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Hedging With Futures:
Contract in the Indian Stock Market

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ABSTRACT

This research explores the utilization of wavelet transform decomposition as an effective tool for hedging in the Indian stock market, particularly focusing on hedging with index futures contracts. Utilizing daily data obtained from the National Stock Exchange (NSE) of India spanning from 2010 to 2022, the study investigates the lead-lag relationships, correlations, and hedge ratios across different time scales through the wavelet transform method. The findings indicate a clear relationship between the Nifty 50, Nifty Bank, and Index futures in both short and longer time frames. However, in intermediate time scales, the Nifty Bank contract exhibits a leading position in the market. The correlation analysis underscores that time plays a crucial role in determining the variations, resulting in a wide range of correlations. The effectiveness of hedging, measured by the hedge ratio, displays an increasing trend across different time zones.

KEYWORDS

Index Futures, Lead-Lag Relationship, Mean Variance Hedge Ratio, MODWT Wavelet Coefficients, Wavelet Covariance

1. INTRODUCTION

Financial markets are characterized by high volatility. Since then, fluctuations in foreign exchange rates, commodities prices, interest rates, and stock prices have been extreme and unpredictable. It increased the pressure on stock market investors to efficiently manage risk. Price changes make predicting future returns difficult for investors. Derivative instruments are quite useful for hedging in this situation. Index futures are one type of derivatives instrument that is typically utilized for hedging. Index futures contracts allow market players to easily reduce their exposure of adverse price changes. This requires investors to assess the relationship between futures and the underlying stock. Regulators, financial institutions, and investors, on the other hand, make choices on a separate time scale. They operate minute-by-minute, hour-by-hour, day-by-day, month-by-month or year-by year. Due to the different decision-making time horizons among investors, the dynamic structure of stock futures and its underlying stock varies over different time scales. Typically, only the short-run and long-run time frames are illustrated by economists and financial analysts. The inability to divide the data into more than two time periods is caused by the lack of mathematical or statistical techniques.

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The time-varying nature of the covariance in many financial markets, as in Lee,1999's study, makes the traditional assumption of the time-invariant optimal hedge ratio unsuitable. Early research merely used the slope of an ordinary least squares regression of stock prices on futures prices to estimate such a ratio. Adopting the stochastic volatility (SV) model (see Anderson and Sorensen 1996; Lien and Wilson 2001) or the bivariate generalized autoregressive conditional heteroskedasticity (GARCH) framework has improved the situation (see Kroner and Sultan 1993; Lien and Luo 1994; Moschini and Myers 2002). The time-varying covariance/correlation aspects are successfully captured in this research, however a lot of them concentrate on the myopic hedging issue. Lien and Luo's (1993, 1994), Howard and D'Antonio's (1991), Geppert (1995), and Lien and Wilson (2001) are not subject to this criticism.

Determining the optimal hedge ratio (OHR) in futures hedging is a critical challenge. Chang et al. (2011) investigated minimum variance hedge ratios for Brent and WTI crude oil using various multivariate conditional volatility models like constant conditional correlation (CCC), dynamic conditional correlation (DCC), vector autoregressive moving average (VARMA-GARCH), and VARMA-asymmetric GARCH models. Their findings highlighted the dependence of the hedge ratio on the specific model employed. In a similar vein, Cotter and Hanly (2012) utilized quadratic, logarithmic, and exponential utility functions to derive optimum hedge ratios. They incorporated GARCH-M to estimate time-varying risk aversion coefficients in analyzing crude oil and natural gas futures at different frequencies (5-day and 20-day). Notably, they observed substantial disparities between utility-based OHRs, particularly in datasets exhibiting skewness and kurtosis. Conlon and Cotter (2013) employed hedge ratios based on minimum variance, Value-at-Risk (VaR), and conditional VaR (CVaR) at varying confidence levels. They also applied wavelet transform to assess hedging effectiveness across different horizons, discovering an increased effectiveness in hedging at longer horizons, particularly using heating oil futures. Moreover, Alexander et al. (2013) considered hedge ratios based on minimum variance and quadratic utility functions for crude oil, gasoline, and heating crack spreads. Their analysis revealed that the variance reduction achieved by all models was statistically and economically indistinguishable from a simple one-to-one "naïve" hedge.

To decompose the hedging difficulties between stock and futures contracts over various time periods, the present study uses wavelet analysis. Wavelets can help in dealing with non-stationarity by decomposing the data into different frequency components. This can aid in understanding how the relationship between Nifty and Index futures varies over time, adapting to changing market conditions. Wang & Xie (2013) points out consistent positivity of cross-correlations between spot and futures markets over time indicates that China's securities markets currently lack maturity and efficiency. To determine the short-run and long-run relationship in Indian stock market, an association between the stock futures and its underlying stock is looked at by forming first hypothesis. **Ho_1:** There is no cross correlation between the index futures and other indices of NSE. The second hypothesis is structured within the framework of lead-lag relationships between index futures and other indices because in the US and Hong Kong stock markets, the index future leads the index, while the index option leads the index future during stable or upward index trends. However, this relationship switches when the index experiences a downturn. In the Chinese mainland stock market, the index leads the index future, and throughout our study, the index option consistently leads the index future (Ren et al 2019). **Ho_2:** There is no lead-lag relation between the index futures and other stock indices in Indian stock market.

It assists investors in analyzing stock market price fluctuations that lead to efficient hedging. This research investigates the hedging possibilities of index futures contracts in the Indian stock market using wavelet analysis which examines the link with stock.

The current study documents data obtained from the website of the National Stock Exchange of India (NSE). It includes index futures as well as other indexes such as the Nifty 50 and the Nifty Bank. First, the lead-lag relationship between two markets is investigated by examining the return and volatility trend. The Granger causality test is used to investigate this at various time scales. Second, the price cointegration between marketplaces is assessed. The correlation between the two markets is then determined using wavelet coefficients. Finally, because futures contracts are utilized to hedge, the futures hedging ratio and conditional covariance heteroskedasticity are examined. Both Park and Bera (1987) and Park (1991) contend that the spot and futures prices in the basic regression should undergo a Box-Cox transformation. Although it is challenging to determine the ideal hedge ratio based on the resultant slope estimate.

