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Abstract

An election year is expected to be of high volatility and movement in the stock markets, reflecting the aspirations and expectations of the common people from the upcoming government. In this paper, we explore Functional Principal Component Analysis to show how a big event like the general elections affects the stock market in the country. We take the Indian general election years of 2009, 2014, and 2019 and demonstrate how the unique circumstances before the elections affect the absorption of election sentiments and how this method can be used to find and foresee the effect of other such events through a detailed analysis of eigenfunctions.

Keywords: PCA, FPCA, General elections effect, Functional Data Analysis.

Contents

1 Introduction

The government of any country is responsible for making key decisions about its economic policy, economic goals, and its execution. Along with making these choices, governments are also responsible for instilling hope and positivity among the market players in the form of the promise of socio-economic-political stability in the country.

Through this paper, we try to identify how these sentiments and expectations of the people get captured in the stock market. We consider the election years of 2009, 2014, and 2019. These three years have some unique features of their own which we bring out through our analysis. The year 2009 witnessed a huge uncertainty and confusion regarding the outcome of the elections. In 2014, although the results of the elections were very predictable, it brought a change of government. In 2019, it was again evident which party would turn out to be the biggest, but a clear majority was still being debated. There was no change in government in 2019 ultimately. The three years respectively reflect the three states: complete confusion about the results, clarity about results with a change in the ruling party, and clarity about the results but no change in the ruling party. These are the three common broad situations that any democracy may face during elections.

2 Literature Review

2.1 Elections and Stock Markets

The uncertainty around election results can have significant implications for investors and business owners. Baker et al., 2013 created an economic policy uncertainty index which was found to be positively correlated with S&P 500 volatility [Pástor and Veronesi, 2013]. Studies have shown that national elections induce high volatility in the stock market [Białkowski et al., 2008]. Further, a study of stock market dependencies in many markets in different countries has shown a remarkable increase in non-linear dependencies during election periods, which means high volatility in the market in that period [Barbi and Prataviera, 2019]. We propose to use non-linear, non-parametric methods of data analysis to understand the data. It is different from most of the studies done on stock markets as they have assumed a linear relationship in their models to study how different stocks interact with each other and get affected due to events like national elections. Whereas recent studies in data analysis have shown that non-linear relationships between the stocks are more pronounced than linear ones [Fiedor, 2014]. To show how stock markets were affected in the three years that we study (2009, 2014, 2019), we observe them and try to trace out, out of the ordinary movements in the stock market around elections.

We decided to explore our data using the functional variant of Principal Component Analysis (PCA) known as Functional Principal Component Analysis (FPCA). This technique is applied where the sample points in the working dataset can be regarded as functions. Over the past two decades, Ramsay and Silverman [Ramsay et al., 1996, Silverman et al., 1997, Ramsay, 1998, Ramsay, 2000, Ramsay and Ramsey, 2001, Ramsay, n.d.] have shown many real world applications in the field of Functional data analysis based on variants of FPCA.

In 2014, Wang et al., 2014 studied the principle components of Shanghai stock exchange's 50 index by means of FPCA where they treated stock price rate of return series as random function in a space spanned by finite dimensional functional bases. They showed that compared to standard principal component analysis (PCA), functional principal component analysis (FPCA) addresses the issue of varying dimensions within samples. Additionally, FPCA provides a convenient method for extracting the primary variance factors. In our analysis, we not only worked with the rate of returns of stock prices but also their respective volume series with reference to the Indian Stock Market.

Our paper is broadly divided into 4 sections: data description, methodology, results, application conclusion. Section on data description describes the data used in our analysis. Section on methodology gives an overview of the methods used. Section on results discusses the results obtain and is followed by section on application where we propose how one can use our proposed method as a useful tool to predict election sentiments of the economy. In the last section, we conclude by highlighting the salient observations and interpretations that follow from our analysis.

3 Description of Data

Financial systems are very large and complex structures with hundreds of different observable and unobservable elements interacting with each other. NSE, the biggest stock market of the country and the third largest in the world succeeded only by NASDAQ, and NYSE has been used for collecting all the data used in our analysis. We use the stocks under the NIFTY 100 index of NSE for our analysis. The NIFTY 100 comprises NIFTY 50 and the NIFTY Next 50 together which together represent the 100 most liquid stocks traded on the National Stock Exchange. NIFTY 100 is a diversified 100 stock index representing major sectors of the economy. This index intends to measure the performance of large market capitalization companies and the index represents about 76.8capitalization of the stocks listed on NSE as on March 29, 2019. The total traded value for the last six months ending March 2019 of all index constituents is approximately 66.2traded value of all stocks on the NSE [National Stock Exchange of India, 2019].

