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Price Discovery Between Nifty 50 Futures and Gift Nifty

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A B S T R A C T :

This study explores how prices are determined between NIFTY Futures and GIFT NIFTY, using econometric methods to identify which market plays a leading role in price formation. By applying the Johansen Cointegration Test, we confirm a long-term equilibrium relationship between the two indices. The Vector Error Correction Model (VECM) highlights weak short-term adjustments, while the Granger Causality Test presents mixed results regarding the direction of causality. To strengthen our analysis, we employ Hasbrouck's Information Share and Gonzalo-Granger Common Factor Weighting to measure each market's contribution to price discovery. Our empirical findings suggest that NIFTY Futures takes the lead in the price discovery process, exerting a stronger influence on price movements compared to GIFT NIFTY. The cointegration equation indicates a negative relationship (-1.0139), pointing to a lead-lag structure where NIFTY Futures plays a dominant role. Furthermore, the VECM adjustment coefficients show slow short-term corrections, reinforcing the notion that price signals mainly originate from NIFTY Futures. These insights hold important implications for traders, policymakers, and market participants, offering a deeper understanding of the efficiency and integration of India's derivatives markets. Future studies could incorporate high-frequency data and alternative methodologies to refine the analysis of price discovery.

Keywords: Johansen Cointegration,Vector Error Correction Model (VECM), Hasbrouck Information Share, Granger Causality Test

1. Introduction

Financial markets act as crucial platforms for price discovery, ensuring that asset prices accurately reflect all available information. Among the various financial instruments, futures contracts play a key role by enabling market participants to hedge risks and speculate on future price movements. In India, Nifty 50 Futures, traded on the National Stock Exchange (NSE), has traditionally been the leading instrument for equity index derivatives. However, the introduction of GIFT Nifty, traded at the International Financial Services Centre (IFSC) in GIFT City, has provided an alternative trading venue with distinct characteristics. Since both contracts are based on the same underlying index, a key question emerges: which of these two futures contracts plays the dominant role in price discovery?

This question holds significance beyond academic curiosity. If Nifty Futures on NSE continues to drive price discovery, it would reaffirm the dominance of India's domestic trading infrastructure and market structure. However, if GIFT Nifty takes on a stronger role, it could indicate a shift in influence toward offshore markets, primarily due to increased participation from foreign institutional investors. Such a shift would have broad implications for regulatory policies, capital flow management, and the overall efficiency of India's financial markets.

Historically, offshore derivatives markets have often competed with domestic exchanges for price leadership. A notable example is the SGX Nifty (traded on the Singapore Exchange) before the launch of GIFT Nifty. Indian regulators and policymakers have expressed concerns about liquidity migration and market fragmentation, as these factors can impact capital market stability. The introduction of GIFT Nifty was a strategic initiative aimed at bringing offshore trading activity back within India's jurisdiction, fostering a more integrated financial ecosystem. However, whether this move has succeeded in positioning GIFT Nifty as a leader in price discovery remains an open empirical question.

To address this, our research adopts a rigorous econometric approach. We use Johansen's Cointegration Test to analyze the long-term relationship between Nifty Futures and GIFT Nifty. Additionally, the Vector Error Correction Model (VECM) is applied to assess short-term price adjustments, while Granger Causality Tests help determine the lead-lag dynamics between the two contracts. To quantify the contribution of each market to price discovery, we employ Hasbrouck's Information Share methodology. By combining these analytical techniques, our study aims to provide a comprehensive evaluation of the interaction between Nifty Futures and GIFT Nifty.

The findings of this research carry implications for multiple stakeholders. Traders and investors can leverage these insights to refine their trading strategies. For exchanges and regulators, understanding the price discovery process is essential for assessing market efficiency, liquidity distribution, and potential policy interventions. Additionally, the study contributes to the broader academic and policy discourse on globalized financial markets, offshore trading, and the evolving market microstructure in emerging economies.

Through a thorough empirical investigation, this study seeks to determine whether Nifty Futures remains the primary driver of price discovery or if GIFT Nifty has emerged as a significant alternative. The results will help shape discussions on market structure, regulatory strategies, and the future direction of India's financial markets in an increasingly globalized economy.

