An Empirical Model of India's Nifty VIX Index

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Abstract

As implied volatility is essential for pricing options, analyzing derivative strategies and measuring risk in investment portfolios containing derivatives, and understanding variations in implied volatility also becomes vital. Aside from a secular trend, volatility clustering and calendar effects are two commonly occurring sources of such variation. To analyze volatility clusters in India's implied volatility index (Nifty VIX), daily closing levels for the Nifty VIX were gathered covering trading days from January 2010 through January 2014. ARIMA and GARCH models applied to the de-trended Nifty VIX time series were found to be of limited use for describing this data with its episodic clustering and periodic events. However, an alternative modelling approach using Fourier analysis and Butterworth filters successfully split the time series into two logical parts, one with both clusters and periodic behavior and one with near-white noise. The likely origins of major clusters in India's Nifty implied volatility index appeared to be linked to important global financial events external to India during the study period, thereby supporting evidence of temporal spillover into the Indian market. The half-lives of implied volatility clusters were measured and compared with those in the U.S. market. The full range of Nifty VIX behavior for the study period was seen to consist of four distinct elements: trend, periodic events, clusters of volatility, and noise. When combined, these elements provided an empirical model able to produce successful forecasts for 60-day-ahead periods.

Keywords: India, Nifty, Nifty VIX, implied volatility, volatility clustering, Fourier analysis

JEL Classification: G12, G 13, G14, G15, G17

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An inspection of India's Nifty VIX (NVIX) index (Figure 1) suggests complex behavior in progress. Over the period chosen for this study (January 2010 - January 2014), there is a modestly downward secular trend on which there appear suggestions of periodic behavior likely originating from calendar effects. Furthermore, periodic volatility clusters are present, consisting of sharp spikes in NVIX that gradually decline and revert to the trend. Very likely, these three behaviors are superimposed over a base of random market fluctuations. The primary purpose of this paper is to establish that this picture is correct by analytically identifying these four elements in NVIX data and combining them in an empirical model for forecasting future values. Beneficiaries of better forecasting include important market participants who need to price options, assess option-based risk, and manage investment strategies utilizing options.

Our research contributes to the literature in several ways. For the first-time, NVIX behavior is decomposed into four components which, when recombined, prove to be useful for short term forecasting. Second, when standard ARIMA and GARCH modelling methods were found problematic, replacing these approaches with a simple Fourier model was found to be successful. Such a model does not depend upon an assumption of log

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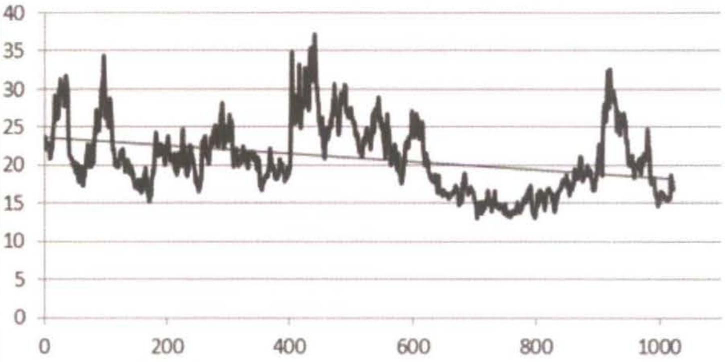
Figure 1. Nifty VIX vs. Trading Days (2010 - 2014)



Source : NSE (2015)

normality. It also does not necessitate a lack of autocorrelation or require GARCH modelling constraints. Next, application of standard filtering processes to Fourier's frequencies allow for identification of the near-white noise on which three other NVIX elements rest. This is the first known Fourier filtering application to NVIX or any other VIX data. Separately, specific implied volatility clusters arising from peaks in NVIX are identified with major out-of-country events, thereby supporting evidence of volatility spillover effects in the Indian market noted by other scholars. Finally, a new, simple analytical method is introduced for measuring the rate at which implied volatility clusters revert to normal NVIX behavior. This half-life measure allows for a convenient, standardized way to assess how quickly major events are incorporated into implied volatility.

