Journal of
Risk and Financial Management

CITESCORE
5.0

Article

Information Transmission Performance of the GIFT Nifty Futures: Evidence from High-Frequency Data

Rajib Sarkar, Soumya Guha Deb and Amrit Panda

Special Issue
Advancing Research in International Finance

Edited by
Dr. Kirill Shakhnov

MDPI

https://doi.org/10.3390/jrfm18090527

Journal of
Risk and Financial Management

Article

Information Transmission Performance of the GIFT Nifty Futures: Evidence from High-Frequency Data

Rajib Sarkar [1,*], Soumya Guha Deb [2] and Amrit Panda [3]

1 Jindal Global Business School, O.P. Jindal Global University, Sonipat 131001, Haryana, India
2 Finance and Accounting Area, Indian Institute of Management Sambalpur, Sambalpur 768019, Odisha, India; soumya@iimsambalpur.ac.in
3 Finance and Accounting Area, Indian Institute of Management Bodh Gaya, Turi Khurd 824234, Bihar, India
* Correspondence: rajib.sarkar@jgu.edu.in or rajibsarkar@yahoo.com

Abstract

This paper investigates the information transmission performance of GIFT Nifty futures using high-frequency data, a novel area of study given their recent introduction. We employ Johansen cointegration tests, Granger causality tests, GARCH models, Hasbrouck's Information Share (IS) model, and Gonzalo–Granger's Component Share (CS) model to assess market integration, volatility, and price discovery dynamics. Our findings reveal significant bidirectional Granger causality and cointegration between the GIFT Nifty futures price and the Nifty index price, indicating a stable long-term equilibrium. Additionally, the GARCH model captures substantial volatility, reflecting the market's responsiveness to new information. The IS and CS models confirm that the GIFT Nifty futures play a crucial role in the price discovery process, leading the Nifty index. This research is timely, within eight months of the first anniversary of GIFT Nifty futures trading since its launch. The findings highlight the information transmission performance and importance of the GIFT Nifty futures in enhancing market stability and transparency, offering valuable insights into market behaviour, integration, and forecasting abilities.

Keywords: price discovery; gift nifty; nifty; volatility

Academic Editor: Thanasis Stengos

Received: 9 July 2025
Revised: 11 September 2025
Accepted: 12 September 2025
Published: 19 September 2025

Citation: Sarkar, R., Guha Deb, S., & Panda, A. (2025). Information Transmission Performance of the GIFT Nifty Futures: Evidence from High-Frequency Data. *Journal of Risk and Financial Management*, *18*(9), 527. https://doi.org/10.3390/jrfm18090527

1. Introduction

In financial markets, spot and futures markets should incorporate new information concurrently (Hu et al., 2020). However, due to institutional differences, futures markets often lead to price discovery and volatility spillover, benefiting from lower transaction costs, greater liquidity, and the ability to leverage and short sell (Tse, 1999; Chan, 1992). Studies show futures markets frequently dominate in price discovery and contribute to volatility spillovers (Fassas & Siriopoulos, 2019; Alemany et al., 2020). This paper investigates the information transmission performance of the GIFT Nifty futures using high-frequency data. The primary research questions addressed in this study are (a) whether the GIFT Nifty futures prices are integrated with their underlying index such that long-term equilibrium is maintained, (b) the usefulness of the GIFT Nifty futures in forecasting the underlying series, (c) the extent to which the return series of the GIFT Nifty futures captures volatility from new information, and (d) the relative speed at which the GIFT Nifty futures incorporate new information compared to the underlying index. The study focuses on evaluating the price transmission performance of the GIFT Nifty futures on an absolute (not relative) basis.

The National Stock Exchange of India (NSE), which was incorporated in November 1992 and began operations in 1994[1], is India's largest (in market capitalisation) stock exchange and one of the largest in the world. In June 2000, NSE introduced the Nifty index, comprising 50 representative stocks traded on its platform. Subsequently, derivatives such as futures contracts based on this index were launched. To facilitate foreign investor participation, the SGX Nifty was introduced in September 2000 on the Singapore Stock Exchange as a collaboration between both exchanges. SGX Nifty futures made it possible for foreign investors to trade in dollars on the movements of the Indian stock market, circumventing the foreign exchange volatility of the Indian rupee[2].

Despite SGX Nifty's acceptance among global investors, concerns about liquidity migration and market fragmentation led Indian policymakers to decide on a strategic initiative to bring offshore trading activity within India's jurisdiction, enhancing the integration of Indian financial security markets. Thus, to capture the offshore trading volume associated with the SGX Nifty futures, consolidate regulatory oversight, integrate Indian financial security markets and also to enhance GIFT City's appeal as an international financial hub, this USD-denominated index future was shifted to the newly developed India's international exchange, NSE International Exchange (NSE IX), in International Financial Services Centre (IFSC) within GIFT City, Gandhinagar, India, on 3 July 2023. SGX Nifty got rebranded as the GIFT Nifty. The GIFT Nifty mirrors the Nifty index, representing the performance of the same 50 stocks which constitute the latter in the same ratio.

Compared with the erstwhile SGX Nifty, one of the key distinctive features of the GIFT Nifty futures is its extended trading hours, operating over 21 hours a day. This schedule targets investors from different time zones, including the US, Europe, and the Far East, and overlaps with domestic Indian market hours, facilitating the capture of domestic trading trends. Trading in the GIFT Nifty futures thus offers distinct advantages to foreign investors by allowing them to take a position in the underlying Nifty Index when its trading is otherwise impossible for them. The GIFT Nifty provides common trading hours with the US, European and Asian markets.

A key regulatory feature of GIFT Nifty is that the NSE IX Exchange, on which the futures contract is traded, operates under the regulatory supervision of the International Financial Services Centres Authority (IFSCA). Globally accepted standards of IFSCA provide international investors with confidence that trading of GIFT Nifty is on a safe and transparent platform.