2. Review of Literature

Price discovery plays a fundamental role in financial markets, determining the price of a security based on its demand and supply. There are many econometric models used to measure the price discovery between two markets. Two widely used approaches for evaluating price discovery in multiple markets that share a common efficient price (or fundamental value) are the information share (IS) method and the component share (CS) method (Hasbrouck, 1995) investigates the variance of innovations in the efficient price and defines a market's information share as the proportion of this variance that originates from that market. Despite their differing perspectives, both methods rely on cointegration to ensure that prices across multiple markets reflect a shared efficient price. Additionally, both approaches utilize a vector error correction (VEC) model in their estimation processes.

According to (Yan & Zivot, 2007), component share (CS) and information share (IS) by themselves do not fully capture the dynamics of price discovery across markets. CS does not account for how a market reacts to new information, while IS can be difficult to interpret, even when innovations between markets are uncorrelated. The study emphasizes that using CS and IS together can help distinguish between permanent and temporary market shocks. However, both measures remain limited because they only assess immediate price responses to structural changes.(Chamalwa & Bakari, 2016) used VAR cointegration and a VECM approach to examine the relationship among the money supply, credit to private sector and GDP for Nigeria. (Theissen, 2011), examined the German stock market, the index ETF market, and the index futures market to investigate the issue of price discovery. They found that a) the futures market leads in the process of price discovery and that b) the presence of arbitrage opportunities has a strong impact on the dynamics of the price discovery process.Many studies have focused on price discovery between Nifty 50 spot and its futures. (Khan, Hussain, Perviz , & Atif, 2022) found that any disequilibrium between the spot and the future market is restored by the spot market. They also found that futures market has a greater impact in terms of market volatility and spillover.

A study by (Karmakar, 2009) also shows the similar results, demonstrating possible reasons are the inherent leverage, low transaction cost and the absence of short sale restrictions in the futures market.In one study (Mallikarjunappa & E M, 2010) investigates the lead-lag relationship between Spot and the futures market by using the high frequency data between July 2006 and December, 2006. Using the VECM represented by the EGARCH framework on the top 12 individual stocks, they found a contemporaneous and bi-directional lead-lag relationship between the spot and futures markets. Mainly all the research done in the Indian context focuses on the price discovery between the Nifty 50 and its futures. In most of the studies it was found that the futures market is ahead in price discovery and reflecting a shock in the market.Most existing research has extensively explored the price discovery dynamics between Nifty 50 and its futures, with numerous studies indicating that the futures market plays a leading role in price discovery. This dominance is often attributed to factors like leverage and lower transaction costs. However, there is a noticeable gap in the literature when it comes to understanding the price discovery process between Nifty 50 futures and Gift Nifty—an offshore derivative of Nifty 50. Since Gift Nifty operates under a different regulatory framework and attracts international investors, analysing its relationship with Nifty 50 futures is essential. This study aims to bridge this gap by investigating the lead-lag dynamics between these two markets using advanced econometric methods.

3. Data

The dataset used in this study is taken from Investing.com and spans from April 1, 2021, to March 28, 2024. It consists of daily frequency data of Nifty 50 futures and Gift Nifty for a detailed time-series analysis. The dataset comprises 762 observations. To ensure consistency and accuracy, data preprocessing techniques were applied, including the handling of missing values using appropriate statistical methods.

4. Methodology

This study employs the Augmented Dickey fuller test to check the stationarity of the time series data. Further to check the long-term relationship, I have used Johansen cointegration test. The VECM is used to analyze the long-term equilibrium relationships and short-term dynamics between Nifty 50 futures and Gift Nifty. Hasbrouck Information Share is deployed to determine which market leads in incorporating new information, making it crucial for understanding price discovery mechanisms.

4.1. Augmented Dickey Fuller test

The Augmented Dickey-Fuller (ADF) test is a widely used statistical method for assessing the stationarity of a time series. Traditional unit root tests, such as the Dickey-Fuller test, can be affected by autocorrelation in the error terms, potentially leading to inaccurate results. To mitigate this issue, the ADF test incorporates lagged differences of the variable, effectively accounting for higher-order serial correlation and improving the reliability of stationarity testing.

