Price Discovery Efficiency and Resilience of Financial Futures - A Case Study of Indian Banking Sector

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12 March 2022

Working Paper version of the Article presented in
The International Conference on "*Technology Analysis, Fintech and Financial Services (TAFS), 2022*

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DoI: 10.6084/m9.figshare.22216654

https://dx.doi.org/10.6084/m9.figshare.22216654

Abstract:

India has proven to be the second most attractive emerging market among other large emerging economies in world. S&P has predicted India to be the one among fastest growing emerging markets in FY'22. According to Morgan Stanley report, banking is found to be the dominant sector in most of the emerging markets. Hence the banking sector in an emerging economy like India has the potential to attract fresh investment, so as their financial derivatives instruments. In this backdrop, the present work explores the price discovery mechanism between futures and spot markets in particular to Indian banking industry to bring forth sector specific insights. Alongside the paper tries to capture the impact of global slowdown due to Covid-19 pandemic during 2020-21on the Indian banking industry to check for its 'resilience' which is always a major concern for any emerging markets. The authors have used Bi-variate VEC-EGARCH framework to examine the price-discovery mechanism in the Bank-Nifty futures and spot markets. The short run impact of Covid-19 shock is measured with help of the 'market model' under 'event study' methodology.

Key Words: Market Model, E-GARCH, VECM, Granger Causality, Resilience, Abnormal Return

JEL Code: G12

1. Introduction:

India attracts investors from various segments. High potential of growth in the banking and financial sectors of the emerging markets (EMs) is reported by various studies. Growth opportunities reflect on low credit penetration and a goof size of financial exclusion. The banking industries are increasing becoming digitized, embracing fintech and mobile/cashless payment modes in the EMs like China and India. Banking and financial services and the derivatives markets are reported to be attracting huge investments.

Hence the present paper focuses to explore how the futures and spot markets of Indian banking sector behave with respect to 'informational efficiency' and whether they are resilient towards any global macroeconomic shock, like Covid-19 pandemic.

1.1 Informational Efficiency and Price Discovery:

Price discovery and risk transfer (i.e. hedging) are reported to be the pivot functions of the futures market in all the economies. Price Discovery is process of convergence of the markets towards the efficient price of the underlying asset containing its intrinsic value. At any point in time any flow of new information into asset markets is incorporated the market prices for the assets through readjustment of those prices. A news deemed by the market participants relevant to asset pricing can be about the international or national macro-economic system, some specific industry or corporate announcements or anything else relevant. Logically if multiple markets of an asset get the same information arriving simultaneously, they should react at the same time in a similar manner. In the case they do not react at the same time, one leads the others. The former is viewed as contributing to price discovery mechanism for that asset. It has been claimed that generally the futures market has a greater speed of assimilation of new information compared to the spot market of the underlying asset because of their inherently high leverage and low transaction costs. Sometimes the inflammation flows in the opposite direction also. i.e. from the spot or cash market to the futures market or sometimes information is reflected simultaneously in both the markets.. The microstructure of a market, the level of transparency, the liquidity flow mechanism, the rules of orders, limitations of short sales and settlement processes decide the contribution of a market to the price discovery process.

Since futures market has lesser trading costs, higher liquidity than spot market the information is first expected to be reflected in the prices of futures and then it is expected to flow to cash market. However, this may not be true in all circumstances. Sometimes it can happen that the information is first discounted in the cash market and then moves on to futures market. Alternatively, information is reflected simultaneously in both the markets.

There are mixed views regarding the price discovery efficiency of Indian equity futures market. Thenmozhi (2002), Karmakar (2009), Pati, & Pradhan (2009), Wats, & Mishra (2009), Pati, & Rajib (2011) reportedly agreed that price discovery happens in CNX-Nifty futures market and it leads the spot market in information transmission. Whereas, Raju, & Karande (2003), Bhatia (2007), Bose (2007), and Gupta, & Singh (2009) are reported to have found that although price discovery happens in both futures and spot markets, as far as the information transmission is considered the futures market leads the spot market of CNX-Nifty. Again, Srinivasan (2009), Mallikarjunappa & E. M. (2010), Sakthivel, & Kamaiah (2010) reportedly concluded that there is clear bi-directional causality between CNX-Nifty futures and spot markets and price discovery happens in both the markets simultaneously. Only, Mukherjee, & Mishra (2003) is reported to have found that there is bi-directional causality between futures and spot market, and spot Nifty is more dominant in disseminating information. In the Indian context most of the studies are reported to have been carried out on CNX Nifty index futures, and a few studies on selected stock futures and that too are reported to have produced mixed results. These studies are deemed failure in throwing any light to industry specific features.