From the Foreign Portfolio Investors' (FPIs) tax liability point of view, GIFT Nifty futures provides two advantages which were not available to SGX Nifty futures. The first benefit is the exemptions from Securities Transaction Tax (STT) and stamp duty on trades executed on the IFSC exchange. The second tax-saving benefit can potentially be enjoyed by FPIs from over a hundred countries that have signed Double Taxation Avoidance Agreements (DTAs) with India.

The significance of this paper also lies in its timely analysis of the GIFT Nifty futures market, which recently celebrated its second anniversary of launch. It is indeed an opportune time to evaluate the performance of this derivative instrument for its price transmission performance.

Our research contributes to the literature by examining the information transmission performance of the GIFT Nifty futures and thereby filling a gap in the evaluative research on a crucial market performance aspect of the newly launched Indian financial security marketplace for overseas investors. This study attempts to answer whether GIFT Nifty futures' information transmission performance indicates the market quality that supports the intended purpose for which this market for overseas investors was established in India. Assessing the information transmission performance of the GIFT Nifty futures is essential for multiple stakeholders, viz., regulators, market participants, including Non-resident Indians (NRIs), Foreign Portfolio Investors (FPIs), and Eligible Foreign Investors (EFIs)

This is a derivative contract that provides insights into market integration, forecasting abilities, and responsiveness to new information. Finally, the study contributes to the broader academic and policy discourse on globalised financial markets.

The remainder of the paper is organised as follows: Section 2 details the review of relevant literature. Section 3 provides the methodology and data used for the study. Section 4 describes the results and analysis. Section 5 provides the conclusion and implications, followed by references and tables.

2. Literature Review

Albert S Kyle, in his seminal paper (Kyle, 1985), presented a model that connects price transmission and market efficiency through the concept of "price discovery" in the presence of asymmetric information. His market microstructure theory explains how the actions of an informed trader impute private information into the market price.

Efficient markets are generally understood as markets where prices and allocations reflect all available information. Fama (1970, p. 383) defined an efficient market as "a market in which prices always 'fully reflect' available information." Grossman (1977) shows that only spot prices are not enough to aggregate information efficiently without corresponding futures prices.

As clarified by derivative market researchers like Tse (1999), perfectly efficient markets, both spot and futures markets, should incorporate new information at the same speed simultaneously. However, they do not do so in the real world due to market microstructure variations. Institutional factors influencing market microstructure variables give rise to a lead-lag relationship between spot and futures markets in the price discovery process.

In general, price discovery is about bringing out complete information about any asset, which leads to arriving at the efficient price of the asset (Figuerola-Ferretti & Gonzalo, 2010). The observable price comprises the permanent efficient price in conjunction with transitory effects arising from the prevalent market microstructure. Lehmann (2002, p. 259) defined price discovery as the "efficient and timely incorporation of the information implicit in investor trading into market prices". Timeliness, here, refers to the relative speed of incorporation of the new information about the fundamental value. Efficiency, on the other hand, relates to the relative absence of noise, i.e., market microstructure frictions, e.g., tick discreteness, bid-ask bounce and insufficient liquidity (Putnins, 2013). Harris et al. (2002, p. 279), on the other hand, emphasised equilibrium transaction price when they stated that "price discovery is the process by which security markets attempt to identify permanent changes in equilibrium prices".

Specifically, in the context of the futures market, price discovery refers to the process by which futures prices serve as market-generated forecasts of future spot prices. As the futures contract draws closer to expiry, these forecasts naturally become more accurate. Thus, the futures market aids the discovery of spot prices at contract maturity (Dahlgran, 2000). As futures markets enjoy greater leverage and hence require smaller capital outlay as compared with spot markets, they attract more speculators, which creates a condition for price innovations to take place in them before getting transmitted to the spot markets (Stoll & Whaley, 1990). This hypothesis is known as the leverage hypothesis (Fleming et al., 1996). Price discovery happens through a recursive bid and ask process while information is produced and transmitted across markets, leading to an equilibrium price. Thus, while in a static sense, price discovery implies the existence of equilibrium prices, in a dynamic sense, it is the process of production and transmission of information across markets (Yang & Leatham, 1999). Studies by Chan (1992), Alemany et al. (2020), and Bohl et al. (2011) further elaborate on the lead-lag relationships and the role of different investor types in price discovery.

While there have been only a handful of studies on the information transmission functions of the NSE Nifty and the SGX Nifty futures (Sundararajan & Balasubramanian, 2023; Shetty et al., 2024), any market evaluation (concerning information transmission) using high-frequency data on the GIFT Nifty futures remains missing.

Previous literature has extensively covered various aspects of price discovery in different contexts. Sifat et al. (2019) and Karmakar and Inani (2019) explore high-frequency data to examine the speed of adjustment between futures and spot markets, highlighting the dominance of spot markets in price discovery.

Kumar and Sampath (2019) investigated what moved the prices of the listed offshore Indian and Chinese futures contracts on the SGX platform when their underlying was not available for trading. They found that in such times, offshore derivative contracts functioned as a proxy for their underlying assets, imputing responses to overnight country-specific currency movements and overnight US stock market movements.

A recent work examined the intraday price discovery process (Khan et al., 2022) using high-frequency price data of the Nifty and its futures during the COVID-19 pandemic (January 2020 to December 2020). Their findings from Hasbrouck's information share (IS) and Gonzalo and Granger's common factor models indicate that Nifty futures leads in forming the common efficient price.

3. Methodology and Data

Given the extant literature, our study aims to fill the gap concerning the empirical analysis of the information transmission performance of GIFT Nifty futures. This assessment will contribute to understanding whether the GIFT Nifty futures market serves its intended purpose of providing a reliable, integrated, and effective price discovery mechanism.