The hedging ratio, which is well derived from wavelet analysis, is calculated as the covariance between stock return and futures return divided by futures return volatility. The primary function of wavelet analysis is the ability to divide the data into several time scales. The empirical findings demonstrate that the index futures and indices at both the shortest and greatest time horizons are directly related. However, the futures contract outperforms the stock market over the intermediate time horizon. In contrast to the traditional methodology, which only examines two-time scales—the short-run and long-run scales—this sort of analysis allows researchers and others to assess the relationship between two variables in a variety of time periods.

Index futures contracts are being implemented in stock exchanges to hedge investments against the risks posed by unforeseen market events. The degree of risk associated in the stock series for a specific period is used to quantify these uncertainties. Hedging with futures contracts is the best way to shift into a safer horizon. So, the question is whether there should be a covariance/correlation between the stock and the stock futures contract. Various approaches have been employed in stock market studies to explore the interconnectivity between stock and indices (Kalsie and Arora in 2019, Sui and Sun in 2016, Narayan et al. in 2013). Accordingly, third hypothesis is framed which states that **Ho_3:** There is no co-integration between the index futures and other stock indices.

To find the hedging effectiveness of futures contracts, fourth hypothesis is outlined. **Ho_4:** There is no Hedging effectiveness possible through index futures in Indian market by taking short- term time horizon. Buyukkara et al. (2022) states that equity futures contracts offer an effective hedging tool for investors seeking to safeguard their current equity portfolios in Turkish futures market.

The relationship-based study will aid investors when trading on stock exchanges or managing their portfolios. This covariance/correlation is measured at various time scales, such as a few minutes, days, months, or a year. A common practice in risk assessment is to calculate the variances on a short-run basis to identify short run hedge ratio. Rather than using the regression approach. The second moments of the joint process of spot and futures prices can be used to calculate the best hedging ratio. The second moment matrix has traditionally been thought to be constant over time. Anderson (1985) and Fackler (1986) show evidence that commodity price volatility fluctuates as markets cycle through periods of high and low uncertainty about future economic conditions. Heteroskedasticity is to be expected in the price process in general.

To get to the result, these short period scales are further transformed into longer horizon with the appropriate scaling quantity. Whether the short-run covariance/correlation between the stock and futures markets is like long-run horizons is the research issue stated here. Is the short-run hedge ratio comparable to the long-run hedge ratio when it comes to hedging? The wavelet transform method, which produces an orthogonal decomposition of the correlation and hedge ratio between the stock and stock futures over various time periods, provides the answers to these study problems.

An overview of the literature is provided in the following section. The main goals of the study, the data sources, and the analysis methods are all defined in Section 3 after that. Results and a discussion of the conclusions are then presented.

2. REVIEW OF LITERATURE

Lee (1999) identified that the classical assumption of the time invariant optimal hedge ration is largely in appropriate, provided the time varying nature of the covariance in the financial markets across the world. Return was computed in his studies while stocks followed a stochastic trend. Foreign exchange rates, commodity prices, interest rates, stock prices etc. tend to show unpredictable movements why financial markets are generally labelled as highly volatile. Investors in secondary market had to be wary about the risks involved as the market movements are not at all predictable and returns cannot be estimated precisely. Ordinary least square model was used earlier to assess the movement in stock market by finding the squared difference i.e., difference between actual values and estimated values.

Akgiray (1989) found that GARCH models outperformed multiple rival models, such as ARMA, nonparametric, and Markov switching ones, in a variety of financial markets. West, Edison, and Cho (1993) demonstrate that GARCH models yield the highest utility, on average, in foreign exchange markets by using a quadratic utility function. A less pronounced mean squared error criterion also favors GARCH. In the context of the bivariate GARCH framework, empirical determination of ideal hedge ratios is discussed in Cecchetti, Cumby, and Figlewski (1988), Baillie and Myers (1991), Kroner and Sultan (1991), Myers (1991), and Sephton (1993). Their findings suggest that the conventional view of an optimal hedging ratio being time-invariant is incorrect. Nevertheless, GARCH models outperform linear models statistically.

Retail investors can minimize their risk from adverse price fluctuation using derivatives like index futures by adapting to the prices of futures and its underlying stock. OLS model and GARCH models are effective in evaluating the effectiveness of hedging. But the regulators, financial institutions and other institutional investors compute and decide things on a whole different time scale. They operate in large volumes and even the small variation might have a large impact because they operate on a minute-by-minute basis. OLS model and GARCH model are less effective in providing a detailed miniscule report. However, it is believed that single standardized model that would fit large investors and retail investors would be appropriate. They employed various methods to examine the multi-period minimum risk hedging strategy but time varying hedge ration is not possible under this strategy.

Graham and Nikkinen (2011 and Aloui and Hkiri (2014) studied the long-term movement of stock in different countries by using wavelet transform. They notice that the hedge ratio varies according to different time zone. But Madaleno and Pinho (2014) point out that the longer time zone are uncertain and most of the series are predicted based on historical data. Zhou, Lin and Li (2018) have different perceptions in analyzing the market with events associated with it. As per their study, the events with higher shocks are likely to affect the stock returns and hedging ratio. Wang, Xie and Chen (2017) adopted multiscale correlation of each stock under different time zones to analyze the hedge using wavelet and they support that investors have diverse hedging horizons. Lin, Yang, Marsh, and Chen (2018) examine the stock-bond return under different time zone and gives suggest shorter time zone for analyzing hedging comparing to longer period.

