(0.42)	(0.44)	(-0.16)
Intercept		0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
		(4.31)	(4.31)	(4.31)	(4.31)	(4.30)	(4.31)
# of obs.		849	849	849	849	849	849
Unadjusted R^2		0.006	0.007	0.008	0.008	0.007	0.007
AIC	Value	−5853.1	−5854.1	−5855.1	−5854.9	−5854.3	−5854.5
	Diff.	0.0	−1.0	−2.0	−1.8	−1.2	−1.4
BG		4.4	3.9	3.8	3.9	3.9	3.8
BP		4.5**	4.5**	2.5	1.6	1.3	8.2***

Notes: This table presents the regression results of the underlying log return on the first-order differences of implied moments, using domain stabilization at intensity levels of 0, 25, 50, 75, and 100 percent. The dependent variable, $\Delta lnS(t)$, represents the log return of the underlying index on day t. The lagged log-return, $\Delta lnS(t-1)$, is included as an independent variable to control for return reversals. $\Delta VOL(t-1)$, $\Delta SKEW(t-1)$, and $\Delta KURT(t-1)$ denote the lagged daily first-order differences of implied volatility, skewness, and kurtosis estimates, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of six selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

removes options until the minimum and maximum values of the integration domain are equally distant from the spot price. Comparing DS with DR shows whether its performance comes mainly from moving weight toward near-the-money prices. Comparing DS with DSym lets us see whether the gains from DS instead reflect a more balanced integration domain. We measure domain symmetry for DSym either in terms of the strike price or d_1.

Table 16 presents the empirical results. Panel A demonstrates the results for the contemporaneous regressions of implied moment levels on the level of the underlying log index. The results suggest that while DSym leads to better explanatory power, DR does not provide such performance. Although DSym can strengthen the explanatory power, the performance is not better than DS. By contrast, when we examine the contemporaneous relationship between underlying returns and first-order differences of implied moments, DSym shows better performance than DR and even DS, as reported in Panel B. This is consistent with LRY, who show that DSym demonstrates better performance than symmetric DS. Although Panel C indicates that DR delivers the largest gain in in-sample return predictive power, Panel D shows that the out-of-sample forecasting accuracy of implied moments is highest when DS is used. Because we do not test an asymmetric version of DS, which LRY reports as the best performer, a suitably asymmetric DS would likely improve forecasting ability further. Overall, DS provides benefits beyond merely shrinking or symmetrizing the integration domain, although its advantage in the KOSPI200 market is smaller than in the U.S. market studied by LRY.

Table 16
Effectiveness of alternative treatment methods.

Panel A. Explanatory power of implied moments: Log price levels

		No treatment	25 % reduction	50 % reduction	75 % reduction	Symmetrization (Strike price)	Symmetrization (d_1)
VOL(*t*)		0.294	0.287	0.276	0.253	0.331	0.380
		(0.91)	(0.89)	(0.84)	(0.77)	(1.01)	(1.06)
SKEW(*t*)		0.134***	0.127**	0.113**	0.073	0.157***	0.140**
		(2.63)	(2.51)	(2.19)	(1.34)	(2.80)	(2.03)
KURT(*t*)		0.027***	0.027***	0.026***	0.020*	0.049***	0.057***
		(2.87)	(2.83)	(2.63)	(1.82)	(2.44)	(3.15)
Intercept		5.641***	5.639***	5.635***	5.634***	5.556***	5.543***
		(125.27)	(124.63)	(123.04)	(119.70)	(73.34)	(91.70)
# of obs.		1703	1703	1703	1703	1703	1703
Unadjusted R^2		0.031	0.030	0.027	0.020	0.038	0.040
AIC	Value	−1470.2	−1468.6	−1464.0	−1451.0	−1482.7	−1486.1
	Diff.	0.0	1.6	6.2	19.2	−12.5	−15.9
BG		1672.9***	1672.4***	1672.7***	1676.6***	1678.3***	1672.0***
BP		25.3***	30.7***	43.9***	93.5***	15.9***	30.0***

Panel B. Explanatory power of implied moments: First-order differences

		No treatment	25 % reduction	50 % reduction	75 % reduction	Symmetrization (Strike price)	Symmetrization (d_1)
ΔVOL(t)		−0.472***	−0.480***	−0.488***	−0.486***	−0.416***	−0.484***
		(-19.20)	(-18.92)	(-18.20)	(-16.02)	(-16.34)	(-17.72)
ΔSKEW(t)		0.003	0.001	−0.002	−0.008	0.020***	0.014***
		(0.90)	(0.32)	(-0.50)	(-1.37)	(4.51)	(3.23)
ΔKURT(t)		0.001**	0.001**	0.001	0.000	0.004***	0.006***
		(2.54)	(2.07)	(1.15)	(-0.19)	(3.15)	(5.63)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.99)	(0.99)	(0.98)	(0.97)	(1.00)	(1.01)
# of obs.		1702	1702	1702	1702	1702	1702
Unadjusted R^2		0.410	0.405	0.393	0.361	0.439	0.426
AIC	Value	−11090.4	−11075.7	−11041.5	−10954.6	−11174.4	−11137.0
	Diff.	0.0	14.7	48.9	145.8	−84.0	−46.6
BG		10.9*	10.7*	10.9*	13.9**	7.8	7.1
BP		1.1	1.3	4.3**	50.4***	0.2	0.8