In the present paper, the authors try to explore the price discovery mechanism and lead-lag relationship, if any, between the spot and futures markets of banking sector in India. They try also to capture the short run impact of Covid-19 shock on the Indian banking spot and futures markets, so as to understand their ‘resilience’ towards any external shock. The present work will surely help to bring forth some sector specific insights for potential investors of the Indian market.

Rest of the paper is organised as follows: Section 2 followed by introductory section 1, describes sample selection, period of the study, data collection, and results from preliminary examinations. Section 3 explains model and methodology adopted for empirical analysis. Results and findings are presented in section 4. Section 5 draws the conclusions of the study.

2. Sample Data and Preliminary Analysis:

2.1 Sample Selection: For selecting the sample of the study the 'Judgmental Sampling' technique is adopted. There are two major stock exchanges in India, viz. Bombay Stock Exchange (BSE) and National Stock Exchange (NSE). Among these two, NSE is the lion in the market as far as derivatives trading is concerned. Since inception in June 2000 till 2011, NSE proudly bears 100-99% turnover in derivatives trading. In 2012, BSE launched new incentive schemes and trading policies to revive its derivatives segment. Consequently, 2012 onwards NSE fetches 80-90% share in total turnover of F&O segment, while BSE is still struggling to manage 10-20% share out of it. Therefore, NSE has been chosen purposefully over BSE.

There are 6 indices for which NSE has 7 products in F&O segment. Among these, Bank Nifty is in the second position after CNX Nifty, in terms of number of contracts traded and turnover value (as on March'2018). As far as the sectoral indices are concerned, Bank Nifty is in the top, leaving IT, Infra and PSE far behind.

2.2 Period of the Study:

a. For understanding the price discovery process, the period is taken from 13th June 2005, i.e. from the inception of Bank Nifty Index, till 27th December 2019.

b. For capturing the short run impact of Covid-19 global pandemic on the banking sector the impact year '2020' is taken into consideration.

2.3 Data Collection: The daily closing prices data for Bank Nifty Index futures and the spot are collected for the above mentioned periods of the study. For futures prices, only the near month contract is accounted for its comparatively high trading volume than the other two contracts (i.e. middle month and far month) available in the market. All the futures and spot prices of Bank Nifty Index are collected from the official website of NSE.

2.4 Preliminary Examinations: The collected data on stock prices are clearly time series data which span over a long period of time on daily basis. Before stepping into the main analysis, some preliminary examinations have been carried out to get an idea about the type and nature of the data, their distributional properties, time series properties, etc.

Most financial studies involve returns, instead of raw prices of the securities. Campbell, Lo, & Mackinlay (1997) cited two main reasons for that: firstly, for average investors returns are complete and scale free summary for investment opportunity, and secondly its attractive statistical properties makes it more amenable for various analysis.
'Returns' are computed as continuously compounded return, i.e. natural logarithmic differences of lagged price series: $FR_t = (\ln F_t - \ln F_{t-1})$, and $SR_t = (\ln S_t - \ln S_{t-1})$.

Here FR_t and SR_t are futures and spot returns respectively, at time 't' and F_t and S_t are futures and spot prices respectively, at time 't'.

The computed values of descriptive statistics reveal the fact that the average daily futures and spot returns are almost equal over the sample period, albeit the volatility sometimes differs from, sometimes matches with each other. The coefficients of skewness and kurtosis of return series reveal that none of the distributions are alike to normal distribution. Moreover, the

Jarque-Bera test statistically proves that futures and spot returns of all the sample variables are not normally distributed. There are evidences that all the series are suffering from the problem of auto correlation. None of the series is an independent series. Moreover, clear ARCH effect is present in all the returns series which implies dynamic conditional variance process. The significant LB^2-Q values and ARCH-LM values double signifies that the residuals of returns have non constant time varying variance which results in to clustering of volatility in the series. (See results in Table.1 in Appendix)

The futures and spot returns of the Bank Nifty Index have been tested for structural break points during the study period following the method of Quandt-Andrews unknown breakpoint test considering 15% trimmed data. The result shows no evidence of any notable structural change during the study period.