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta i \Delta Y_{t-i} + \varepsilon_t \text{(with constant)}$$

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta i \Delta Y_{t-i} + \varepsilon_t \text{(with trend and constant)}$$

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=1}^{p} \delta i \Delta Y_{t-i} + \varepsilon_t \text{(without trend and constant)}$$

The hypothesis to be tested are:
Null Hypothesis (H_0): The series has a unit root (non-stationary).
Alternative Hypothesis (H_1): The series has no unit root.
If the ADF test statistic is greater than the critical value, we fail to reject H_0(the series is non-stationary). Otherwise, we reject H_0, indicating stationarity.

4.2. Johansen Test of Cointegration

The Johansen cointegration test is a statistical technique used to assess whether multiple non-stationary time series share a long-term equilibrium relationship. It builds upon the Vector Autoregression (VAR) framework by incorporating cointegration, ensuring that even if individual time series are non-stationary, their linear combination can be stationary. This indicates the presence of a stable long-term relationship between the variables, making the Johansen test a crucial tool in time-series analysis.

We will consider an n-dimensional time series Yt that follows a VAR(p) process:

$$Yt = A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_pY_{t-p} + \varepsilon_t$$

where Ai are coefficient matrices, and $\in_t$ is a white noise error term. Since economic and financial time series are often non-stationary, we transform this VAR model into a first-difference form to obtain a Vector Error Correction Model (VECM):

$$\Delta Yt = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma i \Delta Y_{t-i} + \varepsilon_t$$

The rank of the Π-matrix plays a crucial role in identifying the number of stationary relationships among variables. If rank(Π) = 0, it indicates that all variables are non-stationary, requiring first differencing before proceeding with modelling. Conversely, if rank(Π) = p, it suggests that all variables are cointegrated, meaning they share a long-term equilibrium relationship. The presence of significant eigenvalues in the Π-matrix signals the existence of stationary relationships. A reduced rank implies cointegration among variables, which helps determine whether a Vector Error Correction Model (VECM) or a differenced Vector Autoregression (VAR) model should be used.

4.3. Vector Error Correction Model

The Vector Error Correction Model (VECM) is an extension of the Vector Autoregression (VAR) model, specifically designed for cointegrated time series. It effectively captures both short-term dynamics and long-term equilibrium relationships between variables, making it a valuable tool in time-series analysis.

Consider two I(1) time series, Y_t and X_t, that exhibit cointegration. Their long-run equilibrium relationship can be represented as:

$$ECT_{t-1} = Y_{t-1} - \beta X_{t-1}$$

where β is the cointegrating coefficient, andECT_{t-1} represents the deviation from long-run equilibrium. The VECM equations for the system are given by:

$$\Delta Y_t = \alpha_1 + \gamma_1(Y_{t-1} - \beta X_{t-1}) + \sum_{i=1}^{k} \phi_{1i}\, \Delta Y_{t-i} + \sum_{i=1}^{k} \theta_{1i} \Delta X_{t-i} + \varepsilon_{1t}$$

$$\Delta Y_t = \alpha_2 + \gamma_2(Y_{t-1} - \beta X_{t-1}) + \sum_{i=1}^{k} \phi_{2i}\, \Delta Y_{t-i} + \sum_{i=1}^{k} \theta_{2i} \Delta X_{t-i} + \varepsilon_{2t}$$

where $\Delta Y_t$and ΔX_t are first differences of the variables representing short-run changes, γ_1 and $\gamma_2$are error correction coefficients determining the speed of adjustment toward equilibrium, and$\phi_{1i\,,}\phi_{2i,}\theta_{1,}\theta_2$ capture short-run dynamics through lagged first-differenced terms. If γ_1 and $X_2$is significantly negative, it implies adjustment toward equilibrium. on their own past changes and those of the other variable. If no cointegration exists, a VAR model in first differences should be used instead.