Accomplishing this modelling task requires analytical tools, both to facilitate decomposition of the NVIX time series and to confirm the presence of the four hypothesized elements of NVIX behavior. Among the standard analytical tools available to research these four NVIX elements are regression, statistical testing, and ARCH-GARCH analysis. We used regression analysis and statistical testing to characterize and remove a trend in our data. While regression analysis is also typically used in the study of calendar or repeating events, we chose to use Fourier analysis to identify and isolate periodic behavior. This non-standard analytical tool also avoids the constraints of GARCH analysis and allows the creative use of filtering methods to isolate the noise contribution to the NVIX time series. Clusters of implied volatility are the fourth element of NVIX behavior. The origins of these clusters are typically episodic and thus, not predictable. However, once they occur, they follow a characteristic pattern of decay in magnitude, which can be conveniently modeled in an exponential form.

Among the four elements of NVIX behavior, the least amenable to analytical modelling are clusters of volatility. Volatility clustering is the name given to the tendency of sudden peaks in the stock market returns to be immediately followed by a series of related return changes of either sign, gradually diminishing in magnitude towards normal market levels. This tendency creates groupings of return volatility for a period and was first mentioned by Mandelborot (1963). The phenomenon has since been observed and modeled in emerging as well as developed global stock markets (Arora, Das, & Jain, 2009 ; Choudhry, 1996 ; Michelfelder & Pandya, 2005). A substantial literature exists on the general topic resting on the innovative work of Bollerslev, Chou, and Kroner (1992) and Bollerslev, Engle, and Nelson (1994) in ARCH and GARCH analysis.

While volatility clustering of market returns has been heavily studied in many markets, there is only a rare analysis of its occurrence, specifically within implied volatility indexes (NYU Stern, 2014). In the Indian market, scholars have applied the GARCH analysis to model the conditional volatility of market returns (Karmakar, 2005; Karmakar, 2007; Mittal & Goyal, 2012; Mishra, 2010). However, there is no comparable known application to India's Nifty VIX. It is important to understand that the present study does not seek to fill this gap by modelling the conditional volatility of Nifty VIX returns. Instead, it seeks to simply model the NiftyVIX itself. Clusters of implied volatility are then considered empirically observed events within the combined context of a trend, periodic variations, and random noise, each present in India's Nifty VIX. All four elements are assembled into an empirical description of NVIX behavior that is helpful in forecasting.

Within the literature on implied volatility, scholars typically have employed this variable to forecast future realized return volatility or to forecast returns themselves. Whether implied volatility itself can be forecasted, however, has been rarely reported. Harvey and Whaley (1992) found that changes in the implied volatility of S&P 100 options were predictable. Brooks and Oozeer (2002) modeled the implied volatility of options on long Gilt futures, and also found that directional changes could be predicted. Guo (2000) successfully modeled implied volatility changes in foreign exchange call and put options and used the results to successfully forecast implied volatility as did Ahoniemi (2006). Each of these authors used traditional econometric models that regressed changes in implied volatility against financial and macroeconomic variables to produce point or one-step-ahead forecasts. This study takes a new and different approach using Fourier analysis to model an implied volatility time series that is then used to produce both successful point and interval forecasts.

Data Sources and Methodology

Implied volatility indexes (VIX indexes) are constructed from implied volatilities observed in option markets. Arbitrage in options markets assures that excessively large or small values of VIX gradually dissipate, causing VIX levels to be mean reverting to a longer term secular trend. Removing the secular trend in the time series for this study produced a series that statistically tested as stationary and mean reverting to zero for the chosen period. Behavioral elements of the revised de-trended series (DNVIX) including clusters of implied volatility could then be decomposed further.

In the Indian market, sharp rises in the DNVIX subsequently exhibit a gradually decreasing magnitude of index level changes that revert to zero, seemingly atop a baseline of market variations, some of which appear periodic, while still others appear random. While the timing of most DNVIX peaks is non-periodic, there are present in the data repeating rises over periods longer than daily, weekly, or even monthly. To understand the structure of these periodic and episodic variations, analytical tools are necessary to decompose the DNVIX time series into its contributing components.