Augmented Dickey Fuller (ADF) test (1979) and KPSS test (1992) have been conducted to check for the 'stationarity' of the collected time series data. Results from the ADF test and the KPSS test revealed that log normal futures and spot prices are first difference stationary and have same order of integration, i.e. I (1). (See results in Table.2 in Appendix)

As all the futures and spot returns are having same order of integration, the next step is to check for their cointegration property. Cointegration analysis provides important information about the long term relationship among any group of time series data whose degree of integration is same. The economic interpretation of cointegration is that if two or more variables are linked to form an equilibrium relationship spanning the long-run, even though the series themselves in the short run may deviate from the equilibrium, they will move close together in the long run equilibrium. Thus, if futures and spot price series are found to be cointegrated, it ensures that there exists a stable long-run relationship between futures and its underlying spot market. By deploying Johansen-Juselius (1990) maximum likelihood method of Cointegration test, it is found that these two related price series are not only having same order of integration, but they are also sharing same stochastic trend, i.e. futures and spot prices are cointegrated of order one, CI(1). This implies co-movement of futures and spot prices and ensures existence of a stable long run equilibrium relationship. For conducting J-J cointegration test, the optimal lag length has been selected following Schwartz Information Criteria (SIC) and the best fitted model has been considered following Pantula Principle[1]. (See Table.3 in Appendix)

Now depending on these findings, for further analysis model specifications has been set such as to incorporate non-normal distribution, serial correlation, and ARCH effects in residual process. And the fitted models have been tested for their adequacy along these lines.

3. Model Specification:

3.1 Model to identify the Price Discovery Mechanism -

Granger (1988) is reported to have pointed out that, if a pair of time series is cointegrated then there must be some causality between the two series in at least one direction, and if possible in both the directions. This causality is the reason behind the co-movements of two cointegrated time series. The study tries to detect the direction of causal relationship between futures and spot prices by applying standard Granger Causality test augmented with a lagged Error Correction Term, i.e. Error Correction Model (hereafter ECM). Error correction model is capable to capture the short run and long run components of Granger causality distinctly. The effect of causality that flows from long run equilibrium relation between the two variables, during temporary deviations from long run equilibrium path, which gets captured by the coefficient of lagged Error Correction Term, i.e. the long run component, and the effect of causality that arises from previous period's spot price or futures price, i.e. the short run

[1] Pantula Principle is the method of testing the joint hypothesis of both the rank order and deterministic components as discussed in Johansen (1992).

component. Thus ECM is an appropriate statistical tool to examine the immediate impact of news flows on asset prices and its transmission process from one market to another and the speed of adjustment to the long run equilibrium between the futures and spot markets, under static set up.

In the present study, the traditional VECM is extended to Vector Error Correction- Exponential Generalized Auto Regressive Conditional Heteroscedasticity (hereafter VEC-EGARCH) Model. VECM, being a restricted version of VAR set up can tackle the problem of serial correlation by incorporating the auto regressive terms of dependent variable as regressors of the model equations. But to address the problem of heteroscedasticity in residual process, i.e. the ARCH effect, there is a need to extend the VECM to a GARCH set up. The VEC-EGARCH framework helps to incorporate the time varying volatility effect in interpreting the dynamics of Granger causality from ECM. In addition, the Exponential GARCH specification will help to understand the asymmetric effect of volatility, i.e. how market responds to good and bad news differently. Nelson (1991) showed that negative or bad news bear more impact on market volatility, than any positive or good news to the market. This asymmetric response of the market can be well captured by this exponential variant of GARCH family, as the EGARCH specification avoids the non-negativity constraint on the conditional variance parameters, in addition to incorporating asymmetry in return volatilities (Nelson, 1991). The proposed model is superior to VECM, since the traditional approach is limiting in several ways. First, the model does not leave scope for the possibility that volatility may be time varying in nature. Secondly, the traditional VECM framework can only address linear price dynamics in the conditional mean of price changes. Finally, VECM estimation that relies on ordinary least squares (OLS) assumes that the distribution of price changes is characterized by a constant variance.

Past studies in Indian context have reportedly mostly applied VECM to identify the price discovery efficiency of equity futures markets. Some studies have gone little far by deploying

Impulse Response Functions (IRFs) and Variance Decomposition (VD) to capture the mechanism in dynamic set up. But the problem lies in the very basic if the time varying volatility, i.e. the inherent nature of the financial series, is not accounted for and hence could lead to spurious results.