Empirical studies show up a direct relation between index futures and other indices at the long- and short-time horizons, but at the medium time horizon, the future contracts outcast the stock market. These type of relations in varying time horizons make it important to consider the intermediate performance as well, over and above the traditional way of just 2-time scales – short and long. From the literature it is understood that there is no study about the indices in stock market about hedging other indices in same market.

3. DATA AND METHODOLOGY

3.1 Data

The study's dataset is sourced from the National Stock Exchange of India (NSE) and encompasses daily data for one-month index futures contracts of Nifty 50 and Nifty Bank, spanning from January 2010 to January 2022. The chosen period of January 2010 to January 2022, spanning a full decade, provides a robust dataset for analysis. This extended timeframe facilitates the investigation of various market conditions, which includes bull and bear markets, economic cycles, and geopolitical events. This comprehensive dataset is invaluable for gaining insights into how the instruments being studied respond under diverse circumstances.

The primary objective of this study is to assess the efficacy of in-sample hedge ratios. The chosen indices, Nifty 50, and Nifty Bank, represent some of the most dynamic and highly traded stocks in the Indian market. Given their significance, their performance is intricately linked to the broader trends and health of the Indian economy and financial markets. As a result, analyzing the effectiveness of hedging strategies involving these indices holds substantial relevance for investors and traders in India.

To perform comparative analyses and compute hedge ratios, two sets of portfolios are constructed: (1) comprising index futures and Nifty 50 and (2) comprising index futures and Nifty Bank. These portfolios are designed to evaluate the extent to which index futures serve as effective hedges for the other indices. The data utilized for this study is sourced from CMIE Prowess IQ, ensuring data quality and reliability in the research process.

3.2 Methodology

3.2.1 Mean Variance Hedge Ratio

The minimum variance hedge ratio is computed to calculate how much unit of futures contract is taken to hedge the spot position with time t:

$$MinVar\left(\Delta Hedge_t\right) = Var\left(\Delta Nifty_t + h_t \Delta IF_t\right)$$
$$= Var\left(\Delta Nifty_t\right) + h_t^2 Var\left(\Delta IF_t\right) + 2h_t Cov\left(\Delta Nifty_t, \Delta IF_t\right) \quad (1)$$

where:

$\Delta Hedge_t$ = the variation in the value of the hedge portfolio during period t

$\Delta Nifty_t$ = the variation in the log of the $Nifty$ Index prices at time t

ΔIF_t = the variation in the log of the Index futures prices at time *t*

h_t = the optimal hedge ratio

Suppose the hedger decides to pursue a dynamic hedging strategy. The optimal hedge is determined by solving the equation (1):

$$h_t = Cov\left(\Delta Nifty_t, \Delta IF_t\right) / Var\left(\Delta IF_t\right) \quad (2)$$

The tradition hedge ratio is related to the equation 2 when Nifty Index and Index futures series are homoscedastic. Then, the optimal hedge ratio signifies the conditional covariance between the prices of Nifty Index and Index futures series. In absenteeism of conditional heteroskedasticity in the prices, both $Cov\left(\Delta Nifty_t, \Delta IF_t\right)$ and $Var\left(\Delta IF_t\right)$ are independent of the data set. As an outcome, h_t is a constant term Thus, the grade of hedging effectiveness can be stated as follows:

$$HedgeEffectiveness = 1 - \frac{Var\left(\Delta Hedge_t\right)}{Var\left(\Delta Nifty_t\right)} \quad (3)$$

Equation 2 and 3 will determine the hedge ratio and hedge effectiveness using Nifty and Index Futures of NSE market.

3.3 Wavelet Analysis

Wavelet technique used in the study assists in analyzing the connection between the Nifty and Index futures while taking data pertaining to different time scales from the NSE market. Accordingly, the correlation, covariance, lead-lag relations, and hedge ratio can be determined. Here, discrete wavelet transform (DWT) is employed since the series are discrete. Also, the Fourier analysis is used to arrest the frequency and time in formation.

Wavelet variance is projected using the DWT coefficients for measure $\in_a = 2^{b-1}$ through:

$$Vr_x^2\left(\in_a\right) = \frac{1}{N_a}\sum_{t=L_a}^{N}\left(W_{a,t}^X\right)^2 \tag{4}$$

where $N_a = \frac{N}{2^a} - h_a$ and $h_a = \left[\left(h-2\right)\left(1-2^{-a}\right)\right]$.

The near a wavelet variance is just the change of wavelet coefficients and may be valued by wavelet coefficients which is not affected by the borderline (Gençay et al., 2002):

$$\sum_{a=1}^{\infty} V_X^2\left(\in_a\right) = Var\left(Nifty_t\right) \tag{5}$$

The maximum overlap discrete wavelet transforms (MODWT) coefficients of $Nifty_t, \ldots, Nifty_N$ as $W_{a,t}$ for a= 1, J and t = 1… $\frac{N}{2^a}$. The wavelet variance valued by the MODWT coefficients for measure $\in_j$ is following:

$$\tilde{V}_x^2\left(\in_a\right) = \frac{1}{\tilde{N}_a}\sum_{t=h_a}^{N}\left(\tilde{W}_{a,t}^X\right)^2 \tag{6}$$

where $\tilde{N}_a = N - h_a$ and $L_a = \left(2^a - 1\right)\left(h-1\right)$. Equivalent to equation (3), the variance of another time series, say, Y_t, is defined as follows:

$$\tilde{V}_Y^2\left(\in_a\right) = \frac{1}{\tilde{N}_a}\sum_{t=h_a}^{N}\left(\tilde{W}_{a,t}^Y\right)^2 \tag{7}$$

Next, the covariance among two time series, $Nifty_t$ and IF_t is defined as:

$$Cov_{Nifty\ IF}\left(\in_a\right) = \frac{1}{\tilde{N}_a}\sum_{t=h_a}^{N}\widetilde{W}_{a,t}^{Nifty}\tilde{W}_{a,t}^{IF} \tag{8}$$

The univariate time series will not count the covariance. Thus, it is important to conduct the wavelet correlation analysis for better results. Here, the wavelet covariance decomposes the stochastic series present in the data. These principals calculate the wavelet correlation. The wavelet correlation is purely made up of the wavelet covariance for { $Nifty_t$, IF_t }, and wavelet variances for { $Nifty_t$ and IF_t }. The MODWT estimator of the wavelet correlation can be expressed as follow using the equations (9):

$$\tilde{\rho}_{Nifty\ IF}\left(\in_a\right) = \frac{Cov_{Nifty\ IF}\left(\in_a\right)}{\tilde{V}_{Nifty}\left(\in_a\right)\tilde{V}_{IF}\left(\in_a\right)} \tag{9}$$

The wavelet correlation is equivalent to its Fourier equivalent, the multifaceted coherency (Gençay et al., 2001b, p 258).