Slivka, Chang, and Yu (2014) began such a decomposition process by gathering and sequentially numbering 1024 daily closing NVIX levels for trading days in 2010 through January 31, 2014. A linear trend line was subtracted from the data to form a de-trended NVIX time series (DNVIX). This data was not found to be normally distributed using the Jarque-Bara test (JB). It contained autocorrelation measured at the 5% significance level with the Ljung-Box Q (LBQ) test and was found stationary at the 1% level of significance using the Augmented Dickey-Fuller (ADF) test. Removal of a trend line was a standard step necessary to avoid inaccurately identifying prominent frequency components present in the power spectrum of a Fourier analysis which followed. The authors found that only four dominant Fourier frequencies appeared to make meaningful contributions to the DNVIX levels. These four prominent Fourier frequencies provided an encouraging fit to the full data set and were used to form a simple Fourier model of the DNVIX. We use an equivalent expression here of their model for the DNVIX, which is as follows :

$$DNVIX(t) - \Sigma^{1}_{4} A_k \cos(2\Pi f_k t + \varphi_k) \qquad (1)$$

where,

A_k = amplitude of k th component,

f_k = kth frequency,

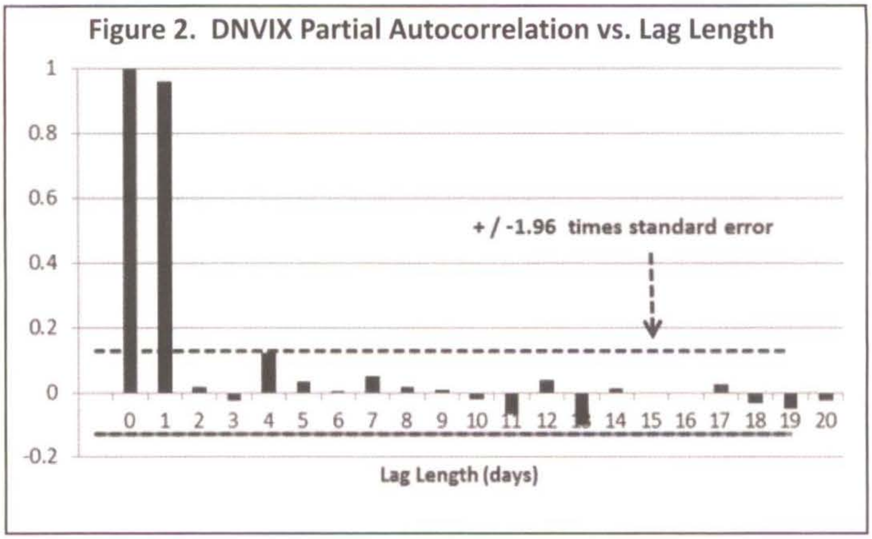
φ_k = k th phase angle,

t = sequentially numbered trade date.

The amplitudes and phase angles for each of the four Fourier terms appear in the Table 1. The Fourier model used by Slivka et al. (2014) was successful in identifying the temporal location of DNVIX extrema within about

Table 1. Primary Fourier Amplitudes, Frequencies, and Phase Angles in the Power Spectrum for De-trended Nifty VIX

k	Amplitude (Index Points)	Frequency (per Trade Day)	Phase Angle (Radians)
1	3.800	0.001953	0.505
2	1.598	0.005859	3.013
3	1.555	0.009766	-0.361
4	1.508	0.015625	-3.131



six trading days of their observed occurrence. In contrast to widely reported higher frequency calendar events, this model was able to identify two new quarterly and biannual occurrences, suggesting calendar event types previously unreported in the literature.

The authors did not use their simple Fourier model to forecast DNVIX values or to possibly improve forecast accuracy with ARIMA or GARCH modelling. Neither was there an attempt to identify and analyze the origins of volatility clusters nor to separate volatility peaks from background noise. This study seeks to address each of these tasks and to combine the results in the form of an empirical model of NVIX behavior.

For these objectives, the same data and study period (January 2010 - January 2014) used by Slivka et al. (2014) were used in the current paper to more easily complement and extend prior research findings. Methods used in the present study include Fourier analysis but extend the analysis by employing frequency filtering and forecasting methods along with examination of ARIMA and GARCH modelling.