Bi-variate VEC-EGARCH (1, 1, 1) Framework:

$FR_t = \kappa_f + \alpha_f (FR_{t-1}) + \beta_s (SR_{t-1}) + \delta_f (EC_{f, t-1}) + \varepsilon_{f, t}$ …………….…………..……… (1)

where, $\varepsilon_{f, t} \mid I_{t-1} \sim t$ distribution with conditional variance $h_{f,t}$

$\ln(h_{f,t}) = \omega_{0,f} + \theta_{1,f} (z_{f,t-1}) + \gamma_{1,f} [\mid z_{f,t-1}\mid - E(\mid z_{f,t-1}\mid)] + \varphi_{1,f} \ln(h_{f, t-1})$ ………..…. (1.a)

where, $z_{f,t} = \frac{\varepsilon_{f,t}}{\sqrt{h_{f,t}}}$ is the standardized residual of FR_t

$SR_t = \kappa_s + \alpha_s (SR_{t-1}) + \beta_f (FR_{t-1}) + \delta_s (EC_{s, t-1}) + \varepsilon_{s, t}$ ……………………………….... (2)

where, $\varepsilon_{s, t} \mid I_{t-1} \sim t$ distribution with conditional variance $h_{s,t}$

$\ln(h_{s,t}) = \omega_{0,s} + \theta_{1,s} (z_{s,t-1}) + \gamma_{1,s} [\mid z_{s,t-1}\mid - E(\mid z_{s,t-1}\mid)] + \varphi_{1,s} \ln(h_{s, t-1})$ ………….. (2.a)

where, $z_{s,t} = \frac{\varepsilon_{s,t}}{\sqrt{h_{s,t}}}$ is the standardized residual of SR_t

Here for sake of simplicity, the VEC-EGARCH framework is reported to have been presented in order (1, 1, 1), i.e. the conditional variance equation has the ARCH term of order one, asymmetry of order one, and GARCH term of order one. This is deemed to be the simplest form of the model and it could take higher order also depending on the sample data. In addition, only one period lagged difference variable, (i.e. FR_{t-1}, SR_{t-1}) in the mean equations was considered. This lag order depends on the VAR optimal lag selection, where SIC has been followed. I_{t-1} is the set of all information regarding spot and futures markets in first as well as in second moments, available at period ‘t-1’. Since preliminary examinations reportedly reveal that none of the futures and spot returns follow normal distribution, and they have fat tailed high kurtosis distributions, here the residuals were reportedly considered to follow t-distribution. Enders (2004) is reported to have shown how t-distribution places a greater likelihood on large realizations in any financial series than does the normal distribution.

Model Interpretation:

Mean Equations: The mean equations were prescribed for estimating the mean returns (futures and spot) of sample data. In the Equations (1) and (2), the **‘β’** coefficients are deemed to capture the effect of **short run causality** from one market to another. The statistically significant non-zero value of β_s (β_f) are found to imply that spot (futures) return Granger causes futures (spot) return in short run. That is, previous period’s value of spot (futures) return are deemed to help predicting the current futures (spot) return, in a better way than only the past values of futures (spot) returns do. If both the β_s and β_f are statistically significant, these may indicate ‘feedback effect’ from one market to another, i.e. there is bi-directional causality in between futures and spot markets. If any one of the β’s is significant, then there may be a flow of unidirectional Granger causality either from spot to futures market or from futures to spot market. The **‘α’** coefficients may be taken as the **‘own price effect’**, i.e. how the past price changes of a market can affect its current price changes. Statistically significant α value indicates that a change in the past market price has either positive or negative impact on its today’s market price moves. The **Error Correction Term ‘EC’** indicates temporary deviations from the long run equilibrium path of the futures and spot prices. The adjustments in the first moments of the futures and spot returns to this temporary deviation should be captured by the mean equation of the VEC-EGARCH model. The magnitudes of these EC terms are generally derived from the cointegrating equations between the futures and spot prices. Thus the lagged error correction terms, $EC_{f,\,t-1} = (\ln F_{t-1} - c_2 \ln S_{t-1} - c_1)$, and $EC_{s,\,t-1} = (\ln S_{t-1} - c_4 \ln F_{t-1} - c_3)$, are taken as the long run equilibrium deviations in the previous period which can be corrected in the next current period. The presence of this lagged EC term indicates the dynamics of long run relation linking the two series. The loading **δ_f (δ_s)** is interpreted as the '**speed of adjustment**' of futures (spot) return towards the equilibrium path. Hence the values of these δ coefficients indicate how speedy one market is to rectify the previous period's deviation from long run equilibrium, through the causality effect of another market. Here is the effect of **long run Granger causality found**. If δ_f (δ_s) appears to highly different from zero, the spot (futures) prices impact futures (spot) price changes through the long run price equilibrium channel. Thus, a statistically significant non zero value of δ_f (δ_s) indicates that the spot (futures) market Granger causes the futures (spot) market in long run.

Conditional Variance Equations: In the Equations (1.a) and (2.a), **'ω'** is the intercept term in conditional variance equations. **'θ'** being the coefficient of asymmetry, captures how the positive (good news) and negative (bad news) innovations in past affect the current volatility of the market. Hence θ measures the **'sign effect'** of past innovations. **'γ'** is the ARCH coefficient which measures the impact of past innovations on the current volatility of the market, i.e. the **'size effect'**. Thus θ and γ together capture the effect of past innovations on current volatility.