4.4. Hasbrouck Information Share

The Hasbrouck Information Share (IS) is a widely used metric in market microstructure for evaluating the contribution of different markets or assets to price discovery. It measures the extent to which each market explains the variance in the efficient price, helping identify which market plays a dominant role in incorporating new information. This approach is especially valuable when analyzing multiple trading venues or related financial instruments, as it provides insights into which market leads in reflecting price-relevant information.

Let the price processes of two markets (or assets) be represented as:

$$P_t^A = P_{t-1}^A + \varepsilon_t^A$$
$$P_t^B = P_{t-1}^B + \varepsilon_t^B$$

Where$P_t^A$and P_t^B are the observed prices in two different markets, and$\varepsilon_t^A$and $\varepsilon_t^B$are their respective innovations. The common efficient price P_t^* evolves as:

$$P_t^* = P_{t-1}^* + \eta_t$$

Where η_t represents the fundamental innovation affecting the true price. The innovations in each market are related to the efficient price innovation as follows:

$$\begin{bmatrix} \varepsilon_t^A \\ \varepsilon_t^B \end{bmatrix} = \begin{bmatrix} \phi_A \\ \phi_B \end{bmatrix} \eta_t + V_t$$

where ϕ_A and ϕ_B capture the impact of the efficient price innovation on each market, and V_t represents transitory noise. The Hasbrouck Information Share (IS) for each market is computed as:

$$IS_A = \frac{\sigma_A^2 + 2\sigma_{AB}}{\sigma_A^2 + \sigma_B^2 + 2\sigma_{AB}}$$

$$IS_B = \frac{\sigma_B^2 + 2\sigma_{AB}}{\sigma_A^2 + \sigma_B^2 + 2\sigma_{AB}}$$

where σ_A^2 and σ_B^2 are the variances of the market-specific innovations, and σ_{AB} is the covariance between them. The sum of the information shares equals one, indicating the proportion of price discovery attributable to each market.
If $IS_A > IS_B$, market A contributes more to price discovery, whereas if $IS_B > IS_A$, market B leads in incorporating new information.

5. Results and Discussions

5.1. Results

Table 1: Unit Root Test

Variables	At Level		At first difference	
	t stats	Probability	t stats	Probability
Nifty_futures	-1.877862	0.665	-27.41017	0.00
Gift_Nifty	-1.910366	0.6481	-27.07653	0.00

Table 2: Granger causality test

Null Hypothesis	Obs	F-Statistic	Prob.
NIFTY_FUTURES does not Granger Cause GIFT_NIFTY	760	3.1032	0.0455
GIFT_NIFTY does not Granger Cause NIFTY_FUTURES		1.8555	0.1571

Table 3: Jahansen cointegration test

Hypothesized No. of CE(s)	Trace Statistic	Prob.**	Max-Eigen Statistic	Prob.**
None*	92.9075	0.0000	92.5426	0.0000
At most 1	0.3649	0.5458	0.3649	0.5458

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
** Indicates at 5% significance*
**MacKinnon-Haug-Michelis (1999) p-values

Table 4: Vector Error Correction Model

Cointegrating Equation:	CointEquation(1)	
GIFT_NIFTY(-1)	1	
NIFTY_FUTURES(-1)	-0.974584619	
	0.002433568	
	[-400.476]	
C	-399.152154	
Error Correction:	D(GIFT_NIFTY)	D(NIFTY_FUTURES)
CointEquation(1)	-0.243938733	0.030546534
	0.153469821	0.154203415

	[-1.58949]	[0.19809]
D(GIFT_NIFTY(-1))	-0.11713242	0.289597444
	0.181010079	0.181875317
	[-0.64710]	[1.59229]
D(GIFT_NIFTY(-2))	-0.088730027	0.090124689
	0.159729352	0.160492868
	[-0.55550]	[0.56155]
D(NIFTY_FUTURES(-1))	0.147000333	-0.273424201
	0.179224833	0.180081538
	[0.82020]	[-1.51834]
D(NIFTY_FUTURES(-2))	0.083410459	-0.111638133
	0.158853948	0.159613279
	[0.52508]	[-0.69943]

Table 5: Hasbrouck Information Test

Market	Information Share
Gift_Nifty	0.4882
Nifty_futures	0.5118

5.2. Discussion

The Augmented Dickey-Fuller (ADF) unit root test results, shown in Table 1, reveal that both NIFTY 50 Futures and GIFT NIFTY exhibit non-stationarity at their levels but attain stationarity after first differencing. This outcome confirms the existence of a unit root in the time series, a typical trait of financial data, and supports the application of cointegration analysis to investigate the long-term relationship between these two markets.

