How did Markets and Public Sentiment React During Demonetization? Study of a Significant Event in the Indian Economy

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Abstract

The present study aims to determine the impact of shock of demonetization which happened in November 2016 in India. It has been observed in literature that while the market moves due to unforeseen events, market movements are largely affected by news reports on such events. Considering these two threads and the association between them, the study follows mixed method research methodology and assesses the impact of demonetization on stock market movement through time series analysis and text analytics of news items generated during the period. This study examines, through time series analysis, the impact of demonetization as an unexpected event on stock market movement. Time series analysis evaluates the impact on overall stock market movements and on sectoral indices, liquidity shocks in the emerging Indian economy due to demonetization. This study integrates time series analysis with robustness tests and follows text analytics, news analytics and sentiment analytics to gauge public sentiment (influenced by media coverage) during the event. These evaluations validate negative movements in the market and most of the sectors due to the negative sentiment of people about demonetization.

JEL: C5, E4, E5, E6

Keywords: Demonetization, Market Volatility, Liquidity shock, Public Sentiments, Indian Economy, Event Study.

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Introduction

The behaviour of financial markets and the factors affecting the movements of the stock market have been subjects of significant academic research and business interest. As envisaged by Efficient market hypothesis, if markets follow a random walk, prediction of stock market movements becomes difficult as random walk theory postulates that markets reflect all past and future information available. The concept of random walk originated from the Efficient Market Hypothesis (EMH) proposed by (Fama, 1991) (Fama, Fisher, Jensen, & Roll, 1969) ; efficient markets reflect all information present in the public domain and therefore any fluctuation can only be due to new information or news not predicted by market participants (Nguyen & Shirai, 2015). Unexpected events are seen as those macro-economic events which possess the ability to influence volatility of markets but up to a limited extent only (Schwert, 1989). However, news and pieces of information arising out of the shocks provide signals to the market and media, financial analysts, or other third parties who in turn regularly provide signals about markets (Daniel & Titman, 2006) (Deephouse, 2000) (Rindova & Fombrun, 1998). Therefore, efficient markets also exhibit information efficiency by reflecting information in prices (Ball, 1989).

These arguments by previous studies in financial literature suggest that the movement of stock prices is not solely due to historical prices or fundamentals of markets, but largely information and news of an event unforeseen by market participants. Media reports on such events not only provide information to the market, but also influence sentiments of society which ultimately affect market movements (Nguyen & Shirai, 2015) (Guldiken, Tupper, Nair, & Yu, 2017). In the recent past, researchers have observed causal association between information and sentiments disseminated by social networking and micro-blogging sites (sources of information facilitating quick dissemination among masses) and functioning of financial markets (Juan, Marcos, & Ada, 2017). Though the influence may not be significant, yet it supports prediction of market movement along with external factors (Sprenger, Tumasjan, Sandner, & Welpe, 2014) (Zhang, Fuehres, & .Gloor, 2011) (Bissattini & Christodoulou, 2013) (Oliveira, Cortez, & Areal, 2013).

Efficient market hypothesis holds true in the case of developed markets. However, it is interesting to assess the impact of unforeseen events, news/information and sentiments of investors on market movements in emerging economies. A study in the Australian context by (Bilson, 2000) concluded that emerging stock markets were partially segmented from global stock markets. The study stressed the importance of local risk factors against global risk factors in making an impact on volatility of returns. (Bilson, 2000) The Demonetization of high denomination currency notes in India in 2016 could be seen as a shock to the economic system since it happened abruptly. Also, this was a local event specific to India with possible impacts everywhere in the economy.

The present study aims to determine the impact of shock of demonetization which happened in November 2016 in India. It has been observed in literature that while the market moves due to unforeseen events, market movements are largely affected by news reports on such events. Considering these two threads and the association between them, the study follows mixed method research methodology and assesses the impact of demonetization on stock market movement through time series analysis and text analytics of news items generated during the period.

Following seminal studies of (Brown & Warner, 1985) (Brown & Warner, 1985) (Schwert, 1989), the study follows event based methodology considering daily stock return, price movement and money supply to assess significant change in market volatility during times of shock to the market.

Observations and findings of event based methodology are further validated using textual analysis of news items during the event and sentiments aroused by news articles following natural language processing and using several different textual representations: Bag of Words, topic model analysis and bi-gram analysis (Guldiken *et al.*, 2017).