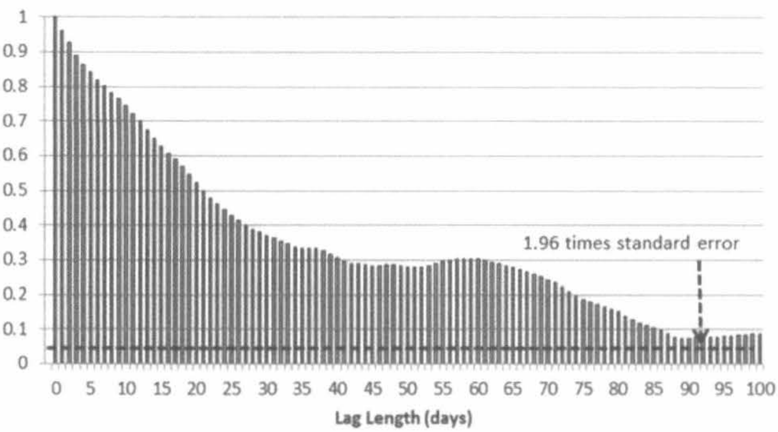
Data Analysis, Results, and Discussion

A standard step in time series forecasting is to apply ARIMA and GARCH modelling. We have found that these approaches for the DNVIX time series present significant difficulties and that an alternative approach would be promising.

ARIMA and GARCH Modelling

Fitting an ARIMA (p,d,q) model to DNVIX (t) is equivalent to fitting an ARMA (p,q) model since DNVIX (t) is

Figure 3. DNVIX Autocorrelation vs. Lag Length



already stationary and no further differencing of data is required ($d = 0$). Inspection of the partial autocorrelation function suggests a correct lag choice of $p = 1$ (Figure 2). However, the residuals for the resulting AR (1) model proved to be non-normal, thereby considerably weakening the validity for this form of modelling.

A MA(q) model also proved to be unsatisfactory due to the presence of a large number of significant autocorrelation coefficients in the DNVIX correlogram. The correlogram (Figure 3) reveals a need for 100 lags alone within the first 100 autocorrelations. For a complete ARMA model, far more lag orders are needed with q reaching into the hundreds. Such a large value for q makes modelling impractical, and likely to result in unacceptable over-fitting of data.

While fitting an ARMA model is impractical, there might still be some marginal value in a simple AR(1) model as an approximate way to forecast one step ahead levels of DNVIX. To test this idea, parameters for the following AR(1) model were fitted.

$$DNVIX(t) - b + a\, DNVIX(t-1) + e(t) \qquad (2)$$

$e(t) = error\ term$

In fitting the parameters a and b only, the coefficient a was found to be significant, so the AR(1) model reduces to :

$$DNVIX(t) = 0.965\, DNVIX(t-1) + e(t) \qquad (3)$$

This AR(1) model is close to a Gaussian random walk model which would occur for $a = 1$. The Engle ARCH test of residuals for this AR(1) model reveals ARCH effects, suggesting that a GARCH process might be used to model the conditional variance σ^2_t . The most frequently chosen model for a GARCH process is the GARCH (1,1) model.

$$\sigma^2_t = K + \gamma_1 \sigma^2_{t-1} + \alpha_1 \varepsilon^2_{t-1} \qquad (4)$$

where,

K = constant,

γ_1 = GARCH coefficient,

α_1 = ARCH coefficient,

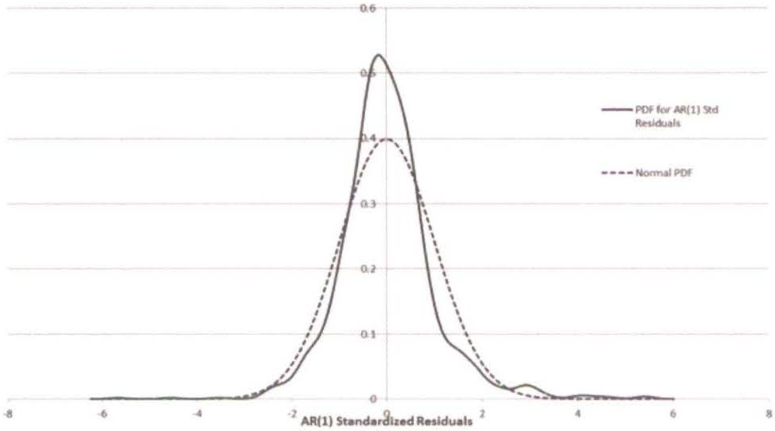
The model parameters appear in the Table 2.