Now let us consider, $F_i (Z_{i,\,t-1}) = \theta_i Z_{i,\,t-1} + \gamma_i\,[\,|\,Z_{i,\,t-1}| - E\,(|\,Z_{i,\,t-1}|)]$, where i = f, s;

Here F_i is the function of lagged standardized innovation of i^{th} market,

i.e. $z_{i,t-1} = \frac{\varepsilon_{i,t-1}}{\sqrt{h_{i,t-1}}}$,

where $h_{i,t-1}$ is the conditional variance of innovation at time 't-1', $\varepsilon_{i,t-1}$.

Then the asymmetric effect of standardised past innovations on current volatility may be measured by,

$$\frac{\partial F_i}{\partial z_{i,t-1}} = \begin{cases} \theta_i + \gamma_{i,} & if\ Z_{i,t-1} > 0 \\ \theta_i - \gamma_i, & if\ Z_{i,t-1} < 0 \end{cases}$$

The ‘**Relative Asymmetry’** may be defined as, $\xi_i = \frac{|\theta_i - \gamma_i|}{\theta_i + \gamma_i}$

The magnitude of ξ_i is greater than, equal to, or less than one for negative asymmetry, symmetry, and positive asymmetry, respectively. If negative asymmetry is supposed to characterize the market volatility, it may mean that the impact of any negative shock to the market on its return volatility is more in impact, as compared to the same amount of positive shock.

The ‘φ’ parameter is considered to represent the volatility persistence level of a market, which means how the previous period’s conditional volatility continues to affect the return volatility in current period. In other words, φ coefficient detects the phenomena of ‘**volatility-clustering’** in the return series, i.e. the **GARCH effect**. For the conditional volatility process to be stationary, it should be $|\varphi| < 1$.

3.2 Model to identify the short run impact of Covid-19 pandemic –

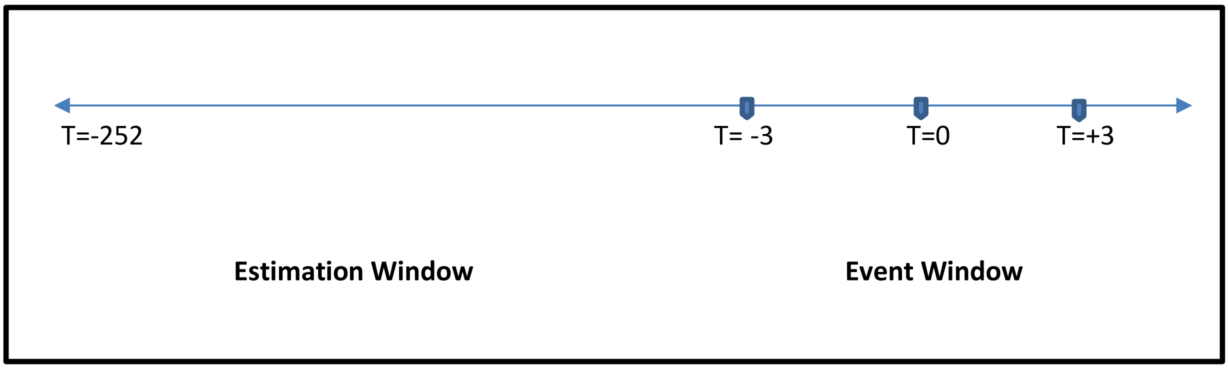
To understand the short run impact of the global pandemic on the Indian banking sector, a separate methodology is adopted and the period of this pandemic is treated separately to avoid the structural break in the data set. For this the ‘market model’ of ‘event study’ is applied as described in Benninga (2014).

Methodology of Event Study -

The initial step in an event analysis is to define the event of interest and the event window. The Government of India (GoI) imposed a nationwide lockdown on the evening of 24th March 2020. Since the impact of that announcement on the stock market is expected to get realised on the next day, i.e. 25th March 2020, is considered as the 'event day'. The event window is the time period during which the security prices get affected due to a particular event. The event window consists of two components—the anticipation window and the adjustment window. The day of impact or the event day is set as day '0'.

The authors have tried to capture the immediate or 'very short run' impact of the event, i.e. the announcement of nationwide lockdown, on the Indian banking stocks.

In this study '*estimation period*' of total 252 trading days have been considered to get the anticipated return. In between ±3 days surrounding the *event day* (T=0) are considered as '*event window*'. Thus we get,



Here a very short event window is considered, as a long event window (i) decreases the power of the test statistics, (ii) leads to confounding effects, and (iii) results in false conclusions (McWilliams and Siegel, 1997).