Theoretical Framework

To develop the theoretical framework, this study follows economic theories and arguments on interdependence of money supply, monetary policy and volatility in the stock market and how the same was observed during the event of demonetization with respect to demonetization in India. Validation of theoretical framework has been developed through efficient market theory of Fama, (1991) and media & signaling theory (Spence, 1973; Guldiken et al., 2017) to address the research question: *How media reports on demonetization affected market sentiment, and how media coverage tone influenced overall market volatility?*

Money Supply, Monetary Policy and Stock Market Movement

Economic theories support the contention that rising money supply influences demand and positively affects stock prices. Econometric studies in the context of US stock markets have established the impact of money supply on development of stock prices (Sirucek, 2012). An anticipated change in money supply may have a different impact than an unanticipated change in money supply. A study done in the context of the US concluded that both anticipated and unanticipated changes in money supply had positive impact on stock prices. The study argued that anticipated changes in money supply had more impact on stock prices than unanticipated changes (Maskay, 2007). Another study in the context of Nigerian stock markets found that unanticipated changes in money supply had a destabilizing impact on stock market returns. The same relationship was not found for anticipated changes in money supply (Aliyu, 2012).

Studies examining interdependence between stock markets and monetary policy have found significant relationships between the two. A structural VAR study of interdependence between US stock markets and US monetary policy found that real stock prices immediately fall by 7-9% due to a monetary policy shock that raised federal funds rate by 100 basis points (Bjørnland & Leitemo, 2009). Studying the relationship between monetary policy and stock prices is a difficult exercise as it suffers from identification difficulties. A study pointed out that there was a possibility that stock returns and monetary policy variables jointly reacted to some other macroeconomic variable (Rigobon & Sack, 2003). Demonetization as a sudden event might have had the kind of impact where both monetary policy variables and stock markets tried to adjust to the shock simultaneously. Routinely, when we hear of impulse response function of a conventional VAR study (as in the previous case), there is evidence of a delayed response of asset prices to monetary shocks. A recent paper by the European Central Bank says that delayed response is not in congruence with economic theory. The argument forwarded is based on the fact that asset prices factor in expectations, as a result, they reflect discounted expected payoffs (Alessi & Kerssenfischer, 2016). Thus, the event of demonetization in India is likely to show up its impact in the immediate period following the event.

In the class of VAR models looking at this relationship, a 2010 study in context of Canada and United States examined the impact of monetary policy shocks and their transmission to stock prices. The response to a shock has been understood in the context of immediate and dynamic, meaning that whether the shocks are in the same quarter and for how many quarters the shocks extend. In the case of the US, it was found that a 50 basis point shock in policy rate brought about a 1 percent drop in stock prices and the dynamic response continued for about a year and a half, bringing about an 8% drop in that period. For Canada, the numbers were zero (immediately) and about 1.5% in a period of 4 months (Li, Iscan,D., B., & Xu, 2010). It is noteworthy that even though US and Canada are neighboring countries, there was heterogeneity in responses. Whether this heterogeneity of responses is a pattern is a subject of a cross-country study. A cross country study of eight advanced economies found heterogeneity in stock price responses (Neri, 2004). In this study of G-7 Countries and Spain, the author found that a contractionary shock had negative and temporary effect on stock markets, yet there were significant cross-country differences when it came to timing, persistence and magnitude of these impacts. In terms of dynamic impact, the effect in these countries ranged from 2 to 12 months, achieving a highest drop of 3% in stock prices during the period.

The identification problem as envisaged by Sack and Rigobon (2015) found relevance in a 2015 study done again in the context of US stock markets. Initially, their focus was on observing the dynamic response of stock prices to an exogenous hike in interest rates. The results that the authors got defied economic logic as an interest rate increase shock led to a rise in stock prices. However, when the authors treated interest rate as an endogenous variable, they got consistent results as stock prices declined in response to the shock mentioned earlier. However, the authors found that the magnitude of the decline was just about 1% and lasted only 4 months (Galí & Gambetti, 2015).

As far as understanding the impact of an unanticipated event on equities is concerned, the approach adopted by Kuttner (2001) comes in handy. He suggested future funds rate as a measure of anticipated funds rate and any deviation therefrom became the surprise event. Using the aforementioned approach, Bernanke and Kenneth (2005) tried estimating the reaction of the equity market to surprise changes. They found that markets showed strong reaction to surprise changes in funds rate. In fact, their study (which was done in the context of the US markets) saw that a cut in funds rate by 25 basis points raised the market index by more than 1 percentage point (Bernanke & Kenneth N., 2005).

Demonetization and the Indian Stock Markets

The Prime Minister of India announced the scrapping of the old Rs 500 and Rs 1000 notes on 8th of November 2016 at midnight. These denominations of currency notes comprised around 86% of the total currency in circulation in India. The replacement of such a huge amount of liquidity required time and in the period that immediately followed the announcement of demonetization, the Indian economy struggled to adapt to the new situation. In 2015, a study entitled, “The Cost of Cash in India” mentioned that until 2012, 87 percent of the transactions in India were cash based

(Institute for Business in the Global Context, 2015). The report said, "*India's cash intensity also stands out in contrast to other developing countries. The value of notes and coins in circulation as a percentage of GDP in India is 12.04 per cent, compared to 3.93 percent in Brazil, 5.32 percent in Mexico and 3.72 percent in South Africa".* The study also highlighted the behavioural patterns that drive the demand for cash. It said, "*Most consumers see three main benefits of cash. Cash confers power on buyers, since they can offer fixed bids for a bundle of goods and services… Twothirds of the respondents appreciate that cash assures exact payment…We also find that cash only consumers know far less about credit cards."*