However, the Jarque-Bara and Kolmogorov-Smirnov tests of standardized residuals reveal that the distribution

Table 2. GARCH (1,1) Model Parameters

Parameter	Value	*t*- statistics
K	0.043	4.848
γ	0.857	47.104
α	0.114	7.406

Figure 4. Probability Distribution Function for AR(1) Standardized Residuals vs. Normal Distribution



is not normal and so GARCH (1,1) requirements for normality are violated. The probability distribution function for the residuals appears in Figure 4 and is skewed right with excess kurtosis.

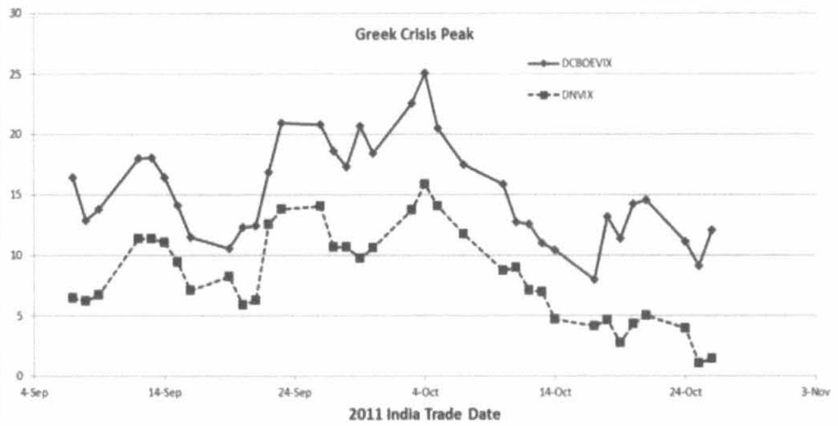
Furthermore, these standardized residuals test positive for autocorrelation. This result could have been expected since a time series dominated by periodic behavior comprised of cosines will always produce, when differenced, a new time series dominated by sines and cosines also containing significant autocorrelation. In summary, applications of ARMA and GARCH models are of questionable value for the data being examined, and it would be useful to seek other means for modelling and forecasting this DNVIX time series.

Identification of Volatility Clusters

While the DNVIX time series carries a statistically zero mean for the period of the study, there are sub - periods in which the mean is interrupted by sharp peaks followed by a gradual reversion towards the mean along with a decline in the magnitude of implied volatility. Such behavior is characteristic of volatility clustering. These volatility clusters can have origins in information events that are periodic or episodic. Clusters can originate from events internal to India or external in global financial markets. One example can be seen in the period immediately following global market fears of a Greek sovereign debt default reaching a peak first in Europe on October 4, 2011. In the Figure 5, the DNVIX and the de-trended CBOE VIX (DCBOEVIX) each are made in irregular steps towards a peak on October 4 before declining towards a minimum on October 28, 2011. The close correspondence in Figure 5 between VIX levels in two global markets reflects a spillover effect for U.S. and India from events in Greece. Spillover effects have been noted by other scholars (Ajio, 2007 ; Badshah, 2009 ; Skiadopoulos, 2004 ; Wagner & Szimayer, 2004) and have been observed for the Indian market (Adrangi, Chatrath, Raffiee, & Sharma, 2013 ; Narwal, Sheera, & Mittal, 2012), but have not been studied in the context of Nifty VIX.

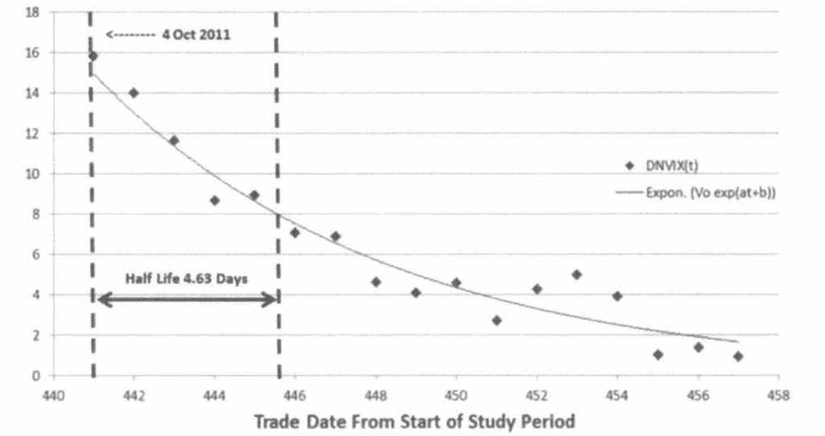
If the observed peak on October 4 is V_0 and the decline is modeled as an exponential decay (Figure 6), then the mean reversion process is characterized by :