To assess the overall information transmission performance of the GIFT Nifty futures, we seek empirical answers to the following four questions:

1. Is the GIFT Nifty futures price cointegrated with the Nifty index price?
2. Does the GIFT Nifty futures return Granger-cause the Nifty index return?
3. How robust is the GARCH model for the GIFT Nifty returns?
4. What is the lead or lag of the GIFT Nifty futures relative to its underlying Nifty index in the price discovery process?

Our empirical inquiry is based on the following econometric methods:

1. We employ the Johansen cointegration test to examine whether the GIFT Nifty futures price is cointegrated with the Nifty index price.
2. We use the Granger causality test to determine the directionality between the GIFT Nifty futures returns and its underlying Nifty index returns.
3. We apply the univariate GARCH model to examine what the volatility of the GIFT Nifty futures returns reveals.
4. We make use of both Hasbrouck's Information Share (IS) model and Gonzalo–Granger's Component Share (CS) model to find out whether the GIFT Nifty futures is leading or lagging relative to its underlying Nifty index in the price discovery process.

The combination of all the above-mentioned analytical techniques, our study aims to evaluate different aspects of the information transmission performance of GIFT Nifty futures. Simply put, the Johansen cointegration test answers whether the Nifty index and GIFT Nifty futures prices share common long-run information. The Granger causality test answers the question of whether GIFT Nifty futures' return information helps predict the Nifty index's return movements in the short run or vice versa. The IS and CS models answer the question of whether the Nifty index or GIFT Nifty futures leads in imputing the news in price and which market contributes more to the long-run efficient price, respectively.

The GARCH analysis answers the question of how information, when it arrives as price shocks, affects the dynamics and persistence of volatility in the GIFT Nifty futures market.

3.1. Johansen Cointegration Test

We employ the Johansen cointegration test (Johansen, 1991) to determine whether the GIFT Nifty futures price and the Nifty index price share a long-term equilibrium relationship. Cointegration implies that the futures and the underlying index prices do not drift apart over time, indicating market efficiency and integration. The Johansen cointegration test is based on the Vector Error Correction Model (VECM):

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \varepsilon_t$$

where Δy_t is the vector of differenced series, α is the matrix of adjustment coefficients, β is the cointegration vector that captures the long-run relationships, Γ_j are the matrices of coefficients for lagged differences and ε_t is the error term. This model allows us to test for the presence of cointegration vectors, indicating a stable long-term relationship between the series.

3.2. Granger Causality Test

The Granger causality test checks whether past values of the GIFT Nifty futures can predict future values of the Nifty index and vice versa. This is implemented using the following bivariate time series regression model with q lags of the regressor and p lags of the regressand:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \delta_{11} X_{1t-1} + \delta_{12} X_{1t-2} + \cdots + \delta_{1q} X_{1t-q} + u_t$$

The F-statistic from this model (termed as Granger causality statistic) tests the hypothesis that the coefficients of the lagged regressors are zero, indicating whether the regressor has predictive power.

3.3. GARCH Model

To study the volatility of the GIFT Nifty futures returns, we use the GARCH (1, 1) model. According to Ross' (1989) theorem, volatility is a proxy for information flow. The mean and variance equations for the standard GARCH (1, 1) model are as follows (Bollerslev, 1986):

$$y_t = a_0 + a_1 y_{t-1} + \varepsilon_t, \ \varepsilon \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \omega + \alpha\mu_{t-1}^2 + \beta\sigma_{t-1}^2$$

where σ_t^2 is the conditional variance (the variance at the current period), $\alpha\mu_{t-1}^2$ is the information on the volatility during the previous period, $\beta\sigma_{t-1}^2$ is the fitted variance from the model during the previous period, and ω is a weighted value of the long-term average variance (unconditional variance). The α parameter—the ARCH effect—is also referred to as the news coefficient because it captures the impact of news. The β parameter—the GARCH effect—on the other hand, estimates persistence in conditional volatility. It is also referred to as the persistence coefficient because it indicates the extent of the persistence of the existing pattern.

3.4. Hasbrouck's Information Share and Gonzalo–Granger's Component Share Models

To determine the contributions to price discovery by the GIFT Nifty futures and the Nifty index, we use Hasbrouck's Information Share (IS) model (Hasbrouck, 1995) and Gonzalo–Granger's Component Share (CS) model (Gonzalo & Granger, 1995).

For securities traded across multiple markets, the information share (IS) measures indicate how much each market's innovations contribute to the overall price change in the security. Hasbrouck defined the price discovery contribution of the i-th market as its contribution to the permanent shock variance.

The IS is computed following Sultan and Zivot (2015):

Situation 1: When Σ is diagonal

$$IS_1 = \frac{(\Psi\sigma_1)^2}{\Psi'\Sigma\Psi}, i = 1, 2, 3, \ldots n$$

Situation 1: When Σ is non-diagonal

$$IS_2 = \frac{\left((\Psi'\,F)_i\right)^2}{\Psi'\Sigma\Psi}, i = 1, 2, 3, \ldots n$$

Here $\left((\Psi'\,F\right)_i$ is the i-th element of $\Psi'\,F$ and F is the Cholesky factor such that $FF' = \sum$. This means the ordering of the contributing price series that get imputed into the vector of price P_t.

The CS model, on the other hand, is based on identifying and estimating common long-memory components in cointegrated systems. As expressed formally (Harris et al., 2002) when p is a cointegrated series as a linear function of K common factor(s) f_t and r stationary error correction term $Z_t = \alpha' P_{t-1}$ where α' being an $r \times p$ matrix of cointegrating vectors and Z_t is $I(0)$. This leads to:

$$P_t = A_1 f_1 + A_2\, Z_1 = A_1 \gamma'_{\perp}\, P_{t-1}$$

Here, P_t is a $p \times 1$ vector of cointegrated prices; A_1 and A_2 are loading matrices; $\gamma'_{\perp}$ is a $k \times p$ matrix of common factor weights on the contemporaneous prices in the k common factor vector f_t where $k = (p - r)$.