The event of demonetization gave a shock to the money supply in India. Studies on the Great Depression have linked the event to a more than required stringent monetary policy. Friedman and Schwartz studied the sharp contraction during 1929-1933 and observed a shift in the preference of investors from portfolios which were considered risky to non-risky assets like currency (Friedman & Schwartz, 1963). Many studies have documented the reasons for the Great Depression and in general recessionary shocks to the economy to a portfolio allocation shock that arise out of a contractionary monetary policy ((Eichengreen & Temin, 2000; Cole, Hal, & Ohanian., 2001; Christiano, Eichenbaum, & Evans, 2003). Given the important contribution of currency in the overall money supply in India, demonetization was akin to a monetary shock, and it was imperative that portfolio rebalancing activities be carried out by investors after such a shock. The impact of such rebalancing would be felt by stock markets in terms of movements in the index.

Methodology

The methodology tries to bring in the wisdom that quantitative analysis should be robustly supported by qualitative ones. In this regard, this work is a "quantitative dominant mixed method research" (Jhonson, Onwuegbuzie, & Turner, 2007). Jhonson, Onwuegbuzie, & Turner (2007) have defined the quantitative dominant mixed method research as the type "of mixed method research in which one relies on a quantitative, post positivist view of the research process, while concurrently recognizing that the addition of qualitative data and approaches are likely to benefit most research projects." This paper attempts to integrate the quantitative and the qualitative in a manner in which both support the enquiry process. Johnson, Grove, & Clarke (2017) have pointed out four common techniques of data integration in a mixed methods approach. We have made use of the very first approach enunciated by them viz. data transformation or conversion which involves transforming qualitative textual data into quantitative numerical data. The sentiment analysis that we have done relies on this approach. We have also made use of the fourth technique as suggested by them which is triangulation involving comparison of the two approaches. This triangulation is achieved by confirming the results of the quantitative analysis with the qualitative one.

Literature cited in this work emphasizes that anticipated and unanticipated monetary shocks may have different kinds of impact on equity markets. All studies cited above show that although there are negative responses to such contractionary shocks, yet the timing, persistence and magnitude of these responses differ across countries. In general, response persistence differs within a range of 2 to 12 months. Accordingly, we have considered a period of approximately 3 months or 90 trading days in the near middle of which lies the event of demonetization. The reason behind considering this time frame was to observe whether there were any changes in indices that could be termed structural breaks owing to the event of demonetization. In our understanding of the various sectoral indices, we observed that 'Real Estate, Media and IT sectors' suggested some kind of structural change post the event of demonetization. Accordingly, our first hypothesis is:

Hypothesis 1: There is a structural break in the index values of real estate, media and IT sector post the event of demonetization.

Studies cited in literature (Sirucek, 2012; Galí & Gambetti, 2015) have emphasized the impact of money supply on volatility of stock markets. The study by Sirucek (2012) looked at 25 years of past data to conclude that monetary aggregate was significantly associated with changes in market volume and volatility. As emphasized earlier, demonetization was akin to an unanticipated monetary shock and this study seeks to determine if the event had an impact on the volatility of stock markets in India.

Hypothesis 2: There was no impact on the volatility of stock market returns due to demonetization.

Hypothesis 3: Liquidity in the market has no impact on the stock index.

Since we are tracking daily stock index values, it is imperative that we look for a measure of daily liquidity to ensure adequate comparability. Therefore, we formed our third hypothesis on the basis of liquidity and its impact on the stock index.

Sample

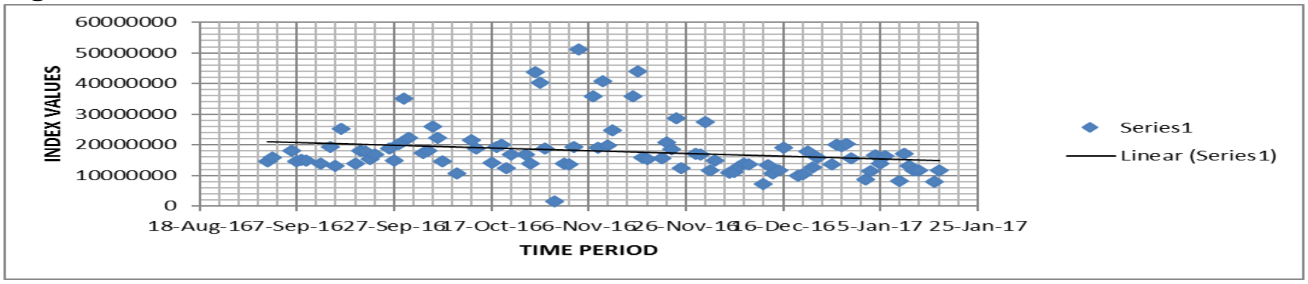
To gauge the impact of the event on various sectors' equity, we considered Nifty sectoral indices. We have looked at daily data for a period of approximately 90 days of trading from September 1, 2016 to January 1, 2017.