Figure 5.De-Trended CBOE VIX and Nifty VIX vs. 2011 India Trade Dates



Source: National Stock Exchange of India (2015) and Chicago Board Options Exchange (2015)

Figure 6. DNVIX Decay Following 2011 Greek Default Crisis vs. Trade Date



$$V(t) = V_0 \exp(at + b) \qquad (5)$$

where,

t is the number of successive trading days measured from the start of the study period and a and b are constants. For the peak in DNVIX occurring on October 4, 201, t = 441 and a and b are statistically significant with values :

a = -0.00732

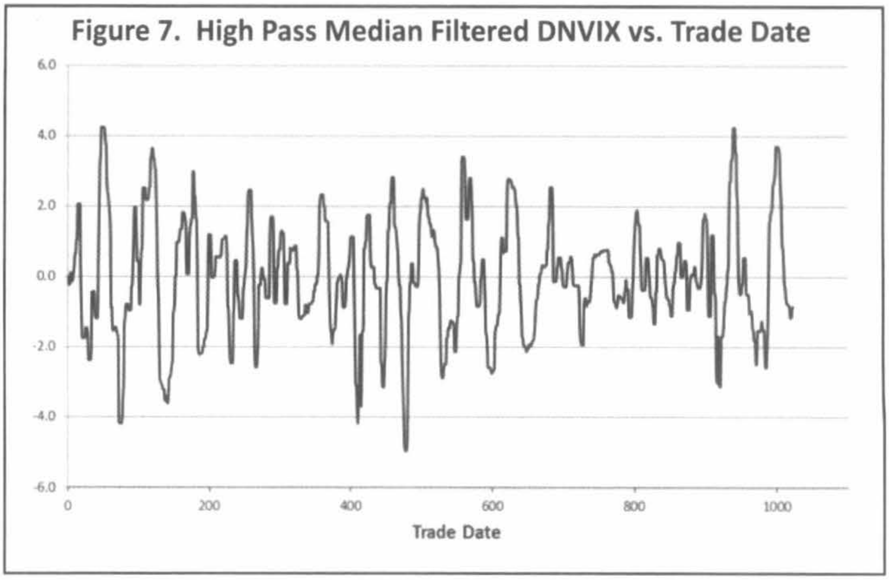
b = 2.438

$V(t)$ reaches half its peak value at time t'.

$$t' = \frac{[\ln(0.5) - b]}{a} = 445.63 \qquad (6)$$

Thus, DNVIX (t) reached half its peak value in 4.63 days (445.63 - 441) following a peak on trade date 441. The time of 4.63 days taken to reach this level is defined as the half-life of the exponential decay process.

Similar analysis of DNVIX half-lives following the Euro Debt Fears (May 25, 2010), Black Monday (August 8, 2011), and fears of U.S. air strikes in Syria (August 28, 2013) yielded values in the range of 3.60 to 7.09 days. These half-lives were found to be comparable to those measured in the de-trended CBOE VIX time series for the



same events. The magnitude of measured half-lives provides a convenient, standardized indication of the approximate time taken for half of the peak fear in DNVIX to dissipate.