4. RESULTS AND DISCUSSION

Firstly, returns are computed from the index futures and other indices to check the cross-correlation outcome by:

Rm = ln (Pm /Pm – 1)

where, Pm = present price and *Pm*–1= previous day's price. Table 1 gives the results of statistical summary of Index futures and other indices.

The index futures are highly volatile as they show greater standard deviation compared to their underlying indices. The skewness and kurtosis indicate that the series are to be tested for normality. Hence, Jarque-Bera test is conducted at 5 per cent significance level. Since the values are greater than the p value, the null hypothesis is accepted, implying that the series follow normal distribution. The Q-Stat of index futures, Nifty 50 and Nifty Bank returns are measured at 1 per cent significance level. The series depict negative values in both first difference and second difference level, indicating the presence of heteroscedasticity. Since the series were autocorrelated at the initial stages of observation,

Table 1. Statistics of Index Futures, Nifty 50, and Nifty Bank

	Index Futures	Nifty 50	Nifty Bank
Mean	1224.518	1224.524	2489.653
Std. Dev.	0.727158	0.68471	1.214419
Skewness	-0.130800	-0.282886	-0.290703
Kurtosis	2.698489	2.846067	2.334332
Jarque-Bera	1.493850	3.223059	7.323252
Probability	0.473821	0.199582	0.025691
Autocorrelation			
First Diff	-0.088	-0.068	-0.021
Q-Stat	26.354 (0.002)	26.618 (0.002)	20.891 (0.003)
Second Diff	0.07145	-0.516	-0.457
Q-Stat	65.560 (0.002)	65.716 (0.002)	50.946 (0.002)

Note: Significance level in parentheses

the data are filtered to discard the effect of auto correlation. Then, cross correlation test is conducted to check the relationship between the futures and the indices of NSE. The test of cross correlation is shown in Table 2.

Based on the AIC criteria, Lag 4 (i) is selected to define the correlation between the index futures, Nifty 50 and Nifty Bank. This correlation also leads to identification of the lead lag relationship between the variables. Several research papers have previously documented that small-cap stocks tend to be influenced by large-cap stocks, as exemplified in the work of Poshakwale and Theobald (2004). It is understood that when the lag period increases, high difference in the lead-lag relationship occurs. This indicates that the shorter period will give best results for hedging. As the period increases, the difference between the index futures and other indices also increases. The companies in the banking sector have higher fluctuations in their prices because of the change in the interest rate and inflation in market, which influence the hedging. Under the historical cross correlation function, appropriate lag period is to be selected to describe the relation. But in the wavelet transformation, correlation function is depicted in each time horizon without selecting the lag period. Here, the time horizon is set to analyze and evaluate the result. Daily data are used with a scale of 10-20 day, 20-40, 40-80, 80-160, 160-320, 320-640, 640-1280, 1280-2560 days period. Granger causality test is done from level 1 (d1= 10-20 days) to level 8 (d8=1280-2560 days). The vector auto-regression (VAR) estimation is used for joint F test in Granger causality. The lag period is selected according to SIC criteria. The causality will be resulted when the null hypothesis is rejected. Rejection of both the hypotheses is known as feedback relation. Table 3 gives the result of Granger causality.

There exists a feedback relation between the index futures and its underlying indices as both the hypothesis is rejected under 5 per cent significance level. It denotes that the slight change in the index futures prices automatically shows reflection in the futures prices also. This itself troughs light on the

Table 2. Cross correlation of Index Futures, Nifty 50, and Nifty Bank

i	Nifty 50		Nifty Bank	
	Lag	Lead	Lag	Lead
0	0.6768	0.6967	0.7671	0.7952
1	0.6446	0.7013	0.7284	0.7942
2	0.6146	0.7202	0.6826	0.7943
3	0.5753	0.7425	0.6382	0.8006
4	0.5486	0.7738	0.5898	0.8153

Table 3. Test of Granger causality

Sl No.	Null Hypothesis	d1	d2	d3	d4	d5	d6	d7	d8
1	IF does not Granger Cause Nifty 50	0.0629 (0.00)	0.0168 (0.00)	0.0487 (0.00)	0.0428 (0.00)	0.0974 (0.00)	0.1247 (0.00)	0.2064 (0.00)	0.0968 (0.00)
2	Nifty 50 does not Granger Cause IF	13.895 (0.00)	26.961 (0.00)	21.618 (0.00)	16.359 (0.00)	29.315 (0.00)	32.167 (0.00)	31.568 (0.00)	35.138 (0.00)
3	IF does not Granger Cause Nifty Bank	0.7424 (0.00)	0.1154 (0.00)	0.0861 (0.00)	0.2416 (0.00)	0.0843 (0.00)	0.9131 (0.00)	0.4391 (0.00)	0.2156 (0.00)
4	Nifty Bank does not Granger Cause IF	21.467 (0.01)	35.217 (0.00)	28.369 (0.00)	25.384 (0.00)	31.642 (0.00)	20.138 (0.00)	15.263 (0.00)	18.398 (0.00)

Note: IF denotes Index Futures and F value in parentheses.

emergence of risk management concept. The results signify that index futures lead in NSE market while comparing with Nifty 50 and Nifty Bank. These are the two major indices of NSE market. Next MODWT wavelet variance is projected in Figure 1 to examine the variance in different time zone.