Data Analysis and Results

Hypothesis 1: There is a structural break in the index values of real estate, media and IT sector post the event of demonetization.

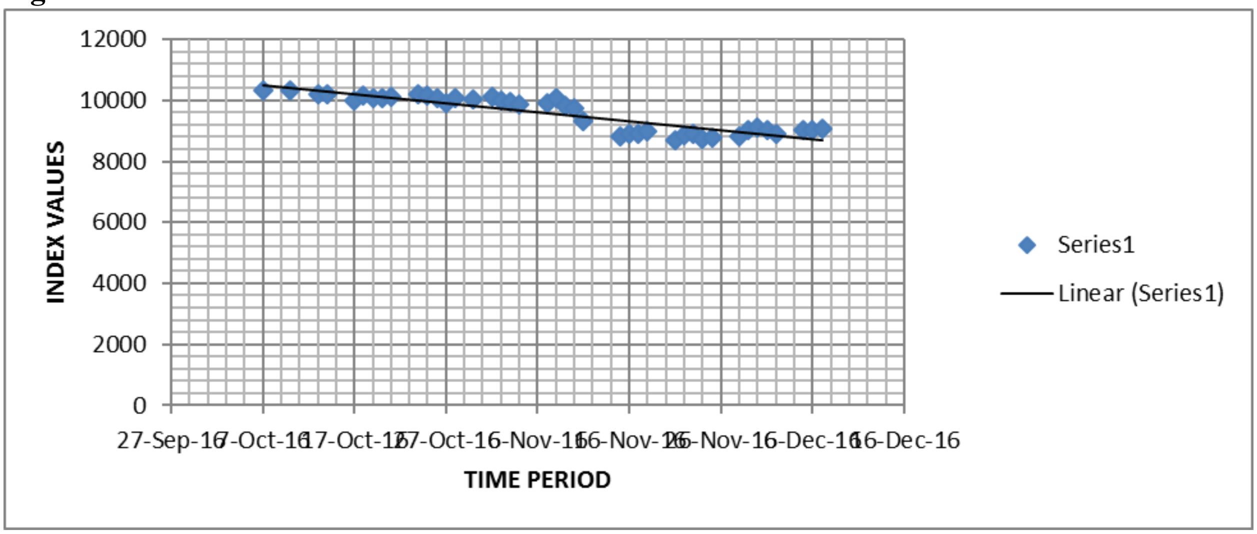
The reason why the hypothesis considers the aforementioned three sectors only is because of the clear break in trend which is visible in their plots. The daily closing index values have been plotted against time across various sectors to identify patterns, make comparisons between predemonetization and post demonetization time periods, and test the first hypothesis. The plots are shown in figures 1 to 10.