As per this model:

$$f_t = \alpha'_{\perp} P_t$$

where $\alpha_{\perp}$ is a column vector orthogonal to the adjustment coefficient matrix α while $\alpha'_{\perp}$ is its transpose.

When n = 2, for the orthogonality condition to be satisfied and weights sum to be equal to 1, with permanent coefficient vectors (normalised) must satisfy the following two conditions with α_1 and α_2 are adjustment coefficient matrices for spot and futures prices.

$$CS_1\alpha_1 + CS_2\alpha_2 = 0$$

and

$$CS_1 + CS_2 = 1$$

Here CS_1 and CS_2 are permanent coefficient vectors, which, in other words, are component shares or contributions to price discovery for the spot and futures prices, respectively.

Thus, in terms of error correction coefficients (α_1 , α_2), the component shares (contributions to price discovery) of the two markets, 1 (spot) and 2 (futures) represented by CS_1 and CS_2 can be obtained from the above two equations as follows:

$$CS_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}$$

$$CS_2 = \frac{-\,\alpha_1}{\alpha_2 - \alpha_1}$$

Put in words, the market that adjusts most to innovation will have a lower component share value (CS), i.e., it will have a lower contribution to the price discovery as it will be a price taker. The opposite is true for the price setter.

3.5. Data

We utilise a one-minute price series for four monthly expiry of the nearby GIFT Nifty futures contracts, with data spanning 180 trading days, from 29 December 2023 to 27 June 2024. This price data series was sourced from Bloomberg, which obtains it from the NSE IX. Corresponding price data series for the Nifty index was also collected from Bloomberg. This data series was generated from the price data obtained from the NSE IX. Corresponding price data series for the Nifty index was collected from the NSE. The futures prices used in the study are exclusively for the nearby month's futures series. To create an equally spaced synchronous time series, the Nifty index and the GIFT Nifty futures price series were matched from 9:15 a.m. to 3:30 p.m. on days when trading occurred on both NSE and NSE IX. During periods when trading continued on the NSE IX but not on the NSE (6:30 a.m. to 9:15 a.m., 3:30 p.m. to 3:45 p.m., and 4:35 p.m. to 2:45 a.m. the next day), the last available NSE index price was used to extend the series to match each of the GIFT Nifty prices. The data covers the period from 29 December 2023, to 27 June 2024. Trading in the GIFT Nifty did not occur on weekends and on 26 January 2024, a trading holiday for the NSE IX. Meanwhile, the NSE was closed for nine trading holidays (26 January, 8 March, 25 March, 29 March, 11 April, 17 April, 1 May, 20 May, and 17 June) during this period.

Given that during the non-market hours for NSE, when the underlying Nifty is not capturing price information, while GIFT Nifty futures continues to trade, it is acknowledged that our approach potentially introduces an element of non-synchronicity in trading price data. Different markets not updating information simultaneously may lead to biased inferences for the temporal return behaviour of any financial asset (Lo & MacKinlay, 1990). Han et al. (2025) re-examine the price discovery of stock index and futures in China, addressing non-synchronous informational updates and finding that such updates can overestimate the price discovery ability of futures markets. However, this study's findings still remain relevant and important for several reasons. First, the extended trading hours of the GIFT Nifty futures provide additional information about market dynamics that would not be captured if we limited our analysis to synchronous trading periods. This helps us understand how global events impact price discovery when the domestic market is closed. Second, understanding price movements during these extended periods is crucial for foreign investors who trade during non-Indian market hours. It provides a comprehensive view of market behaviour and the efficiency of the GIFT Nifty futures in absorbing global market information.

Table 1 Panels (A and B) below provide information about the GIFT Nifty features and specifications, with the trading hours mentioned per Indian Standard Time (IST). Since NSE is open for trading only from 9.15 a.m. to 3.30 p.m. daily, it is easy to see how the GIFT Nifty futures enjoys much trading time for overseas investors. Lot size and tick size will reflect in the GIFT Nifty price and return series.

Table 1. (**A**) Contract specifications—GIFT Nifty futures. (**B**) GIFT Nifty futures trading hours.

(**A**)	
Underlying stock index	Nifty 50 index
Currency	US dollars ($)
Price quotation	US Dollars per index point
Tick size (minimum price step)	$0.5
Lot size	US$2 Nifty Index
Settlement type	Cash settled
Expiry day	Monthly contracts: Last Thursday for the expiry month

Table 1. *Cont.*

(B)	
Session-1	**Timing**
Pre-open: Open time	06:15 h
Pre-open: Close time	06:25 h
Normal market open time	06:30 h
Normal market close time	15:40 h
Pre-close: Open time	15:45 h
Pre-close: Close time	15:50 h
Pre-close: End time	15:55 h
Position limit/Collateral value set up cut-off time	16:00 h
Trade modification end-time	16:00 h
Session-2	**Timing**
Pre-open: Open time	16:25 h
Pre-open: Close time	16:31 h
Normal market open time	16:35 h
Normal market close Time	02:45 h (Next Day)
Position limit/Collateral value set up cut-off time	02:50 h (Next Day)
Trade modification end-time	02:50 h (Next Day)

Source: NSE IX website.

The descriptive statistics for the GIFT Nifty futures and the corresponding Nifty index price data are given in Table 2 below.

Table 2. Descriptive statistics—price.