The 95 per cent level of significance is adopted for analyzing variance in different time zone. To perform the discrete wavelet, transform, it is essential that the wavelet series serves as a representation of the identity within the L2(R) space. Many discrete wavelets transform constructions rely on a multiresolution analysis, which characterizes the wavelet through a scaling function. This scaling function is derived as a solution to a specific functional equation. Figure 1, shows positive relationship between the index futures and other indices in NSE market. Nifty 50 is backbone of futures market. Thus, any fluctuation in the price of nifty will have an influence in futures. In case of Nifty bank which goes in line with the index futures at the initial stage then increases with larger time zone, slight fluctuation occurs in the market. As government introduced some major reforms in the banking sector mostly the merger between the banks. Investors started trading more into the futures market leading to price discovery. Ederington (1979) also concentrate the dominant role of futures over stock. But the major question points out that is there any association between the stock and futures market. Figure 2 shows the MODWT-based wavelet covariance of Index futures and other indices of NSE market.

The wavelet covariance signifies the trend from level 1 to level 8 which indicates that the index futures and other indices moves distinctly and makes investors confused on to the time trend. As the magnitude of trend is missing in this concept, it becomes very difficult to compare each time zone with range of price. While comparing the Nifty bank with Index futures, the wavelet moves constantly till level 8 but the extent to which its fluctuating is unknown. But in case of Nifty 50 its going vice-versa. Thus, a degree to which the wavelet of index futures and other indices must be pointed out to get the exact nature of trend. To measure the magnitude of trend, wavelet correlation

Figure 1. Estimated wavelet variance of Index Futures, Nifty 50, and Nifty Bank (Note: Color Red signifies Futures and Blue for Nifty)

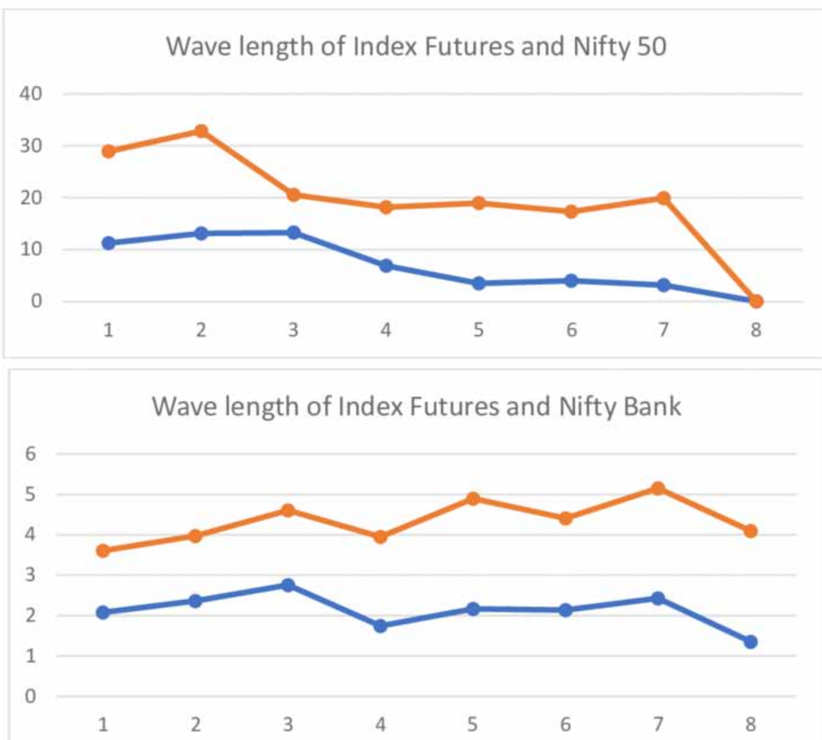
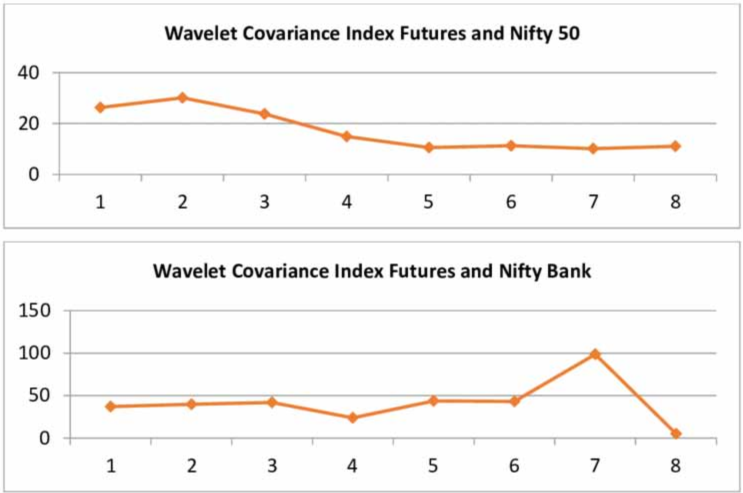
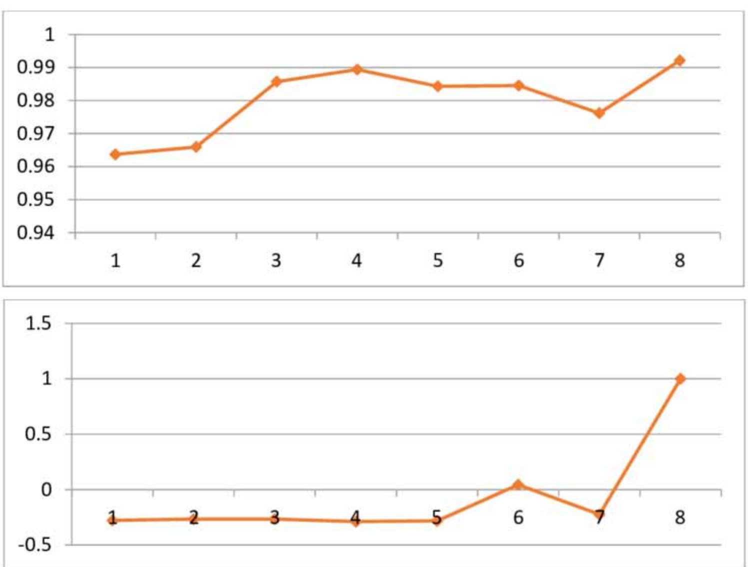