Fig 1: NIFTY FMCG INDEX

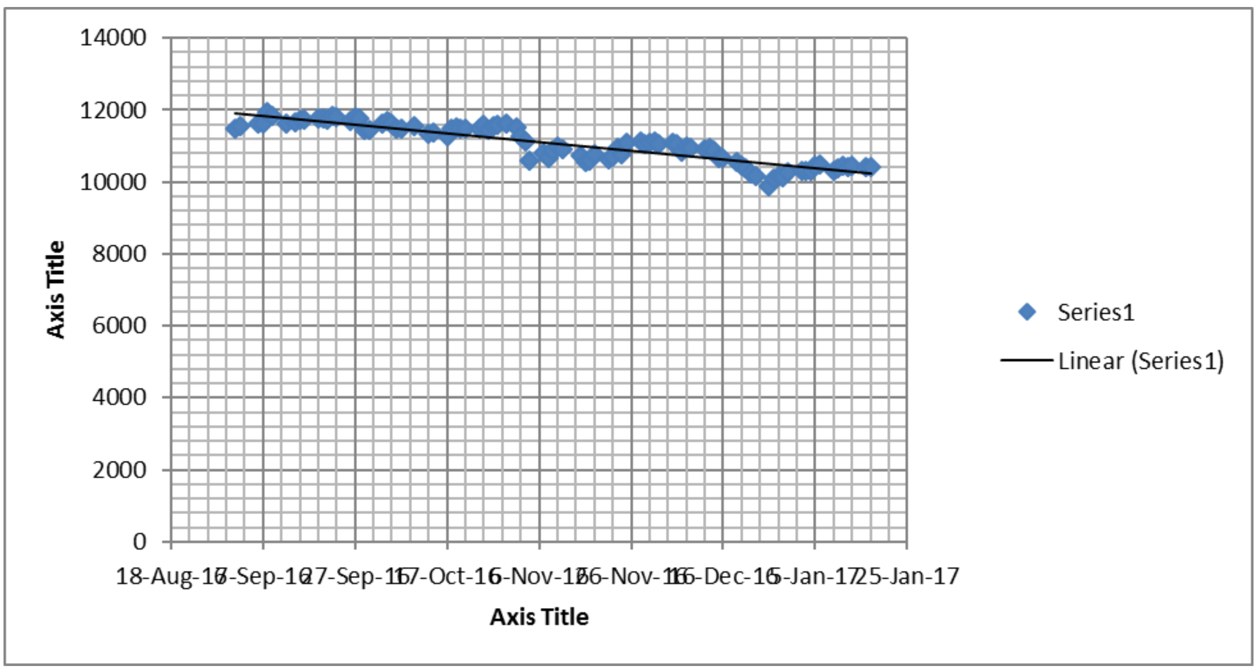


Source-Niftyindices.com

Fig 2: NIFTY AUTO INDEX

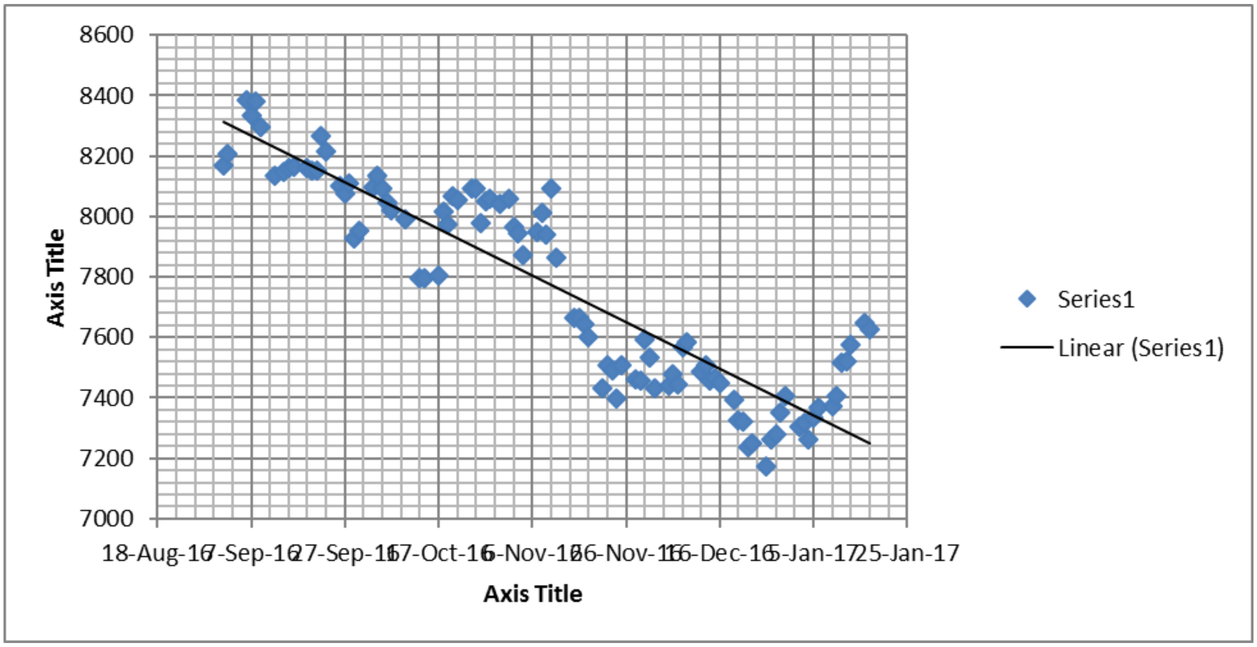


Source-Niftyindices.com Fig 3: NIFTY PHARMA INDEX