Market Model –

'Market model', is an OLS regression model, which regresses security returns against stock market returns to estimate expected returns on each security/index. The model is as follows,

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

where, R_{it} = Return on i^{th} security in period t

R_{mt} = Return on market index in period t

ε_{it} = Error or Residual term

The estimated regression equation is as follows:

$$\widehat{R_{it}} = \hat{\alpha}_i + \hat{\beta}_i R_{mt}$$

In this model the *Abnormal Return* (AR) for any security/index 'i' in any period t, is defined as the difference between the actual and estimated return of that security/index in the same period t. Abnormal Returns are calculated for each individual security/index for their event period as, $AR_{it} = \varepsilon_{it} = (R_{it} - \widehat{R_{it}}) = [R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt})]$

Then to capture the cumulative effect, *Cumulative Abnormal Return* (CAR) has also been calculated for the 'event window' where $\mathbf{CAR_t = CAR_{t-1} + AR_t}$

Hypotheses:

H_0: *Abnormal returns surrounding the event day are zero, i.e. market is resilient to the impact of sudden shock*

H_1: *Abnormal returns surrounding the event day are not zero, i.e. market is not resilient to the impact of sudden shock*

By assumption, abnormal returns being the residuals of the market model follow normal distribution. This justifies conducting t-test (Armitage, 1995) to check whether these ARs are significantly different from zero or not.

4. Results & Findings:

4.1 Findings related to Price Discovery Efficiency of Bank Nifty Futures:

In this section the results of VEC-EGARCH estimations have been presented, and the findings have been discussed in detail.

Table No. 4.1: VEC-EGARCH Results for Bank Nifty Index Futures and Spot Returns

		Futures Return (1, 1, 1)	**Spot Return (1, 1, 1)**
	Coefficients	Estimates (P-values)	Estimates (P-values)
Mean Equation	Intercept (κ)	0.0006*** (0.0674)	0.0006 (0.1066)
	ECT (δ)	-0.1947** (0.0489)	0.0203 (0.8316)
	Own (α)	-0.3652* (0.0082)	0.2099 (0.1339)
	Cross (β)	0.4807* (0.0006)	-0.0788 (0.5659)
Variance Equation	Intercept (ω)	-0.2412* (0.0000)	-0.2218* (0.0000)
	ARCH (γ)	0.1487* (0.0000)	0.1382* (0.0000)
	Asymmetry (θ)	-0.0758* (0.0000)	-0.0726* (0.0000)
	GARCH (φ)	0.9839* (0.0000)	0.9855* (0.0000)
Others	T distribution D.O.F	8.1335* (0.0000)	8.3976* (0.0000)
	Log likelihood	5418.933	5460.477
	Relative Asymmetry (ξ)	3.08	3.21
Residual Diagnostics	LB^2-Q (8)	6.513 (0.5900)	6.554 (0.4340)
	ARCH-LM (8)	6.833 (0.5548)	6.739 (0.5650)

* significant at 1% level, ** significant at 5% level, *** significant at 10% level

The VEC-EGARCH models for estimating Bank Nifty Index futures and spot returns both are having order (1, 1, 1). For VECM the optimal lag orders for differenced endogenous variables are considered according to VAR lag order selection following SIC. In case of Bank Nifty Index futures and spot returns the optimal lag order is (1, 1). For cointegrating equation, the deterministic trend is specified with that of model.3[2] that assumes a linear trend in the data and an intercept in cointegrating equation.

The coefficient of the ECT is significant at 5% level with the value of -0.19 in the FR mean equation, and for the SR mean equation the ECT is positive, but insignificant. This implies that there is long run causality running from spot to futures market which enables the Index futures market to adjust to the short run deviations from equilibrium path with 19% speed of adjustment. Moreover, the insignificant ECT in the SR mean equation indicates exogenity of the variable. The coefficient of lagged SR term in the FR mean equation is significant at 1% level with the value of 0.48, which indicates short run causality from spot to futures market with 48% leading effect. In the SR mean equation, the coefficient of Lagged FR is insignificant implying no trace of causality from futures to index spot market. This clearly proves that there is 'unidirectional' short run causality from Bank Nifty spot to futures market. The own market effect of price change is significant, although negative for futures return. This implies that Index futures market gets negatively affected by its past price changes; however, past price