Figure 2. Estimated wavelet covariance between Index Futures, Nifty 50, and Nifty Bank (Note: Wavelet correlation between Index Futures and Nifty 50)



between the index futures and other indices are plotted. This gives the unit change in the variable with respect to the time. Wavelet correlation is the finest model to picturize these concepts in standard way. Figure 3 will give the result of wavelet correlation of these variables. The trend lines shown in the wavelet correlation transform is analyzed with 95 per cent significance level. Correlation here signifies that as time moves the relationship becomes stronger as shown in Figure 3. Also, its shows positive relationship between Index future and other indices. This indicates that futures play a very significant role in hedging the stock market.

Figure 3. Estimated wavelet correlation between the Index Futures, Nifty 50, Nifty Bank returns (Note: Wavelet correlation between Index Futures and Nifty Bank)



Apart from the historical method of correlation, the wavelet depicts the timely correlation movements under each horizon. This can be segments while trading in the exchanges, as the relationship between the variables is essential for hedging. Wavelet correlation has given the exact structure of magnitude of trend in variable which can be helpful in analyzing the hedging attitude of the index futures. This multiresolution nature of the wavelet transform allows lower frequencies to have a more extensive temporal reach while preserving shorter temporal widths for higher frequencies. This feature broadens traditional time-frequency analysis into a more comprehensive time-scale analysis. Figure 4 gives the result of hedge ratio and hedging effectiveness of Index futures with other indices of NSE market.

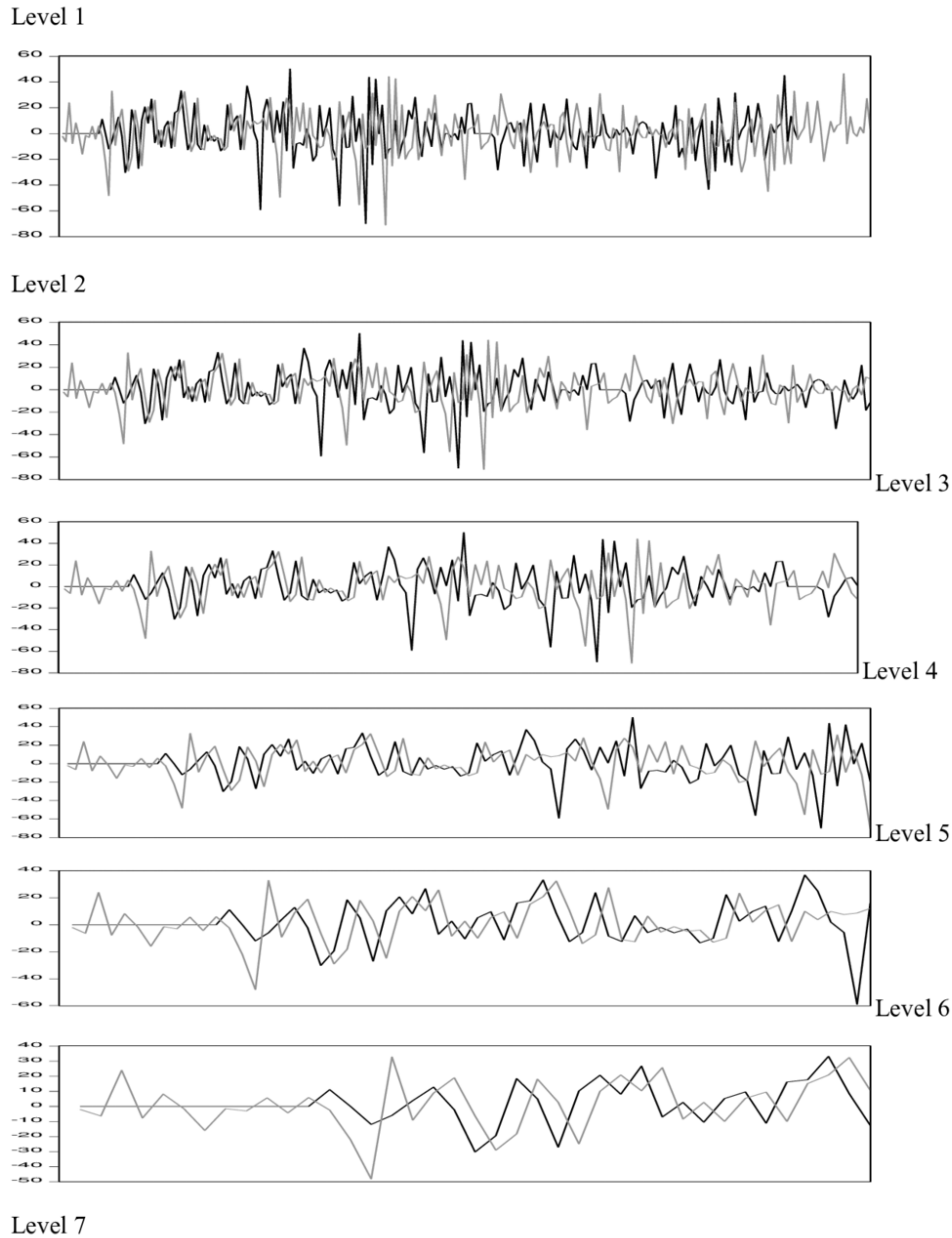
Futures are used as a hedging tool in the stock market and it help to analyze how effective is the tool for hedging in NSE market in accordance to time zone.