Table 1: Data description

Year	**2009**	**2014**	**2019**
No. of stocks	79	83	83
No. of samples for each stock	237	241	243

4 Methodology

Most of the work done and theory taught in the field of data analysis revolves around either cross-sectional data or panel data. But, we often come across data that appear to look like a function because of how smooth they are. This type of data is called functional data. Contemporary research and developments in data analysis focus heavily on methods to analyze such functional datasets. We try to use one such recent developments in fundamental data analysis called the functional principal component analysis (FPCA).

FPCA is the functional equivalent of the principal component analysis tool which is a dimensionality reduction technique that enables you to identify correlations and patterns in a data set so that it can be transformed into a data set of significantly lower dimensions without loss of any important information. Table 2 gives an analogous comparison between PCA and FPCA.

The basic assumption of the FPCA is that the underlying data is smooth and shows functional characteristics. The data collected is a daily adjusted closing price of different stocks.

Table 2: Comparison between PCA and FPCA

Element	**PCA**	**FPCA**
Data	$X \in \mathbb{R}^p$	$X \in L^2(\mathcal{T})$
Dimension	$p < \infty$	∞
Mean	$\mu = \mathrm{E}(X)$	$\mu(t) = \mathrm{E}(X(t))$
Covariance	$\mathrm{Cov}(X) = \Sigma_{p \times p}$	$\mathrm{Cov}(X(s), X(t)) = G(s,t)$
Eigenvalues	$\lambda_1, \lambda_2, \ldots, \lambda_p$	$\lambda_1, \lambda_2, \ldots$
Eigenvectors/Eigenfunctions	$\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_p$	$\varphi_1(t), \varphi_2(t), \ldots$
Inner Product	$\langle \mathbf{X}, \mathbf{Y} \rangle = \sum_{k=1}^{p} X_k Y_k$	$\langle X, Y \rangle = \int_{\mathcal{T}} X(t) Y(t) dt$
Principal Components	$z_k = \langle X - \mu, \mathbf{v_k} \rangle, k = 1, 2, \ldots, p$	$\xi_k = \langle X - \mu, \varphi_k \rangle, k = 1, 2, \ldots$

Each time-series of log returns was approximated by smooth spline functions to give a functional form to our data. Mathematically, a spline function consists of polynomial pieces on sub-intervals joined together with certain continuity conditions. Splines are popular because of the simplicity of their construction, their ease and accuracy of evaluation, and their capacity to approximate complex shapes through curve fitting and interactive curve design. The obtained functional plots for the three years we studied is shown in Figure 1.

Let $\{e_1(t), e_2(t), e_3(t), \ldots, e_k(t)\}$ be the first k eigenfunctions obtained. Then, using properties of eigenfunctions, we can represent log returns of every stock as:

$$X_i(t) = \sum_{j=1}^{k} a_{ij} e_j(t)$$

Log returns	Volume

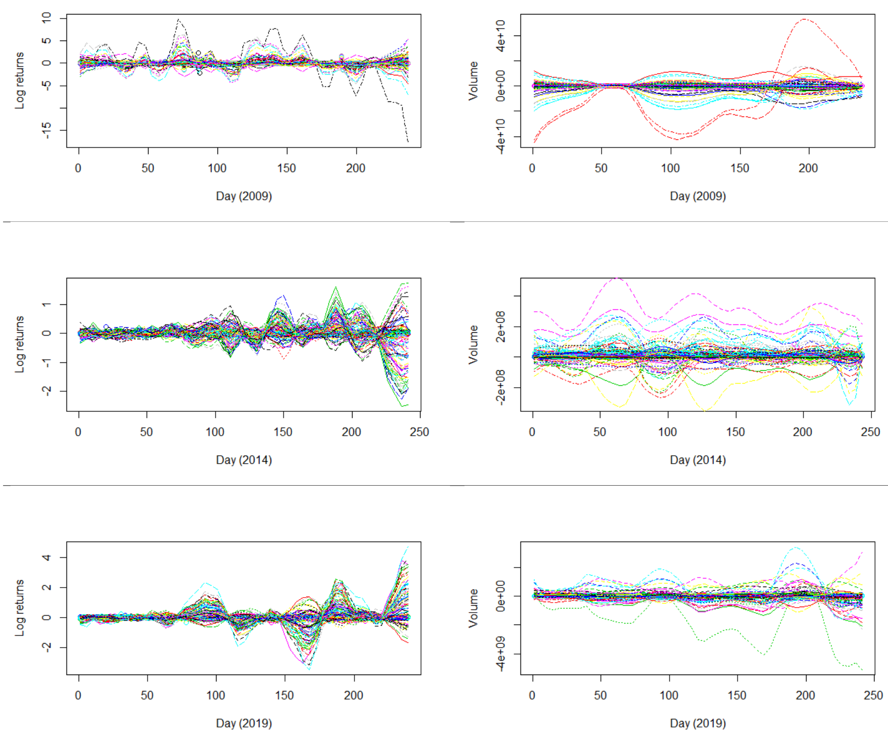

Figure 1: Functional plot of data

where

$$a_{ij} = \langle X_i(t), e_j(t) \rangle = \int_0^T e_j(t) X_i(t)\, dt$$

Here, a_{ij} can be interpreted as how much we should move in the direction of each eigenfunction $e_j(t)$ to reach $X_i(t)$. a_{ij} can also be interpreted as a weighted average of X_i, weighted by the eigenfunction $e_j(t)$.

Consider the first eigenfunction $e_1(t)$ and time intervals where $e_1(t) > 0$ and attains local maxima. Clearly, those time intervals play a key role in determining a_{i1}. If $a_{i1} > 0$, then on average X_i will have the same sign as e_1, thus the i-th stock is seen to have on average positive rate of returns during the time periods when e_1 is positive and vice versa. Thus, time periods where e_1 is positive or e_1 is negative play an important role in the interpretation of the behavior of stocks. By looking at the eigenfunction plots, we can analyze and point out the time periods that will be more crucial in explaining X_i than others.

5 Results

We want to capture the election effect in the stock markets. Since the eigenfunction represents which point in time is more crucial in explaining $X_i(t)$, we look for out of the ordinary behavior in the eigenfunction plot around the election period. If the plot shows out of the ordinary movement around elections against its general trend, it is an indication of election effect in the market. General elections in India happen between the 1st week of April to mid-May. We look at the time period of 3 weeks before and after the elections to be able to observe the absorption of election effects in the market. It translates to the time period between week 13 to week 23 of the year approximately.

5.1 Analysis of log returns

We looked at the eigenfunction plots. We have taken only the first three eigenfunctions as they are in themselves explaining nearly 65election years. Further components seem to lose their explaining ability as visible in the scree plot of eigenfunctions in figure 2.

The eigenfunction plots in figure 3 give many interesting insights when read carefully. Different eigenfunctions seem to have captured different kinds of factors affecting the market.

For the year 2009, we see the first eigenfunction peaks during the election period and almost flattens out later. The second eigenfunction does not show much variation throughout. The time period around the 2009 general elections was full of confusion and unclarity about which party might come into power. A win for any party was expected to bring a big surprise to the people, economy, and the market. The fact that the first eigenfunction which holds the highest explanatory power for any stock shows out of the ordinary behavior during the general elections clearly reflects that the general elections indeed had a huge effect on the market.

For 2014, we again see two very evident peaks during the election period in the first eigenfunction. The second eigenfunction does not behave anything out of the ordinary during the election period. The first eigenfunction peaking during the election period was expected because the year 2014 witnessed a