	GIFT Nifty Futures	Nifty Index
Mean	22,402.88	22,338.02
Median	22,339.5	22,261.08
Standard deviation	560.11	564.93
Skewness	0.6144	0.7314
Kurtosis	−0.106	0.0919
Number of observations	112,925	112,925

The descriptive statistics for the GIFT Nifty futures and the corresponding Nifty index returns data are given in Table 3 below.

Table 3. Descriptive statistics—returns.

	GIFT Nifty Futures	Nifty Index
Mean	-4.89945×10^{-7}	-4.48044×10^{-7}
Median	0	0
Standard deviation	0.000366085	0.00035521
Skewness	−40.27996852	−53.35318454
Kurtosis	6541.128194	9243.853112
Number of observations	112,924	112,924

4. Results and Discussion

Table 4 presents the unit root tests for both the GIFT Nifty futures and Nifty index price and return series, showing significant results at the 1% level for both the Augmented Dickey–Fuller and Phillips-Perron tests for the latter. These results indicate that both price series are non-stationary, but the return series are stationary, which enables a cointegration analysis on the price series to assess how they behave in the long run with respect to each other.

Table 4. Unit root tests.

	Augmented Dickey–Fuller Test	Philips Perron Test
GIFT Nifty futures price	−4.034 #	−31.066 #
Nifty index price	−3.787 #	−27.162 #
GIFT Nifty futures return	−48.611 ***	−116,893 ***
Nifty index return	−48.673 ***	−111,930 ***

Note: # Indicates at 1% significance, the null hypothesis of non-stationarity cannot be rejected. *** Indicates at 1% level of significance; the null hypothesis can be rejected. Source: Authors' work.

Table 5 presents the results of the Johansen cointegration test, showing at the 5% level, the test rejects the null hypothesis that there are at least "r" cointegrating vectors (r = 0 and r ≤ 1). Since there are only two variables (Nifty Index price and GIFT Nifty futures price), the maximum number of cointegrating relations is 1. Therefore, there is one cointegrating relationship between spot and futures prices, indicating a long-term relationship between the GIFT Nifty futures and the Nifty index prices series.

Table 5. Johansen cointegration test.

Null Hypothesis: There Are at Least 'r' Cointegrating Vectors	Trace Statistic	Critical Value (at 5% Significance level)	Max-Eigen Statistic	Critical Value (at 5% Significance Level)	Decision (at 5% Significance Level)
r = 0	31.15	19.96	20.8	15.67	Reject H_0
r ≤ 1	10.35	9.24	10.35	9.24	Reject H_0

Note: Both the Trace and Max-Eigenvalue test statistics reveal the existence of a cointegration equation at a 5% level of significance. Source: Author's work.

Figure 1 below shows the volatility clustering of the GIFT Nifty return series. The optimum ARMA model of the GARCH is found to be (1, 1) order, with AR(1) and MA(1) being the best fit (the model estimation has been provided in the Appendix A). Table 6 gives LM-ARCH test results indicating that the return series of the GIFT Nifty futures shows an ARCH effect (Figure 1), with the null hypothesis (no ARCH effect) being rejected at the 1% significance level. This confirms the presence of ARCH effects in the return series.

Table 6. ARCH-LM test.

Null Hypothesis	Test Statistic (Chi-sq)	df	*p*-Value	Decision
No ARCH effects	1662.00 ***	12	$<2.2 \times 10^{-16}$	Reject H_0 → Strong ARCH effects

Note: *** Indicates significant at 1% level of significance. Source: Authors' work.

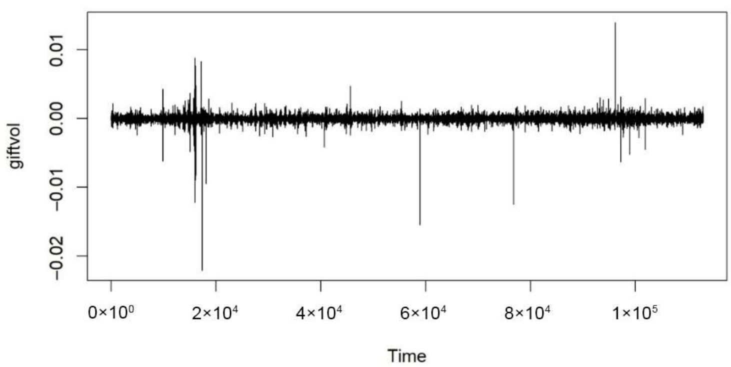

Figure 1. ARCH effect.

Table 7 presents the GARCH (1, 1) model results for the GIFT Nifty futures returns. Figure 2 below shows the symmetry of the news impact curve of this GARCH model. The coefficient of the AR(1) term (0.271) is significant at the 5% level, and the coefficient of the MA(1) term (−0.324) is significant at the 1% level. The ARCH term (news coefficient, α) is 0.055 and significant at the 1% level, while the GARCH term (persistence coefficient, β) is 0.901 and significant at the 1% level. As the GARCH coefficient value is higher than the ARCH coefficient value, we can conclude that the volatility is highly persistent and clustered. The coefficient of the constant is −0.000001, and the unconditional variance (omega) is zero. For the model to be stationary, the sum of α and β must be less than 1 ($\alpha + \beta < 1$). In this case, the sum is less than 1, indicating that the model is stationary. These results show that the GARCH model is robust, effectively capturing the volatility dynamics with significant persistence and the impact of new information, confirming the model's reliability.

Table 7. GARCH analysis.

Coefficient of the Constant	Coefficient of the AR (1) Term	Coefficient of the MA (1) Term	Unconditional Variance (Omega)	ARCH Term (News Coefficient) [Alpha]	GARCH Term (Persistence Coefficient) [Beta]
−0.000001	0.271 **	−0.325 *	0	0.055 *	0.901 *

Note: ** and * indicate significance at a 5% and 1% level of significance, respectively. Source: Authors' work.