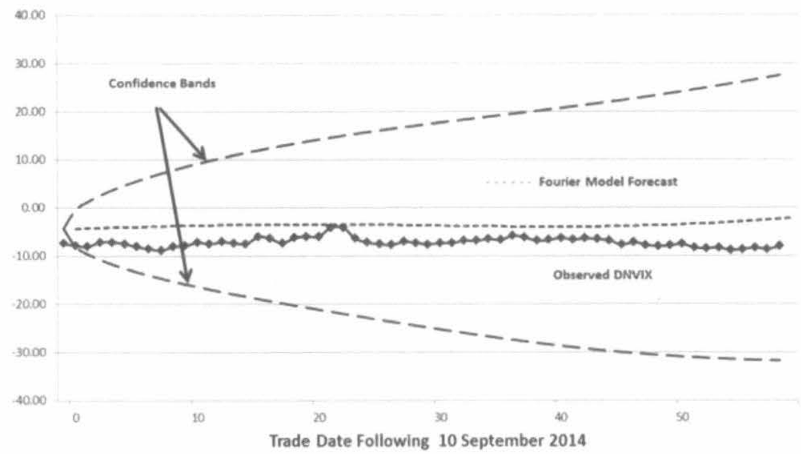
DNVIX Near-White Noise

Allowed to continue without interruption following a sharp rise, the DNVIX appears to mean revert to a pattern of noise centered about zero. This raises the question of whether the DNVIX time series can be separated into a white-noise component overlaid with peaks originating either from periodic or from idiosyncratic events. Slivka et al. (2014) observed that the highest frequency in their simple Fourier model for this study period corresponded to a quarterly repetition, likely originating in the quarterly earnings release cycle among Nifty stocks. The origins of the remaining three frequencies were unknown. However, Fourier's power spectrum contributions above the highest of the four frequencies appeared minimal, suggesting that the frequency spectrum might be separated into two ranges: a range at and below the single highest of the four Fourier model frequencies and a second range representing the balance of frequencies. This separation can be accomplished by application of a standard Butterworth filter.

When applied to the DNVIX data, a Butterworth High Pass filter of order six with a cutoff frequency just above the highest of the four Fourier components creates a HiPass time series of DNVIX. The filter retains 1008 Fourier frequency components of DNVIX and eliminates only 16 components with the lowest frequencies. It is from these lowest 16 components that only four were originally chosen to construct the simple Fourier model of DNVIX (equation 1). The HiPass time series contains a small number of spikes associated with episodic market events such as the U.S. Flash Crash on August 8, 2011 (Black Monday), which are easily removed with the standard time series application of a median filter, leaving the balance of HiPass data minimally affected (Figure 7). A JB test of this series shows the data to be normal with a standard deviation of 1.65 index units. The series was also was found to be stationary using the ADF test. The LBQ test reveals the presence of autocorrelation, suggesting that the background noise is not pure white but near-white, belonging to a multi-fractional Brownian motion process. The results of filtering and testing the DNVIX data suggests strongly that the combined NVIX trend line, DNVIX periodic events, and volatility clusters all rest upon a background of near-white noise.

In summary, the analysis so far suggests that the Nifty VIX time series in this study can be modeled reasonably well using four components :

Figure 8. Observed DNVIX and 60-Day Fourier Forecast With Confidence Bands



(1) A linear trend.

(2) A set of four primary amplitudes and frequencies contained in a simple Fourier model to model periodic behavior.

(3) Episodic volatility clusters with half-lives ranging from 3.60 to 7.09 days.

(4) A base of near-white noise movements originating from random market events.

Forecasting NVIX

The AR (1) model in this study is very nearly a random walk, giving only a limited ability to forecast one step ahead. Furthermore, the validity of an AR(1) model is questionable due to the absence of normality in the standardized residuals. A simple Fourier model, however, does not have these limitations. Fourier model forecasts at any given time carry with them historical information on autocorrelation and trend together with a measure of calendar events. Neither an assumption of log normality nor a lack of autocorrelation is required to develop a forecast. Furthermore, the standard deviation of the HiPass series provides a measure of forecast uncertainty.

To test the forecast accuracy of the simple Fourier model, an in-sample period of 512 days of DNVIX levels was used to calibrate the model and project values for a period of 60 days forward. The mean absolute deviation (MAD) and average error (AE) from observed DNVIX levels were computed, and the process was repeated by moving the in-sample calibration period forward by 60 days. Within the study period, there were 12 such forecast periods of 60 days each. One such 60-days' forecast is displayed in Figure 8 along with 95% confidence bands. For this forecast period, the MAD and AE were 1.04 and -0.46 index points, respectively vs. 0.13 and -0.13 for the AR(1) model. Averaged over the 12 forecast periods, the MAD and AE levels were 5.59 and -1.45, respectively. Observed DNVIX data fell 98% of the time within the 95% confidence bands, a typical result.

Despite the shortcomings of the AR(1) model, its MAD and AE performance measures were better in every forecast period than in the simple Fourier model. However, the AR(1) model is only able to forecast one step ahead. In general, the Fourier model appears reliable and sound for longer forecast periods than simple AR(1) one step ahead results. Further improving the accuracy of the present forecasting model is left for future research.