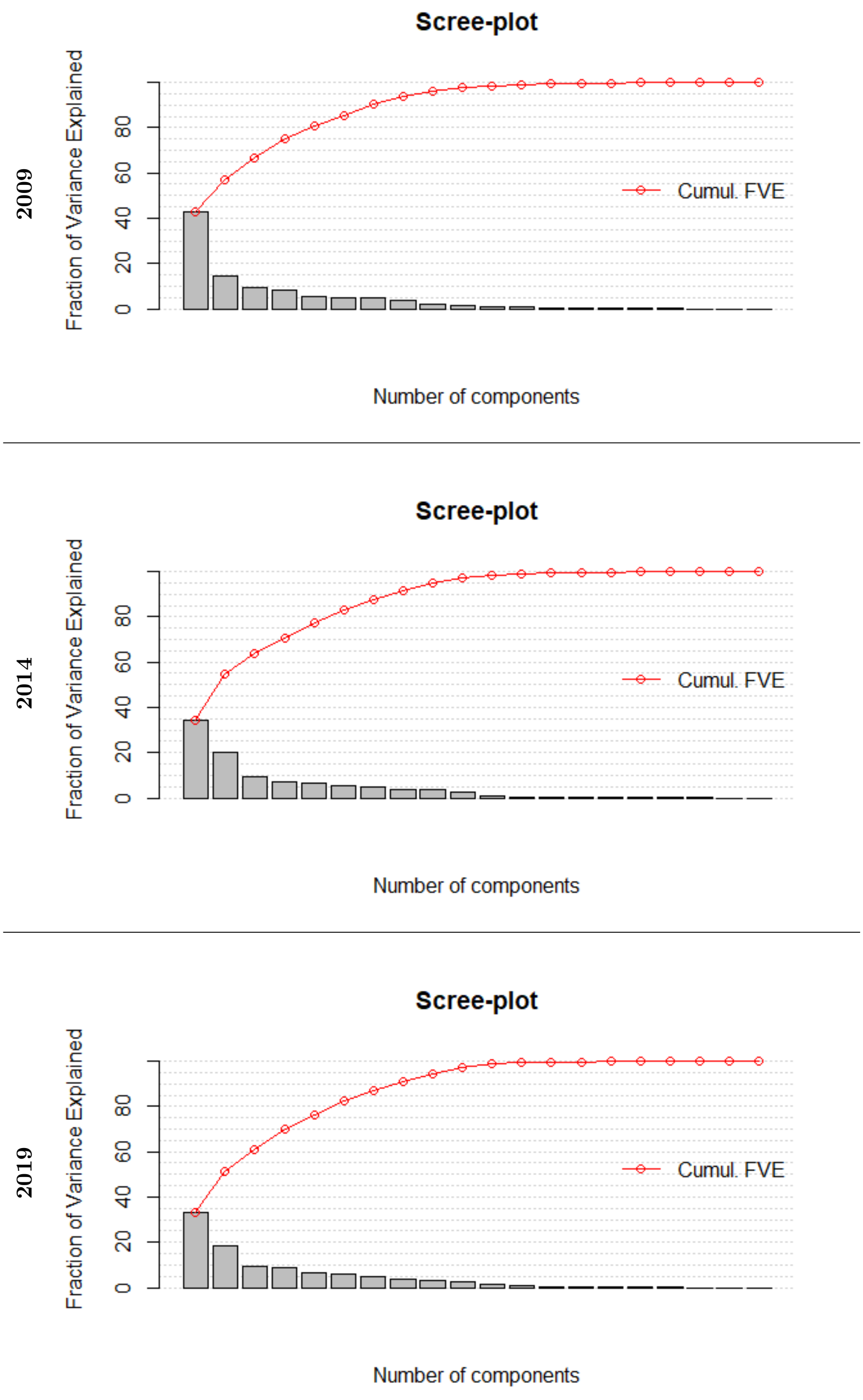

Figure 2: Log returns scree plot of 2009, 2014, 2019 data respectively

Figure 3: Functional principal components of log-returns
Note: 1st eigenfunction (Red), 2nd eigenfunction (Green) and 3rd eigenfunction (Blue)

change in the ruling party which brings with itself loads of aspirations, hopes, and excitement for the people, market, and the economy. How the expectations of the people absorb in the market with a change in the ruling party becomes clearer when we look at the results from 2019.

In the year 2019, the general mood around the election period was quite clearly reflecting a win for the already ruling party. It was a different case from the last two general elections because there was neither any confusion and unclarity like 2009 about the upcoming results nor was there a government changing like 2014. Thus, one would not expect to see a lot of effect of the election period in the market for 2019. This is exactly what we find from the eigenfunction plots. The first eigenfunction appears to follow a general cyclical trend throughout the year and does not show any movement out of the ordinary during the elections. But interestingly for this year, the second eigenfunction appears to peak a little around the election period from week 15 to week 22. Note that the second eigenfunction has lesser explanatory ability than the first eigenfunction. Thus, the fact that the second eigenfunction is capturing election effects means that the election effects were indeed small for this year.