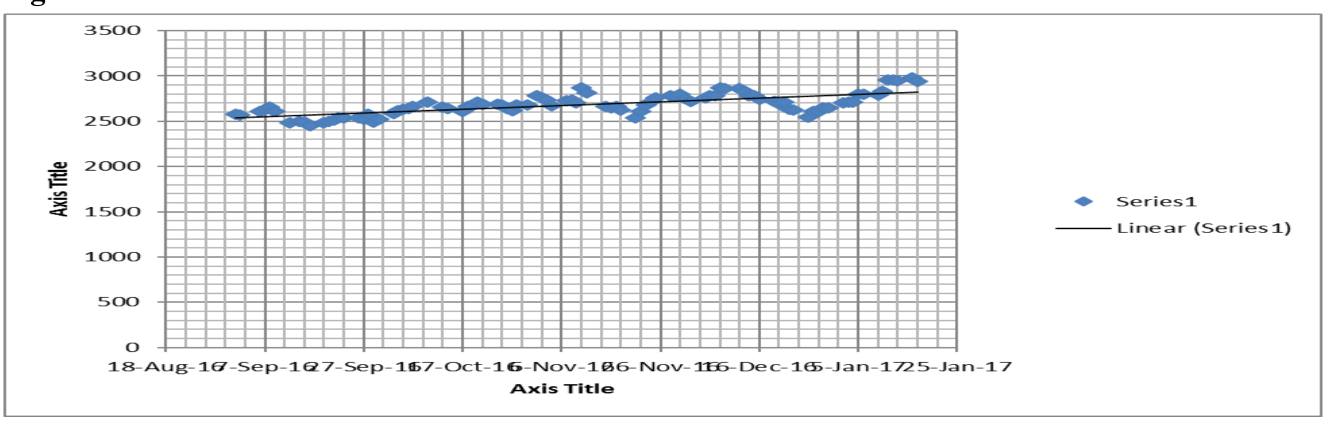
Source-Niftyindices.com

Fig 4: NIFTY FINANCIAL SERVICES INDEX



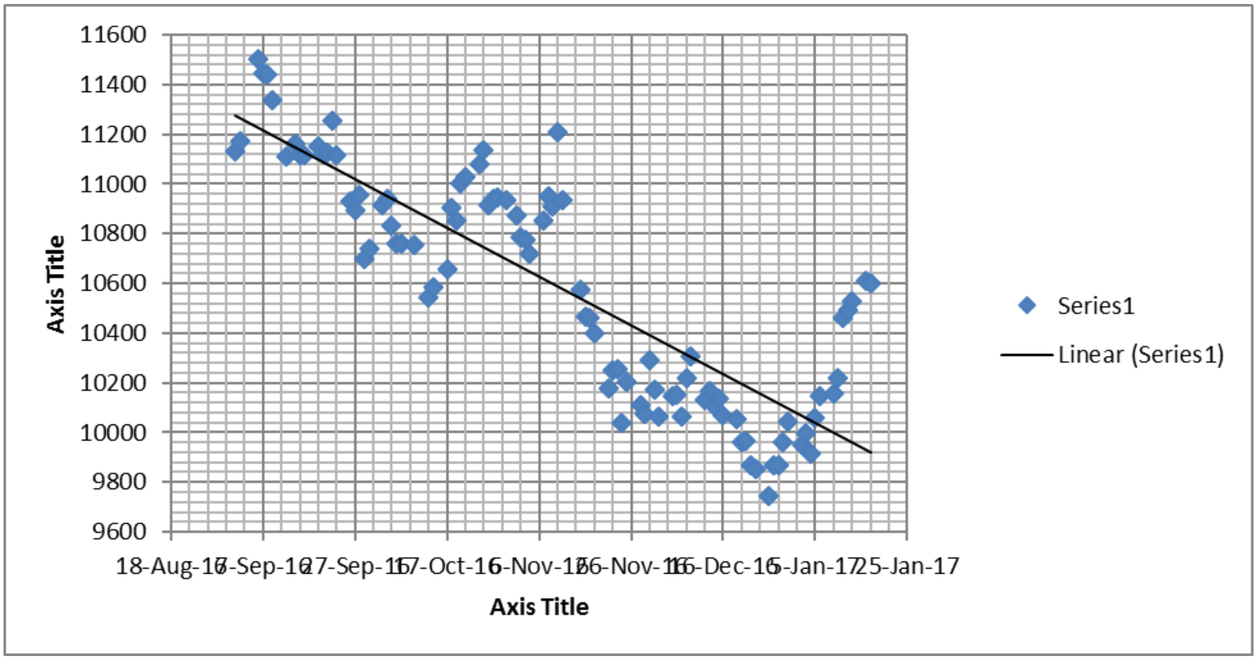
Source-Niftyindices.com