Research Implications

Current stock market literature contains separate studies of volatility clustering, of implied volatility influences on market prices, and still other studies of calendar events, especially those having a monthly or lower frequency. However, there is a notable gap in studies of implied volatility behavior relating either to calendar events or implied volatility clusters. This study addresses such gaps by decomposing implied volatility in the Indian market into four respective components, including a linear trend, periodic events, idiosyncratic informational events, and near-white noise. By combining these distinct elements of the Nifty VIX, an inclusive empirical approach is outlined for future implied volatility time-series analysis.

Non-traditional analytical tools have been used in this study. The standard use of ARIMA and GARCH (1,1) models was found to be problematic, and the standard use of regression analysis, while helpful in the analysis of calendar events with monthly, weekly, daily, or higher frequencies is increasingly impractical at lower frequencies, where data is less abundant. Instead, Fourier analysis, which has proven to be critically effective in revealing distinct periodic contributions with quarterly or fewer frequencies, was employed. A novel use of Butterworth filtering allowed separation, identification, and measurement of the near-white noise component of DNVIX variations. For the first time in India with regard to VIX literature, the parameter of half-life was introduced as a simple means to standardize measurement of the rate at which implied volatility clusters are absorbed by the market as their peak effect relaxes towards market mean behavior. The simple Fourier model, carrying within it periodicity, volatility clusters, and autocorrelation, proved effective in forecasts for 60 trading days ahead. The new analytical tools and measures used in this study have proved to be useful and should be helpful in future VIX studies.

Summary and Conclusions

For the period studied from 2010 - 2014, we surmise and confirm that the behavior of India's implied volatility index (NVIX) is the sum of four separate elements: A linear secular trend; near-white noise with zero mean; contributions from calendar events with differing frequencies; and idiosyncratic events giving rise to volatility clusters. While the market origin of the secular trend is not clear, the trend was statistically confirmed and successfully removed from the NVIX time series using standard regression methods. The amplitudes of four periodic NVIX variations with periods greater than monthly were detected and measured in the power spectrum for the de-trended NVIX (DNVIX). With the use of standard frequency filtering methods, near-white noise variations about DNVIX were isolated and tested. No isolation and measurement of near-white noise variations about an implied volatility trend are known to have been previously reported. Implied volatility clusters detected in the study period often coincided with major global market events, suggesting spillover effects to the Indian market. Other studies have reported such spillover effects for the spot market, but none reported occurrences in implied volatility or specifically to the Nifty VIX. Implied volatility clusters typically decay to trend within approximately 3.60 to 7.09 days.

modelling the DNVIX time series was examined in several ways. ARIMA (p,d,q) modelling was found impractical by the need for hundreds of significant lagged terms in the DNVIX correlogram. Even application of a simple AR(1) model was rejected due to violation of the requirement that standardized residuals be Gaussian normal. While ARCH effects clearly exist in the data for the study period, the application of ARCH-GARCH analysis was inhibited by the continuing presence of long term autocorrelation effects. Only a simple Fourier model of DNVIX variations was found to be helpful in capturing the range of behavior. Such a model does not depend upon assumptions of log normality, nor does it require a lack of autocorrelation or require GARCH modelling constraints. The simple Fourier model successfully forecasted DNVIX values for a period of 60 days ahead that typically included observed values within statistical uncertainty bounds.

Limitations of the Study and Scope for Further Research

Important challenges remain for future modelling of the Nifty VIX. The market origin of secular NVIX trends is not clearly understood and could benefit from an explanation. Further development of robust forecasting of NVIX requires future studies of NVIX in different measurement periods. Implied volatility cluster half-lives and contributions from calendar events with differing frequencies also deserve further analysis. The modelling of a multi-fractional Brownian motion process has not been studied and is likely to be challenging. Implied volatility transmission from other global markets could benefit from a closer analysis. In the simple Fourier model, the magnitude of monthly and weekly repeating NVIX variations reported elsewhere remains to be measured relative to quarterly contributions. In summary, there is much room for further studies to refine the empirical model presented here. The eventual practical application of such a model for asset pricing and strategy development will rest upon the quality of these refinements.

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