Table 3: Election outcomes of 2009, 2014 and 2019

	2009	**2014**	**2019**
Highest seats	INC 37.94 %	BJP 51.93%	BJP 55.9%
Second highest seats	BJP 21.36%	INC 8.1%	INC 9.6%
Third highest seats	SP 4.24%	AIADMK 6.81%	DMK 4.2%

5.2 Volume Analysis

We repeat the same process using the volume of stocks instead of log returns. Volume provides information on how many shares changed hands and at what price in a stock over a given time frame, giving an indication of interest in the stock. The results obtained by applying FPCA on volume displays election effects even more profoundly than log returns. The fraction of variance explained by the eigenfunctions reaches above 90election years in case of volume as shown by the scree plots in figure 4.

The results obtained using the analysis of volume FPCs (Figure 5) are consistent with the log-returns results. We see very prominent peaks in the 1st eigenfunctions during the election period in both the years 2009 and 2014. The first eigenfunctions in case of volume have almost twice the explanatory strength than in case of log returns. The second eigenfunction is rising gradually upwards in the same time period. Similarly, in consistency with log returns results, the first eigenfunction for the year 2019 does not peak or behaves out of the ordinary during the elections. Whereas, the second eigenfunction peaks a little around the same time. The possible explanation for the same has been given when log-returns were discussed.

5.3 The third eigenfunction

The third eigenfunctions (Figure 6) explain nearly 10% of the variation in data for each year. It is not used in explaining the election effects because it did not seem to particularly absorb such effects. Rather, the third eigenfunction seems to be mimicking some other market trend. Figure 6 plots third eigenfunctions only for various elections and random non-election years. The plots in general move in a very periodic cycle of ups and downs for most of the years. This means periods of high and low importance in a business year repeating after periods of 10 to 15 weeks for most of the years. The reason for this may be attributed to some kind of cyclical trend in the financial markets.

6 Applications

The study of eigenfunctions came up as a useful tool to see how election sentiments of the economy and its constituents get absorbed in the stock market. The study was taken up for elections because it is a huge event in any country and is expected to cause significant distortions in the market. But the scope of the process and method explained goes much beyond it.

Analysis of functional principal components can be used to develop trading strategies based on market timing. Market timing is an investment or trading strategy in which a market participant attempts to beat the stock market by predicting its movements and buying and selling accordingly. The time periods where e_i is positive or e_i is negative play an important role in the interpretation of the behavior of stocks. If we approximate $X_i(t) \approx a_{i1}e_1(t)$ and in case of high a_{i1}, we can interpret the stock on an average as having high returns in time intervals where $e_1(t) > 0$ and vice versa. Similarly, the change of sign for the eigenfunction plays a key role in tracking the shock periods. Change from positive to negative helps to segregate stocks which were performing better in an earlier time period in comparison to the later time period.