[2] The statistical package (EViews) offers five options in applying the J-J method of cointegration. The options correspond to different specification of intercept and trend variable in the underlying VAR model. The options are five: Model 1 assumes that there are no deterministic trends in the variables and the underlying data generating process does not contain a deterministic trend. Model 2 is appropriate when the jointly determined variables, i.e. cointegrated variables do not contain a deterministic trend, only restricted intercept. Model 3 assumes unrestricted intercept, but no trends in the VAR model. Model 4 is appropriate when the jointly determined variables in the VAR have a linear deterministic trend as well as unrestricted intercept. Model 5 considers unrestricted intercept, and unrestricted trends in the VAR model. In general, model 1 and 5 are irrelevant. So the present analysis is limited to three options: model 2, 3, and 4.

changes have insignificant effect on relatively more efficient spot Index market. The coefficients of asymmetry in the variance equations of both FR and SR series are negative which implies that both the market reacts to bad news more adversely than the good news. The computed values of relative asymmetry are 3.08 and 3.21 respectively for FR and SR, which states that the spot market reacts to negative shocks 3.21 times more than the same amount of positive shocks; while the reaction is slight lower, i.e. 3.08 times in futures market.

In the above models, the ARCH and GARCH coefficients are significant in both conditional variance equations, indicating that both the futures and spot markets are characterized by time varying volatility and the clustering of volatility is present in their time plots. The significant t-distribution degrees of freedom show that the error distributions for the estimated equations are more alike to follow a t-distribution. Moreover, the models have been checked with Generalized Error Distribution, but with t- distribution the models produce higher Log-likelihood values and lower SIC and AIC values. Model adequacy has been checked for remaining serial correlation in residuals and ARCH effect in residual process. The LB^2-Q (8) test statistics with high P-values indicate that the null of no serial correlation in the squared residual series cannot be rejected, i.e. the models have no problem of serial correlation in residuals. In addition, the computed values for ARCH-LM (8) test statistic are insignificant implying non rejection of the null of no ARCH effect in squared residual series. Hence the estimated models are free from ARCH effects in their residuals. Thus the residual diagnostics prove that the estimated models are good fit for the sample data.

4.2 Findings related to short run impact of Covid-19 on Bank Nifty Spot market:

Following the methodology adopted by Benninga (2014), the estimated model has come as follows –

$$\mathbf{R}_{\textbf{Bank Nifty}} = -\ 0.000658 + 0.459247\ \mathbf{R}_{\textbf{Nifty50}}.$$

where R^2 is 0.13 with Steyx value 0.016. The **Steyx** function measures the standard error of the regression-predicted *y* –values. Here Nifty50 returns are considered as the proxy for market return.

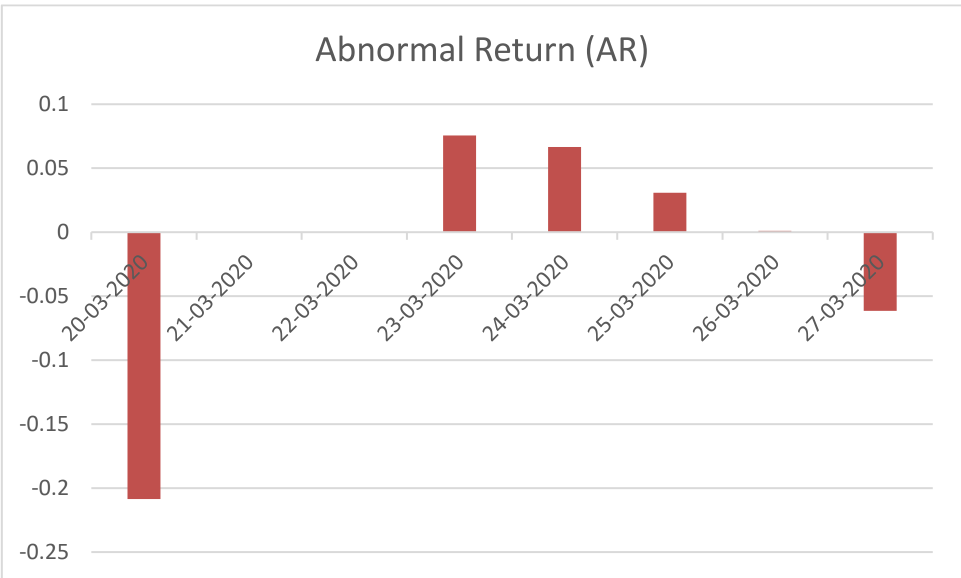
Applying the above market model, the Expected Return is calculated and accordingly Abnormal Return and Cumulative Abnormal Return are calculated as follows -

Table No. 4.2: Market Model Result for Bank Nifty Spot Market

Date	Expected Return	Abnormal Return (AR)	Cumulative Abnormal Return (CAR)
20-03-2020	0.025377384	-0.208507391*	-0.208507391
23-03-2020	-0.064510553	0.075658393*	-0.132848998
24-03-2020	0.010714042	0.066526564*	-0.066322434
25-03-2020	0.028800638	0.030691956	-0.035630478
26-03-2020	0.016869955	0.001072597	-0.034557881
27-03-2020	0.000340057	-0.061600847*	-0.096158728

(* values are significant at 5% level of significance.)