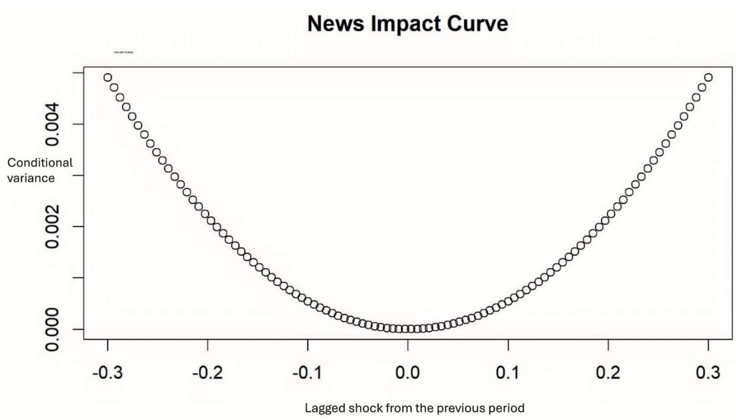

Figure 2. News impact curve.

Table 8 presents the results of the Granger causality test between the Nifty index and the GIFT Nifty futures returns. The null hypothesis that the Nifty index return does not Granger-cause the GIFT Nifty futures return is rejected with a test statistic of 85.625, significant at the 1% level. Similarly, the null hypothesis that the GIFT Nifty futures return does not Granger-cause the Nifty index return is also rejected with a test statistic of 47.714, significant at the 1% level. These results indicate bidirectional causality, meaning that both the GIFT Nifty futures return and the Nifty index return Granger-cause each other, reflecting a dynamic interplay and mutual predictive power between the two markets.

Table 8. Granger causality test.

Null Hypothesis	Test Statistic	Inference
The Nifty index return does not Granger-cause the GIFT Nifty futures return	85.625 ***	Both the GIFT Nifty futures return and the
The GIFT Nifty futures return doesn't Granger-cause the Nifty index return	47.714 ***	Nifty index return Granger-cause each other.

This is the Note: *** Indicates significance at a 1% level of significance. Source: Authors' work.

Table 9 presents the results of the price discovery tests using Hasbrouck's Information Share (IS) and Gonzalo and Granger's Component Share (CS) measures for the GIFT Nifty futures and the Nifty index. Hasbrouck's IS in the original ordering shows a contribution of 39.8% for the GIFT Nifty futures and 60.2% for the Nifty index, while the reverse ordering results are 83.842% for the GIFT Nifty futures and 16.158% for the Nifty index. The combined Hasbrouck's IS indicates a contribution of 61.8% for the GIFT Nifty futures and 38.2% for the Nifty index. Gonzalo and Granger's CS shows a contribution of 68% for the GIFT Nifty futures and 32% for the Nifty index. These results suggest that the GIFT Nifty futures play the leading role in the price discovery process of the Nifty index, highlighting its importance in reflecting new market information. As discussed before, when trading continues in the futures market, when the spot market is closed, it could potentially give rise to non-synchronous trading-related distortions in the estimates.

Table 9. Price discovery.

Price Discovery Contribution Measure	GIFT Nifty Futures	Nifty Index
Hasbrouck's Information Share—Original Ordering	39.8%	60.2%
Hasbrouck's Information Share—Reverse Ordering	83.842%	16.158%
Hasbrouck's Information Share (Combined)	61.8%	38.2%
Gonzalo and Granger's Component Share	68%	32%

Source: Authors' work.

5. Conclusions

This paper evaluates the information transmission performance of the GIFT Nifty futures, focusing on predictive power, its integration with the Nifty index, price discovery, and volatility dynamics. Using one-minute price series data for four monthly expiries of the nearby GIFT Nifty futures contracts and the Nifty index, spanning 180 trading days, from 29 December 2023 to 27 June 2024, we employed Johansen cointegration tests, Granger causality tests, GARCH models, Hasbrouck's Information Share (IS) model, and Gonzalo–Granger's Component Share (CS) model. The significance of this paper lies in its first-ever evaluation of the information transmission performance of the GIFT Nifty futures market using high-frequency data. In addition to providing an indication of the market quality, the relevance of this research lies in its timeliness, as GIFT Nifty futures recently completed its second anniversary of launch.

Our results show that the GIFT Nifty futures and the Nifty index exhibit significant bidirectional causality and cointegration, indicating a stable long-term relationship. The robust GARCH model captures significant volatility dynamics, affirming the market's responsiveness to new information. The test results indicate that the GIFT Nifty futures effectively transmit price information. This is expected as it imparts new information in real-time from Non-resident Indians (NRIs), Foreign Portfolio Investors (FPIs), and Eligible Foreign Investors (EFIs), which do not flow immediately into either the Nifty index or the Nifty futures due to the GIFT Nifty enjoying additional daily trading windows in other parts of the world when the Nifty index prices are not available. Due to time advantages, investors' reluctance to bear foreign exchange risk, or restrictions on non-residents to participate in trading in domestic exchanges, significant real-time price information would have been lost to the Nifty index but for the existence of the GIFT Nifty futures. The findings of this study are likely to increase the confidence of all stakeholders in the GIFT Nifty futures market.

Understanding the information transmission performance of the GIFT Nifty futures is crucial for market participants and regulators, as it provides insights into market behaviour, integration, and forecasting abilities. Our findings highlight the reassuring price discovery performance of the GIFT Nifty futures, which can inform regulators and investors alike about market stability and transparency, bolstering the GIFT Nifty's acceptance globally. The findings of this work are relevant not only to investors but also to stock exchanges and policymakers exploring different pathways to further internationalisation of the Indian capital market.