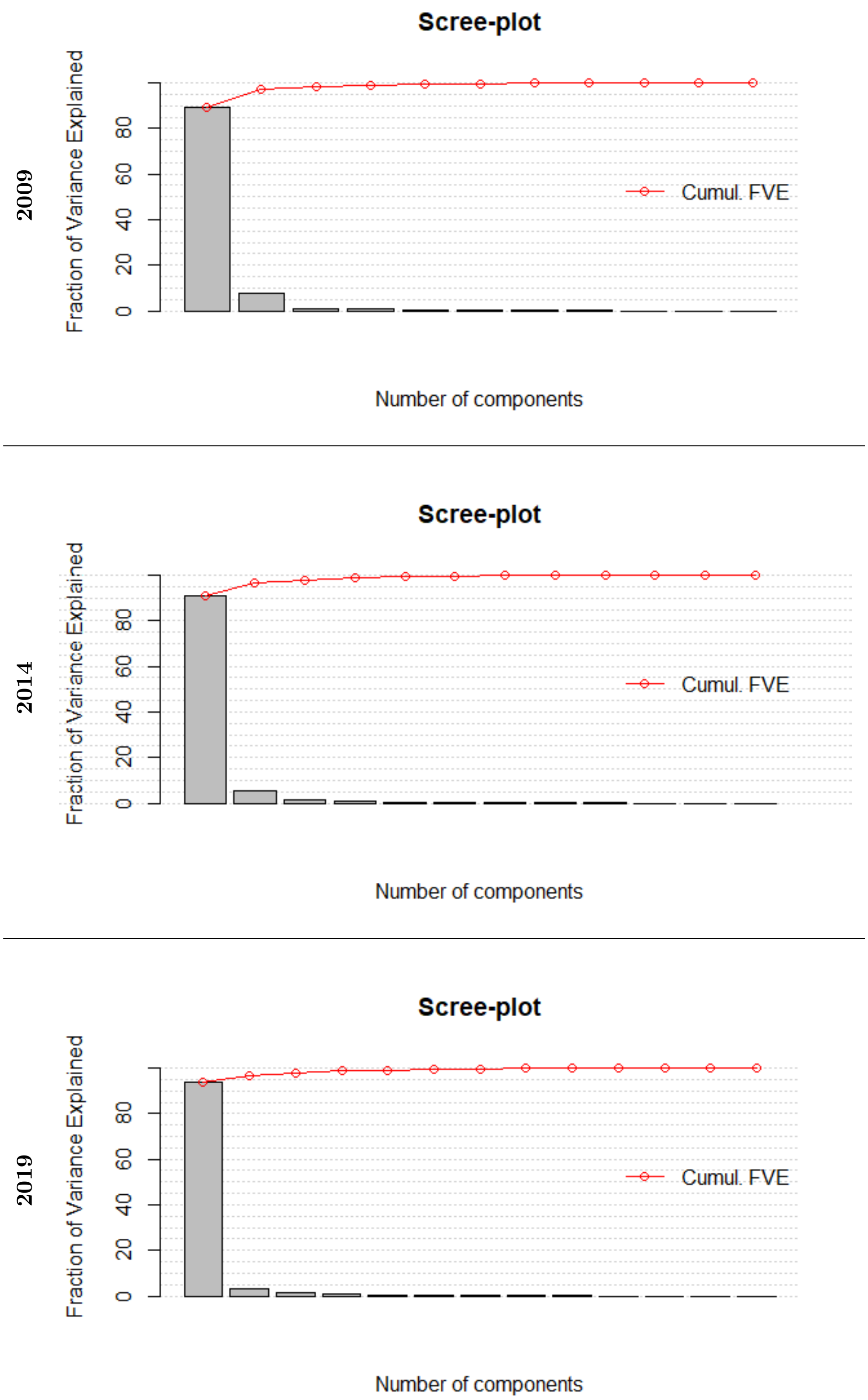

Figure 4: Volume scree plot of 2009, 2014, 2019 data respectively

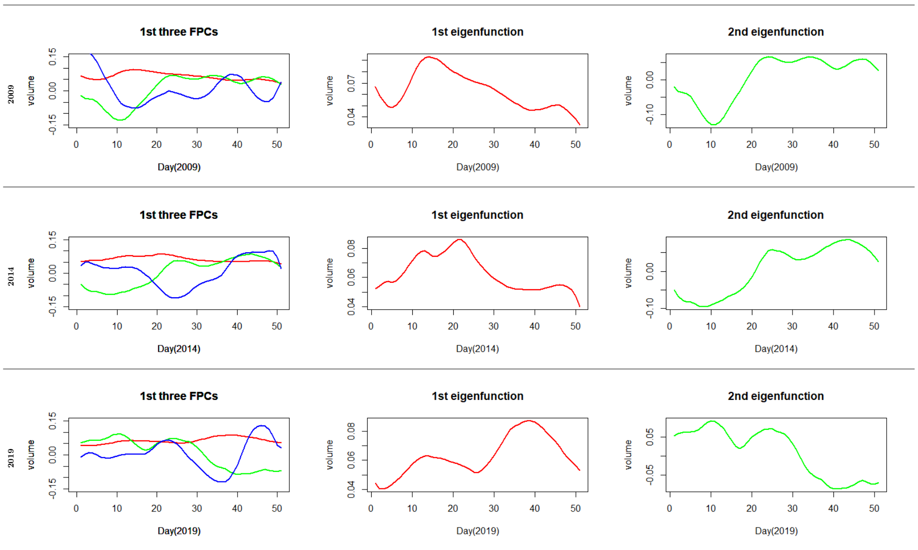

Figure 5: Functional principal components of volume
Note: 1st eigenfunction (Red), 2nd eigenfunction (Green) and 3rd eigenfunction (Blue)