This increases the information content of time with reference to risk management. The hedging effectiveness measured by Hill and Schneeweis (1982) and Malliaris and Urrutia (1991) give more advantages to currency futures as currency is the basic means for trading with other countries. From the time scale of currency futures, the hedging was effectively performed well. The same process is applied here to achieve the effectiveness. The hedge ratio under different time zone from level 1, level 2, level 3, level 4, level 5, level 6, level 7, and level 8 are shown in Figure 4. The variation under each level is increasing also the effectiveness of hedging is in line with time zone. This intimate that investors get better result after analyzing the wave arises with the price changes under each time zone. Before deciding the optimal model for evaluating the hedging effectiveness, the variation in the price about the daily movement will provide exact conclusion about the market.

MODWT model is described in Figure 5 (level 1, level 2, level 3, level 4, level 5, level 6, level 7, and level 8) with wavelet coefficients of Index Futures and Nifty 50 and Figure 6 (level 1, level 2, level 3, level 4, level 5, level 6, level 7, and level 8) as Index Futures and Nifty Bank. The index

Figure 4. Estimated hedge ratio and Hedging effectiveness of Index Futures, Nifty 50, Nifty Bank returns

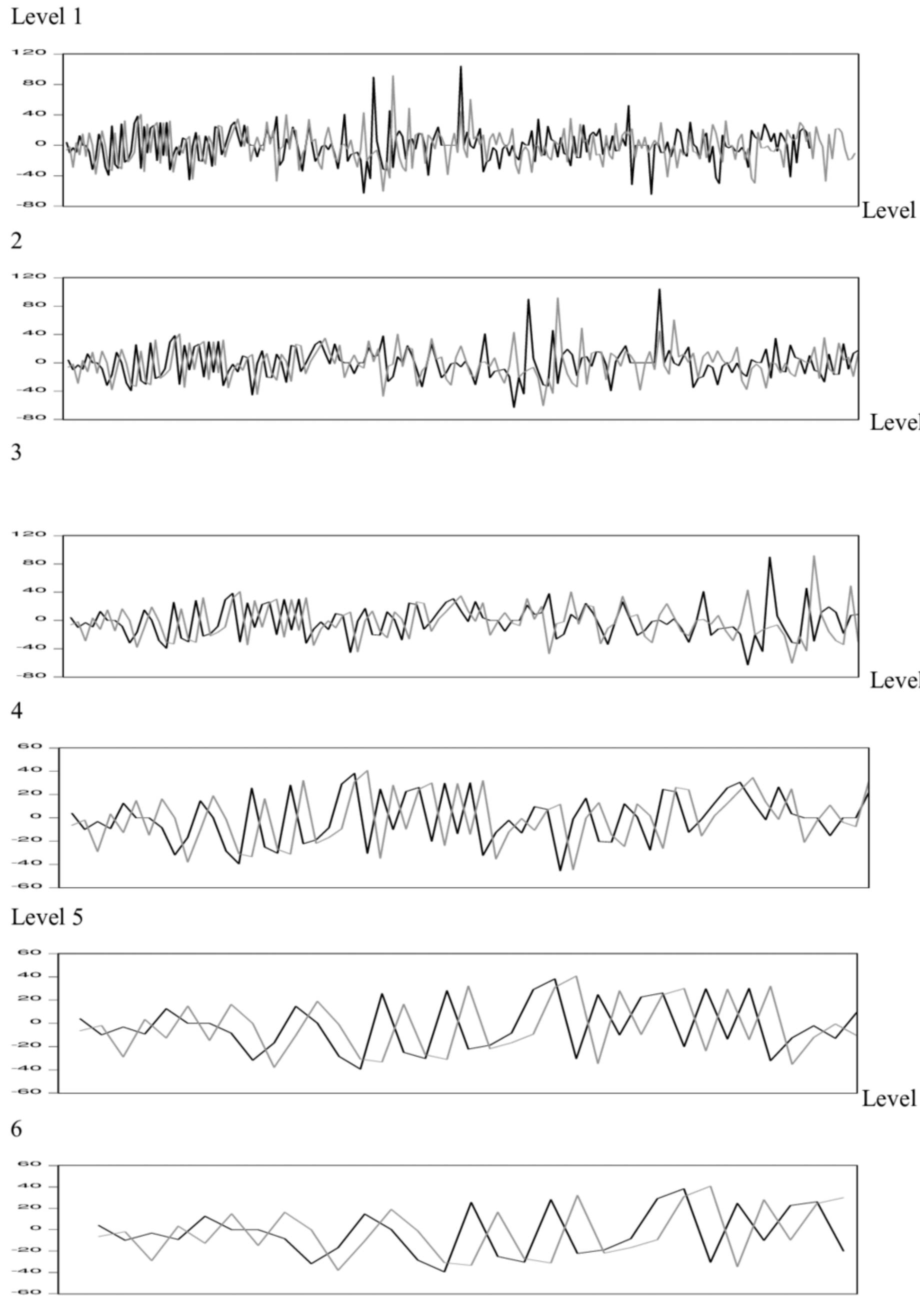
Figure 5. MODWT coefficient of Index Futures and Nifty 50



futures and other indices coefficient are shown in 8 levels. The basic advantage of showing the coefficient under 8 level is that the short- term and long-term movement can be picturize. Here, the index futures are shown in black and the indices in grey.