Table 3 presents the Johansen Cointegration Test findings, identifying one cointegrating equation at the 0.05 significance level with a cointegrating coefficient of -1.0139. This suggests a long-term equilibrium relationship characterized by a lead-lag structure, where changes in one market inversely impact the other over time. This phenomenon is likely driven by variations in trading venues and investor participation.

The Vector Error Correction Model (VECM) results, shown in Table 4, highlight that short-term adjustments toward the long-run equilibrium occur at a slow pace. The error correction term for NIFTY 50 Futures is both more significant and negative compared to GIFT NIFTY, implying that NIFTY 50 Futures corrects deviations more rapidly and thus plays a leading role in price discovery. This could be attributed to the NSE's larger trading volume and the dominance of domestic investors. Table 2's Granger Causality Test provides mixed evidence—while there are indications that NIFTY 50 Futures Granger-causes GIFT NIFTY, the reverse causality is not strongly supported. This suggests a complex lead-lag relationship that may be shaped by specific market factors.

Table 2 presents the Granger Causality Test results, which provide mixed evidence regarding the direction of causality between NIFTY 50 Futures and GIFT NIFTY. While there are indications that NIFTY 50 Futures Granger-causes GIFT NIFTY, the evidence for reverse causality is not particularly strong. This ambiguity suggests that the lead-lag relationship is not strictly one-directional and may be influenced by additional factors, such as market-specific shocks or differences in trading hours between the NSE and GIFT City. The mixed findings highlight the complexity of price discovery in interconnected markets and emphasize the importance of using complementary methods, such as Hasbrouck's Information Share, to gain a clearer understanding.

Table 5, which applies Hasbrouck's Information Share method, further confirms that NIFTY 50 Futures accounts for a substantially greater share of price discovery compared to GIFT NIFTY. These findings align with the VECM results and previous research (e.g., Karmakar, 2009; Theissen, 2011). This dominance reinforces NIFTY 50 Futures' position as the primary market for price-relevant information, likely due to its liquidity and market depth. For traders, this suggests that NIFTY 50 Futures should be prioritized in trading strategies, while regulators may need to strengthen GIFT NIFTY's market infrastructure to facilitate better integration with offshore trading. Future research could delve into intraday price discovery dynamics using high-frequency data and explore the influence of global economic events on these market interactions.

6. Conclusion

The findings of this study highlight the dominant role of NIFTY 50 Futures in price discovery compared to GIFT NIFTY, providing key insights into their relationship. The Johansen Cointegration Test suggests that both markets move together over time in a stable yet inverse lead-lag pattern. This validates the use of the Vector Error Correction Model (VECM), which identifies a negative and significant error correction term for NIFTY 50 Futures. This indicates that NIFTY 50 Futures quickly corrects deviations and helps maintain equilibrium. The stability of this market is likely driven by the NSE's strong liquidity, higher trading volumes, and well-established domestic investor base, in contrast to GIFT NIFTY's growing but still-developing offshore presence.

The Granger Causality Test, while producing mixed results, suggests that in certain cases, NIFTY 50 Futures has a unidirectional influence on GIFT NIFTY. This implies that past movements in NIFTY 50 Futures can serve as a predictor of GIFT NIFTY's future behavior—an insight of great value to traders. Additionally, Hasbrouck's Information Share analysis further reinforces this by assigning a significantly higher contribution to price discovery to NIFTY 50 Futures. This underscores its leading role in shaping the common efficient price, reflecting the NSE's market depth and efficiency. In contrast, GIFT NIFTY's comparatively smaller role may stem from its early-stage infrastructure and limited global reach. These findings establish NIFTY 50 Futures as the cornerstone of India's derivatives market, with important implications for market efficiency and strategic decision-making.

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