Panel C. In-sample return predictive ability

		No treatment	25 % reduction	50 % reduction	75 % reduction	Symmetrization (Strike price)	Symmetrization (d_1)
ΔlnS(t-1)		0.021	0.025	0.030	0.035	0.000	0.015
		(0.61)	(0.67)	(0.78)	(0.92)	(0.01)	(0.42)
ΔVOL(*t-1*)		−0.014	−0.008	0.002	0.017	−0.029	−0.018
		(-0.36)	(-0.22)	(0.06)	(0.53)	(-0.58)	(-0.32)
ΔSKEW(*t-1*)		−0.007*	−0.007*	−0.007*	−0.006**	−0.002	−0.005
		(-1.76)	(-1.77)	(-1.81)	(-2.07)	(-0.45)	(-1.10)
ΔKURT(*t-1*)		−0.001	−0.001	−0.001	−0.001*	0.001	−0.001
		(-1.49)	(-1.51)	(-1.57)	(-1.86)	(0.57)	(-0.93)
Intercept		0.000	0.000	0.000	0.000	0.000	0.000
		(0.74)	(0.74)	(0.74)	(0.73)	(0.76)	(0.75)
# of obs.		1701	1701	1701	1701	1701	1701
Unadjusted R^2		0.006	0.007	0.008	0.011	0.002	0.002
AIC	Value	−10193.9	−10194.7	−10196.6	−10202.0	−10187.0	−10186.3
	Diff.	0.0	−0.8	−2.7	−8.1	6.9	7.6
BG		11.3**	11.4**	11.5**	12.7**	23.4***	19.7***
BP		37.5***	32.2***	23.8***	16.2***	90.4***	42.1***

Panel D. Out-of-sample return forecasting ability

Rolling window length	R^2_{OS} (%)					
	No treatment	25 % reduction	50 % reduction	75 % reduction	Symmetrization (Strike price)	Symmetrization (d_1)
5 months	−9.79	−11.66	−11.84	−16.68	−14.94	−12.78
10 months	−4.77	−5.37	−5.07	−5.84	−8.71	−6.96
15 months	−3.97	−4.47	−4.26	−4.41	−6.08	−5.21
20 months	−2.36	−3.06	−2.84	−2.64	−4.69	−4.20
25 months	−1.93	−2.47	−2.30	−2.07	−3.64	−3.23
30 months	−1.98	−2.37	−2.34	−2.31	−2.84	−2.76

(*continued on next page*)

Table 16 (*continued*)

Panel D. Out-of-sample return forecasting ability

Rolling window length	R^2_{OS} (%)					
	No treatment	25 % reduction	50 % reduction	75 % reduction	Symmetrization (Strike price)	Symmetrization (d_1)
35 months	−1.64	−1.78	−1.75	−1.71	−2.10	−2.14
40 months	−1.53	−1.64	−1.60	−1.46	−2.00	−2.03
45 months	−1.27	−1.23	−1.15	−0.87	−1.70	−1.83
50 months	−0.93	−0.88	−0.74	−0.32	−1.45	−1.52
55 months	−1.01	−0.99	−0.85	−0.35	−1.47	−1.61
60 months	−0.86	−0.59	−0.55	−0.48	−0.87	−0.96
65 months	−1.33	−1.11	−1.10	−1.08	−0.74	−1.02
70 months	−1.00	−0.71	−0.74	−0.82	−0.50	−0.77
75 months	−1.15	−1.13	−1.32	−1.78	−0.42	−0.71
80 months	−2.29	−1.81	−2.23	−3.31	0.18	−0.89

Notes: This table presents the regression results for testing alternative truncation treatment methods, which are domain reduction and symmetrization. $VOL(t)$, $SKEW(t)$, and $KURT(t)$ denote the daily levels of implied volatility, skewness, and kurtosis estimates on day t, respectively. Newey-West standard errors are employed to address residual autocorrelation and heteroskedasticity, with a lag length of six selected according to the Newey-West rule of thumb. The difference in information criteria (*Diff.*) reflects the variation in OLS-based Akaike information criterion (*AIC*) values relative to the no stabilization case. The Breusch-Godfrey (*BG*) and Breusch-Pagan (*BP*) tests report Chi-square statistics for testing autocorrelation and heteroskedasticity for OLS estimation, respectively. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

6. Conclusion

This study investigates the effectiveness of DS in a broader context by examining whether the truncation treatment method enhances the informational content of model-free implied moment estimates in the KOSPI200 options market. As an emerging market, the KOSPI200 options market provides a significantly different environment compared to the U.S. market, which is the focus of LRY. Thus, testing the effectiveness of DS in the KOSPI200 options market offers reliable evidence that the method is valid across diverse market conditions. Moreover, we extend the assessment of DS by adopting a more comprehensive framework to evaluate the informativeness of implied moments. Specifically, we assess not only the in-sample and out-of-sample predictive and forecasting abilities but also the contemporaneous explanatory power of implied moment estimates and their first-order differences with respect to the underlying log price and log returns.

The empirical results indicate that DS enhances the contemporaneous explanatory power, improves in-sample predictive accuracy, and strengthens out-of-sample forecasting performance of implied moment estimates. These findings align with those of LRY, suggesting that DS is a robust truncation treatment method applicable under diverse market conditions. Future research can use DS to enhance the informativeness of implied moment estimates across different options markets and for various aspects of the price-moment relationship. Choosing the right DS intensity is critical. A preliminary analysis should be conducted to identify the optimal intensity level, ensuring the fluctuation in the integration domain width is minimized while avoiding excessive information loss due to the exclusion of OTM price observations.

Conflicts of interest

We confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere. We believe that this manuscript is appropriate for your journal in that it aims to provide useful information for academic researchers, investors, and policymakers. We have no conflicts of interest to disclose. There is no competing interest.

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Data availability

Data will be made available on request.

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