Our study has opened up an unattended area of empirical research on a newly launched instrument. Future studies can be directed towards probing other key market microstructure variables of GIFT Nifty futures, as several unique characteristics of this new market may potentially serve as a source of new insights into price leadership, market integration, and market quality in general. Research can also be conducted to both broaden and deepen the understanding of the relative merits or demerits of different forms of global security market integration, which include, *inter alia*, offshore listing of securities, offshore trading of indices, and setting up of GIFT city-like international finance centres (IFSC) within a country's borders. One of the limitations of this study could be addressed by studying non-synchronous aspects of trading the GIFT Nifty futures vis-à-vis the Nifty. Learnings from the synchronisation mechanisms from other markets can be culled, compared and examined for off-market trading hours. Comparative study on information transmission performance between the Nifty futures and the GIFT Nifty futures, while the Nifty remains the common spot market for both, could be another research area to explore.

Author Contributions: Conceptualization, R.S.; methodology, R.S.; software, R.S.; validation, R.S., S.G.D., and A.P.; formal analysis, R.S.; resources, S.G.D., and A.P.; data curation, A.P.; writing—original draft preparation, R.S.; writing—review and editing, S.G.D. and A.P.; visualization, R.S., and A.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used for the study is proprietary data (from Bloomberg) and cannot be shared.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

GARCH Model Fit	
Conditional Variance Dynamics	
GARCH Model	sGARCH (1, 1)
Mean Model	ARFIMA (1, 0, 1)
Distribution	norm

	Parameters			
	Estimate	**Std. Error**	**t-Value**	***p*-Value**
mu	0.000	0.000	−1.921	0.055
ar1	0.270	0.106	2.544	0.011
ma1	−0.324	0.108	−3.018	0.003
omega	0.000	0.000	0.003	0.998
alpha1	0.055	0.000	980.351	0.000
beta1	0.901	0.000	4685.386	0.000
Log-Likelihood	767,263.500			
AIC	−13.589			

Parameters with Robust Standard Errors				
	Estimate	**Std. Error**	**t-Value**	***p*-Value**
mu	0.000	0.001	−0.002	0.999
ar1	0.270	55.160	0.005	0.996
ma1	−0.324	56.497	−0.006	0.995
omega	0.000	0.000	0.000	1.000
alpha1	0.055	0.227	0.240	0.810
beta1	0.901	0.484	1.864	0.062

Weighted Ljung-Box Test on Standardized Residuals		
	Statistic	***p*-Value**
Lag [1]	109.4	0
Lag [2 × (p + q) + (p + q) −1] [5]	124.3	0
Lag [4 × (p + q) + (p + q) −1] [9]	132.6	0
Degree of Freedom	2	
H0	No Serial Correlation	

Weighted Ljung-Box Test on Standardized Squared Residuals		
	Statistic	***p*-Value**
Lag [1]	1.192	0.275
Lag [2 × (p + q) + (p + q) − 1] [5]	1.428	0.758
Lag [4 × (p + q) + (p + q) − 1] [9]	1.774	0.930
Degree of Freedom	2	

Weighted ARCH LM Tests				
	Statistic	**Shape**	**Scale**	***p*-Value**
ARCH Lag [3]	0.100	0.500	2.000	0.751
ARCH Lag [5]	0.492	1.440	1.667	0.886
ARCH Lag [7]	0.581	2.315	1.543	0.970

Nyblom stability test	
Joint Statistic	36,568.55
Individual Statistics	
mu	0.370
ar1	7.811
ma1	7.918
omega	11,340.000
alpha1	570.200
beta1	910.100

Asymptotic Critical Values	10%	5%	1%
Joint Statistic	1.490	1.680	2.120
Individual Statistic	0.350	0.470	0.750

Sign Bias Test		
	t-Value	**Prob**
Sign Bias	0.126	0.900
Negative Sign Bias	3.046	0.002
Positive Sign Bias	1.445	0.148
Joint Effect	12.041	0.007

Adjusted Pearson Goodness of fit Test			
	Group	**Statistic**	**p-Value (g − 1)**
1	20	17,396	0
2	30	23,520	0
3	40	28,536	0
4	50	32,479	0

GARCH Model Forecast (Horizon: 20)		
	Series	**Sigma**
T + 1	-3.14×10^{-5}	2.59×10^{-4}
T + 2	-9.17×10^{-6}	2.54×10^{-4}
T + 3	-3.15×10^{-6}	2.48×10^{-4}
T + 4	-1.53×10^{-6}	2.43×10^{-4}
T + 5	-1.09×10^{-6}	2.37×10^{-4}
T + 6	-9.66×10^{-7}	2.32×10^{-4}
T + 7	-9.34×10^{-7}	2.27×10^{-4}
T + 8	-9.25×10^{-7}	2.22×10^{-4}
T + 9	-9.23×10^{-7}	2.17×10^{-4}
T + 10	-9.23×10^{-7}	2.12×10^{-4}
T + 11	-9.22×10^{-7}	2.08×10^{-4}
T + 12	-9.22×10^{-7}	2.03×10^{-4}
T + 13	-9.22×10^{-7}	1.99×10^{-4}
T + 14	-9.22×10^{-7}	1.94×10^{-4}
T + 15	-9.22×10^{-7}	1.90×10^{-4}
T + 16	-9.22×10^{-7}	1.86×10^{-4}
T + 17	-9.22×10^{-7}	1.82×10^{-4}
T + 18	-9.22×10^{-7}	1.78×10^{-4}
T + 19	-9.22×10^{-7}	1.74×10^{-4}
T + 20	-9.22×10^{-7}	1.70×10^{-4}

Notes

1. https://www.nseindia.com/static/national-stock-exchange/about-nse-company (accessed on 20 August 2025).
2. The sources of the information in this section are the websites of NSE IX (https://www.nseix.com/), GIFT City (https://giftgujarat.in/business/ifsc) and International Financial Services Centres Authority (https://www.ifsca.gov.in/) (as accessed on 18 August 2025).