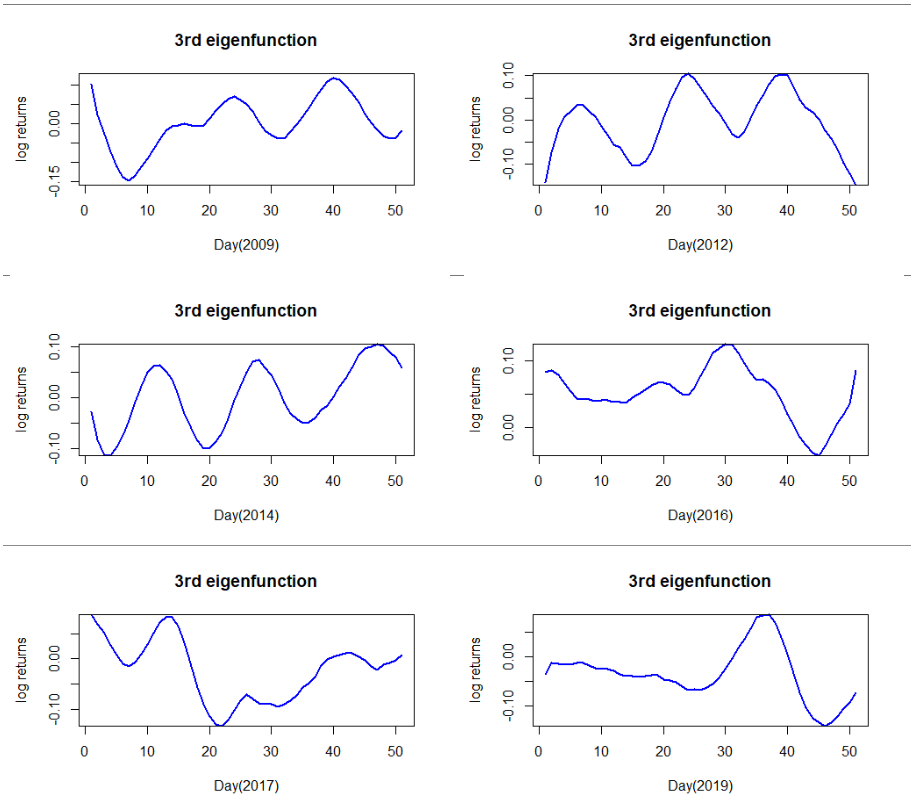

Figure 6: Cyclical trend in the third eigenfunction

This method can be used to identify and perceive how many other events affect or not affect the market and decide on the best strategies to exploit the market around these specific events. It may be used to observe treatment effects that a period had on any variable of interest. It may also point out towards business fluctuations and identify other trends in general affecting any variable of interest.

7 Conclusion

The paper is an attempt on exploring the applications of functional principal component analysis of the Indian Stock market for various years. We tried to point out at specific time periods that may be more crucial in explaining the movement of returns and volume of any stock throughout the year. Election years were chosen in particular because elections are huge events in democracies like India and are expected to have a significant impact on the financial markets. We were able to show that the FPCA method successfully captures these crucial time periods by taking a case of the election years of 2009, 2014 and 2019. All these three years were unique in their own ways because they respectively reflected the three states of complete confusion about the results, clarity about results with a change in the ruling party, and clarity about the results but no change in the ruling party. These are the three common broad situations that any democracy may face during elections. Through our analysis, we were able to show that the FPCA is able to capture the absorption of the election outcomes related sentiments for each of these years.

For the year 2009, when there was a lot of confusion and unclarity about the outcome of the elections a win for any party was expected to bring a big surprise to the people, economy, and the market. The first eigenfunction peaks during the election period and almost flattens out later. The second eigenfunction does not show much variation throughout. For the year 2014, change in the ruling party brought with itself loads of aspirations, hopes, and excitement for the people, market, and the economy. The first eigenfunction peaks again during the election period. For the year 2019, the ruling party was expected to come back to power again. One would not expect major distortions in the financial markets. The FPCA method captures it as the first eigenfunction appears to follow a general cyclical trend throughout the year and does not show any out of the ordinary movement during the election period for 2019. We repeated our analysis using both log returns and volume and obtained the same results. We are also able to capture some cyclical trends in the financial markets that do not seem to be affected by any exogenous distortions like elections.

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