Fig 5: NIFTY METAL INDEX



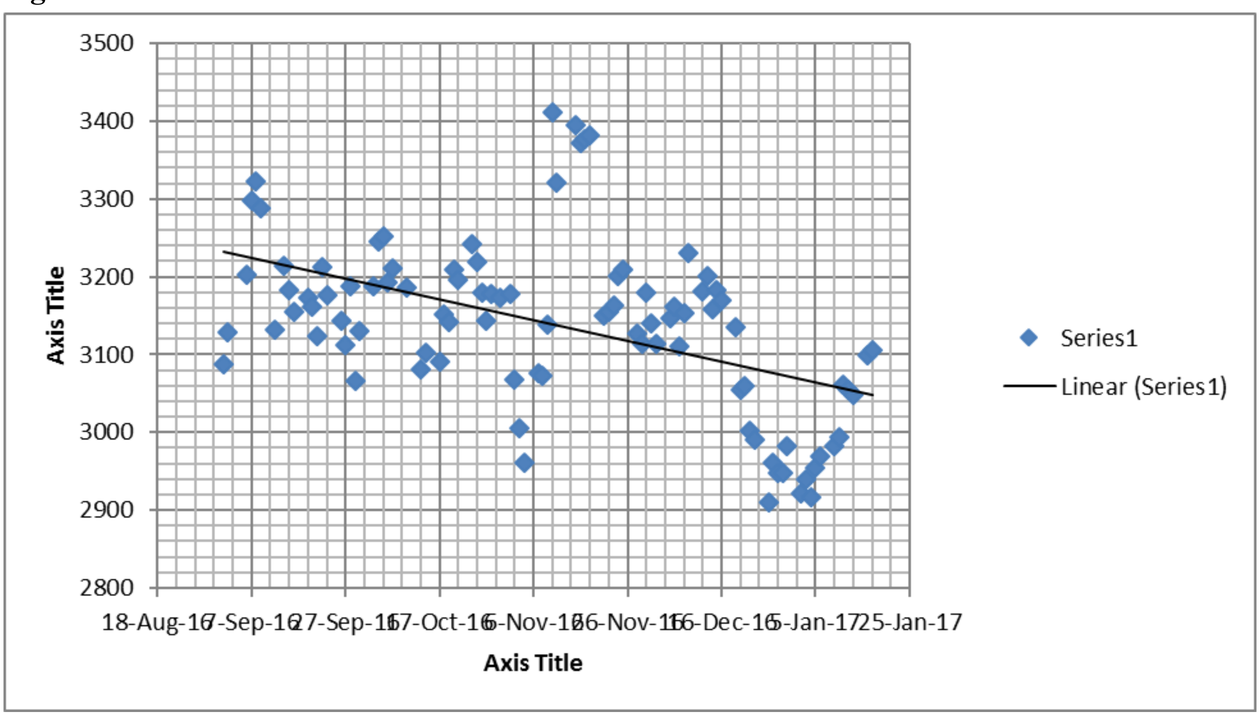
Source-Niftyindices.com

Fig 6: NIFTY PRIVATE BANKS INDEX



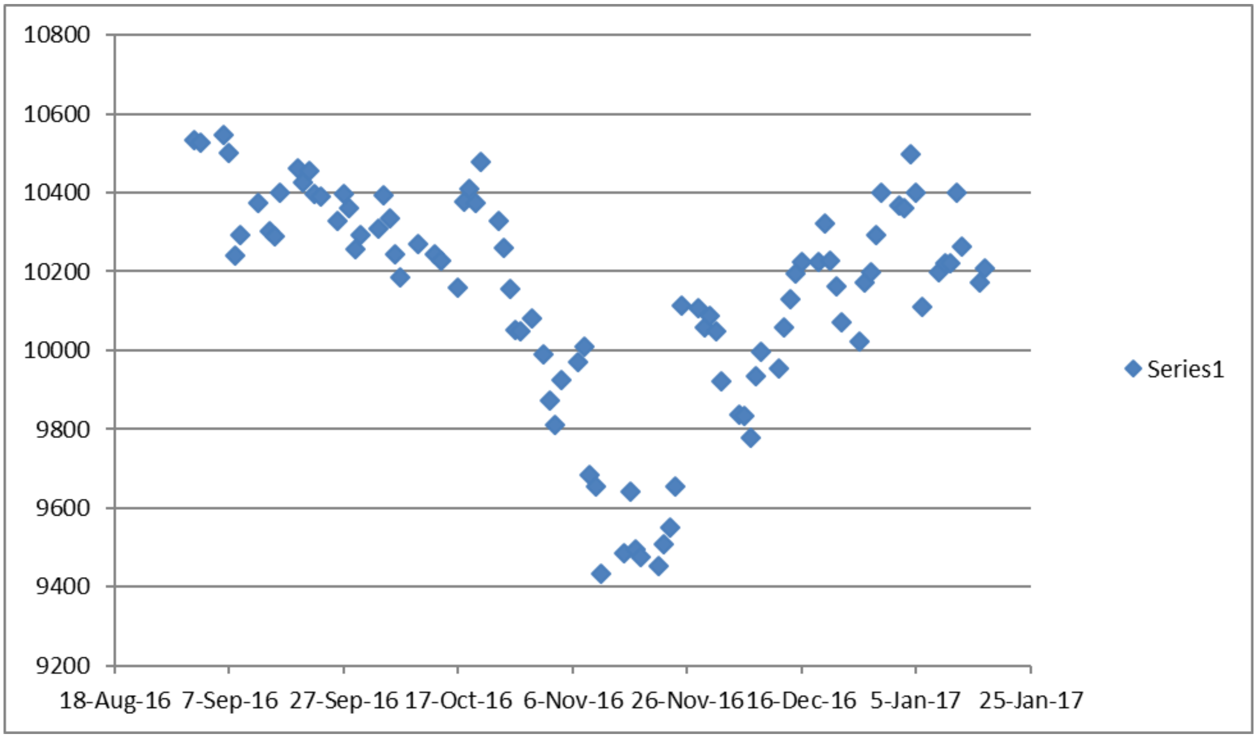
Source-Niftyindices.com