The overall result from Figure 5 and Figure 6 indicates that the futures and sectorial indices are directly connected to each other. Most of the fluctuation based in Nifty 50 is during the level 1 and 2. But later the Nifty Bank fluctuate higher in ratio. As the level increases, the hedging magnitude also

Figure 6. MODWT coefficient of Index Futures and Nifty Bank



increases. Due to the sparsity of signal, larger coefficients are anticipated to predominantly represent signal components. Conversely, smaller magnitude coefficients are more likely to capture a larger proportion of noise rather than significant signal information. Consequently, the process of zeroing out these lower magnitude coefficients is expected to eliminate a significant portion of the noise while preserving much of the essential signal. Usually, coefficients surpassing a certain threshold are left unchanged. However, some wavelet-based denoising algorithms might also reduce larger coefficients based on statistical estimations of the noise level that could be removed through such adjustments. Chen et al. (2004) examines that when data is sub classified, the hedge ratio and the hedge effectiveness increases with increase in time zone. The same is explained by Cotter and Hanly (2009) where, the shorter and longer time scale is selected to compute the hedge ratio of different assets. The present result is supported by the Harris and Shen (2003) which gives insight into the time zone study while calculating the hedge ratio with indices and futures contract. Also, they signify that it is the futures contract who guides the stock market. But the variance and co-variance results shows variant track. This gives the concentration on adopting optimum model for calculating the hedge ratio with respect to the time zone and that is wavelet transform model.

5. DISCUSSIONS AND POLICY IMPLICATIONS

Hedging enhances the value to the firm and to the traders in futures market. This can be analyzed with the price movement in the underlying stock while focusing on to the trend. Most of the traditional model examined earlier to compute optimal hedge ratios are captivating yearly data or on month wise. But the wavelet transform provides short term and long-term relationship between stock and the futures. The hedging scenarios are captured by focusing of indices of National Stock Exchange (NSE), India, as it considered to be the benchmark to decide the trend of the market. Nifty 50 and Nifty Bank indices are included in the study to explore the benefit of hedging in the Indian stock market. The return and volatility trend is analyzed initially to identify the lead-lag relation between the futures and underlying stock using the Granger causality test under different time scales. It is absolute that when the lag period increases, high difference in the lead-lag relationship occurs. This indicates that the shorter period will give best results for hedging. As the period increases, the difference between the index futures and other indices increases. The banking sector has higher fluctuation in their prices because of the change in the interest rate and inflation in market, which influence the hedging. Under the historical cross correlation function, appropriate lag period is to be selected to describe the relation. But in wavelet transform, correlation function is depicted in each time horizon without selecting the lag period. Here, the time horizon is set to analyze and assess the result between the futures and stocks using wavelet coefficients. Also, the hedge ratio and conditional covariance heteroscedasticity of futures are analyzed. Hedge ratio can be very well identified by wavelet analysis which is the covariance between the index futures and indices return which is further divided by the volatility of futures return. Empirical studies show up a direct relation between index futures and other indices at the long- and short-time horizons, but at the medium time horizon, the future contracts outcast the stock market. These type of relations in varying time horizons make it important to consider the intermediate performance as well, over and above the traditional way of just 2-time scales – short and long. Accordingly the policy implication can be framed to benefit the firms and investors in the market.

Implication 1: Wavelet transform used to analyze the hedge ratio and hedging effectiveness is appealing while comparing with traditional methods as it has added features to count the long-run and short-run trend with daily movement on prices.

Implication 2: Hedging with index futures has already gained momentum but the traders require daily price benefit as it includes Mark to Market margin. Wavelet transform coefficient brings the hedging results with each time horizon.

Implication 3: To measure the magnitude of trend, wavelet correlation between the index futures and other indices can be plotted. This gives the unit change in the variable with respect to the time. Wavelet correlation is the finest model to picturize these concepts in standard term.

Implication 4: The results from wavelet signifies that hedging can enhance the value to the firm and to the investors. A further study can be done after taking pandemic condition as the present study has concentrated before COVID-19 period.

6. SUMMARY AND CONCLUSION

Firstly, Granger causality test for various time scale were used to examine the lead lag relationship of the futures and indices taking volatility and return trend. Secondly, price cointegration between the futures and indices are checked and only then correlation is found using the wavelet correlation coefficients. Finally, hedging ratio and conditional heteroskedasticity of the futures are analyzed. The hedge ratio is covariance between stock return and futures return which is further divided by the volatility of futures return. As expected, the wavelet analysis effectively decomposed the data into different time scale. The researchers and others make use of wavelet analysis when they had a series of data spanning huge time, as it enjoys this advantage over conventional models.

Empirical results show that though the correlation of stock and futures varies with time, it remains high. Furthermore, the magnitude of correlation increases as the time scale increases. The multi period hedge ratios are obtained from above two results. The hedge ratio and hedge effectiveness also bend towards the movement of time scale. Nifty Bank showed higher variance when compared to the Nifty 50, which confirms that the decomposition Index futures contract and Nifty Indices over different time scale using wavelet analysis has important implications in studying the lead lag relationship, correlation, and hedge ratio for portfolio management. Further research can be done by taking three- or five-year's data set, which will help the investors and researchers to analyze the trend in stock market. As the markets are highly volatile, the investors should generate a best price prediction while investing in stock market, for which wavelet analysis certainly is an effective tool over other conventional tools specially when its spans over a large time frame.

7. FUTURE SCOPE OF RESEARCH

The study has explored wavelet transform for hedging in Indian stock market. The transform has helped to scrutinize hedging over shorter time duration, ranging from 20 days to around 2500 days. And emphasized on short term and long-term hedging. But the effort to ascertain the hedge ratio during crisis period especially pandemic period is not covered. This insist to travel on future research which can be:

1. Including the financial crisis and pandemic period returns to ascertain the hedging effectiveness of futures.
2. To analyse and compare the hedging scenario of Asian counties derivative products like futures to minimise the risk in the stock market. As the macro-economic factors which influence the stock returns of Indian market will be different in other countries.

Taking other derivative products like options to identify the difference in hedging strategies with futures product. The features of both vary, hence a distinct model can be used for further study.

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