Fig. 4.1: Graph of Abnormal Returns on Bank Nifty Spot during the 'event window'



From the above table, it is evident that the impact of the shock was already expected much ahead of the 'announcement day', and that is why the first day of the event window, i.e. 20th March 2020 shows a significant and the highest 'negative' return. The event day and its next day didn't have any significant impact, rather the market already started its correction process. Hence it is apparent that the Bank Nifty had shown quick and efficient response towards the market corrections which is a sign of 'resilience' for its futures counterpart as well.

5. Conclusions:

The above findings from VEC-EGARCH estimations reveal a different story about futures market functioning in Indian banking industry: it is the spot market where price discovery happens actually. For Bank Nifty Index there are both long run and short run Granger causality, which is flowing unidirectional from spot to futures market. Hence it can be concluded that so far as Bank Nifty is concerned, its' futures market fails to function as a price discovery vehicle. In short run, price discovery happens mainly in the spot markets of Indian banking sector.

Both the markets – futures and spot are characterized by asymmetric nature of market response towards good and bad news, with different thrusts. They react more to any negative shock than to any positive news, and the plunge is more or less same in futures and spot markets of the underlying asset. CNX-Bank Index being composite of individual stocks is the most vulnerable and sensitive towards any shock with comparatively high value of relative asymmetry.

The first part of the work establishes that the 'price discovery' mainly happens in the spot market for Bank Nifty which flows eventually to affect its futures counterpart in short as well as in long run, and thereby they maintain a long run equilibrium with continuous correction processes. Hence in the second part, the authors have examined how the spot Bank Nifty reacted towards the announcement of the news (event) – nationwide lockdown due to Covid-19 pandemic and how long it took to adjust for the same vis-a-vis the national stock market. The event study following the market model have shown that the impact was visible much ahead of the announcement date which gradually dampened over a period of 4-5 days. Hence it can be concluded that the banking sector in India has 'efficiency' to readjust with the market shock though not fully 'resilient'.

The present work leaves scope for future research by conducting the study with intra-day data instead of daily price data, which might capture the speed of information transmission across the markets in a better way. Moreover the study has considered only the concept of linear Granger causality, while accounting for the non-linear causality could enlighten new findings.

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Declaration of Interest Statement: Authors prepared this paper with purely academic interest. It is not funded. It uses secondary data collected from public domain. It is not funded.

Appendix

Table.1: Descriptive Statistics of Sample Variables

	Bank Nifty Index	
	FR	**SR**
Mean	0.0005	0.0005
Median	0.0009	0.0009
Standard Deviation	0.0220	0.0215
Skewness	0.0489	0.0857
Kurtosis	7.2488	7.1557
Jarque-Bera	1597.72*	1530.24*
LB-Q(8)	40.13*	53.88*
LB^2-Q(8)	295.97*	311.50*
ARCH-LM(8)	155.41*	161.67*

* significant at 1% level.

Table.2: Results for Unit Root Tests

Securities	Log Prices in	**Futures Price**	**Spot Price**

		ADF	KPSS	ADF	KPSS
Bank Nifty Index	Level	-1.953	4.474*	-1.939	4.479*
	First Difference	-41.383*	0.064	-40.418*	0.064

Critical Values at 1% level are, ADF = -3.433, and KPSS = 0.739. * significant at 1% level.

Table.3: Results for Cointegration Tests

	Null Hypothesis	**Trace Statistic λ_{Trace}**	**Max-Eigenvalue Statistic λ_{Max}**
Bank Nifty Index	r = 0	189.602* (0.0001)	184.868* (0.0001)
	$r \leq 1$	4.734 (0.3139)	4.734 (0.3139)
	Cointegrating Equation:	lnFP = -1.0026 lnSP + 0.0223 [0.0007] [0.0059]	
	$r \leq 1$	7.513 (0.2940)	7.513 (0.2940)
	Cointegrating Equation:	lnFP = -0.9974 lnSP – $3.03E^{-06}$ T [0.0012] [$9.3E^{-07}$]	

P-values: ( ), Standard Errors: [ ]; *significant at 1% level.