References

Alemany, N., Aragó, V., & Salvador, E. (2020). Lead-lag relationship between spot and futures stock indexes: Intraday data and regime-switching models. *International Review of Economics & Finance*, *68*, 269–280.

Bohl, M. T., Salm, C. A., & Schuppli, M. (2011). Price discovery and investor structure in stock index futures. *Journal of Futures Markets*, *31*(3), 282–306. [CrossRef]

Bollerslev, T. (1986). Generalised autoregressive conditional heteroscedasticity. *Journal of Econometrics*, *31*(3), 307–327. [CrossRef]

Chan, K. (1992). A further analysis of the lead–lag relationship between the cash market and stock index futures market. *The Review of Financial Studies*, *5*(1), 123–152. [CrossRef]

Dahlgran, R. A. (2000, June 29–July 1). *An examination of futures price determination through the lens of market integration*. Western Agricultural Economics Association Annual Meeting, Vancouver, BC, Canada.

Fama, E. F. (1970). Efficient capital markets. *Journal of Finance*, *25*(2), 383–417. [CrossRef]

Fassas, A. P., & Siriopoulos, C. (2019). Intraday price discovery and volatility spillovers in an emerging market. *International Review of Economics & Finance*, *59*, 333–346. [CrossRef]

Figuerola-Ferretti, I., & Gonzalo, J. (2010). Modelling and measuring price discovery in commodity markets. *Journal of Econometrics*, *158*(1), 95–107. [CrossRef]

Fleming, J., Ostdiek, B., & Whaley, R. E. (1996). Trading costs and the relative rates of price discovery in stock, futures, and option markets. *Journal of Futures Markets*, *16*(4), 353–387. [CrossRef]

Gonzalo, J., & Granger, C. (1995). Estimation of common long-memory components in cointegrated systems. *Journal of Business and Economic Statistics*, *13*(1), 27–35. [CrossRef]

Grossman, S. J. (1977). The existence of futures markets, noisy rational expectations and informational externalities. *The Review of Economic Studies*, *44*(3), 431–449. [CrossRef]

Han, Q., Zhao, C., Chen, J., & Guo, Q. (2025). Does asynchronous market update matter? Re-examining the price discovery of stock index and futures in China. *Emerging Markets Review*, *67*, 101307. [CrossRef]

Harris, F. H. B., McInish, T. H., & Wood, R. A. (2002). Security price adjustment across exchanges: An investigation of common factor components for Dow stocks. *Journal of Financial Markets*, *5*(3), 277–308. [CrossRef]

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *Journal of Finance*, *50*(4), 1175–1199. [CrossRef]

Hu, Y., Hou, Y. G., & Oxley, L. (2020). What role do futures markets play in Bitcoin pricing? Causality, cointegration and price discovery from a time-varying perspective? *International Review of Financial Analysis*, *72*, 101569. [CrossRef] [PubMed]

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. *Econometrica*, *59*(6), 1551–1580. [CrossRef]

Karmakar, M., & Inani, S. (2019). Information share and its predictability in the Indian stock market. *Journal of Futures Markets*, *39*(10), 1322–1343. [CrossRef]

Khan, M. A., Hussain, M. M., Pervez, A., Atif, M., Bansal, R., & Alhumoudi, H. A. (2022). Intraday price discovery between spot and futures markets of NIFTY 50: An empirical study during the times of COVID-19. *Journal of Mathematics*, *2022*(1), 2164974. [CrossRef]

Kumar, S. S. S., & Sampath, A. (2019). What drives the offshore futures market? Evidence from India and China. *Finance Research Letters*, *30*, 394–402. [CrossRef]

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, *53*, 1315–1335. [CrossRef]

Lehmann, B. N. (2002). Some desiderata for the measurement of price discovery across markets. *Journal Financial Markets*, *5*(3), 259–276. [CrossRef]

Lo, A. W., & MacKinlay, A. C. (1990). An econometric analysis of non-synchronous trading. *Journal of Econometrics*, *45*(1–2), 181–211. [CrossRef]

Putnins, T. J. (2013). What do price discovery metrics really measure? *Journal of Empirical Finance*, *23*(9), 68–83. [CrossRef]

Ross, S. A. (1989). Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *Journal of Finance*, *44*(1), 1–17.

Shetty, M., Rahiman, H. U., Kodikal, R., & Kumar, R. S. (2024). Analysing stock market linkages: Exploring volatility spillover effects between SGX and NSE Nifty using ADCC GARCH model. In *The AI revolution: Driving business innovation and research* (Vol. 2, pp. 599–613). Springer Nature.

Sifat, I. M., Mohamad, A., & Shariff, M. S. B. M. (2019). Lead-Lag relationship between Bitcoin and Ethereum: Evidence from hourly and daily data. *Research in International Business and Finance*, *50*, 306–321. [CrossRef]

Stoll, H. R., & Whaley, R. E. (1990). The dynamics of stock index and stock index futures returns. *Journal of Financial and Quantitative Analysis*, *25*(04), 441–468. [CrossRef]

Sultan, S. G., & Zivot, E. (2015). *Price discovery share—An order invariant measure of price discovery with application to exchange-traded funds*. University of Washington.

Sundararajan, S., & Balasubramanian, S. A. (2023). Intraday price discovery and volatility transmission between the dual-listed stock index futures and spot markets–new evidence from India. *International Journal of Emerging Markets*, *20*, 1888–1907. [CrossRef]

Tse, Y. (1999). Price discovery and volatility spillovers in the DJIA index and futures markets. *Journal of Futures Markets*, *19*(8), 911–930. [CrossRef]

Yang, J., & Leatham, D. J. (1999). Price discovery in wheat futures markets. *Journal of Agricultural and Applied Economics*, *31*(2), 359–370. [CrossRef]