Fig 7: NIFTY PUBLIC SECTOR BANKS INDEX



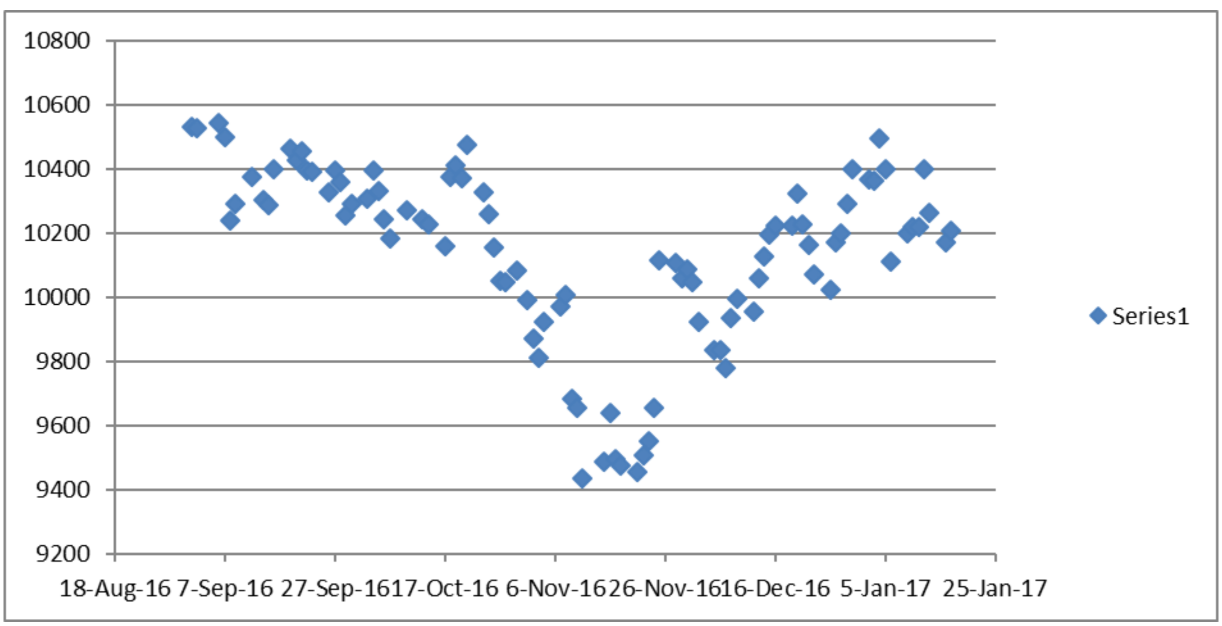
Source-Niftyindices.com

Fig 8: NIFTY IT SECTOR INDEX



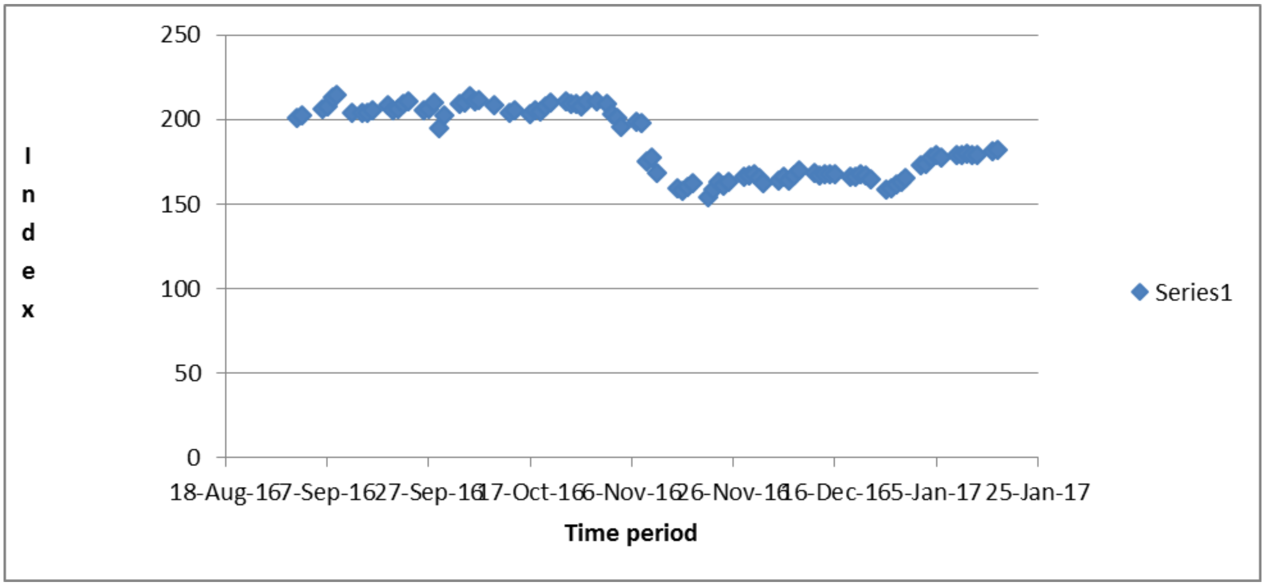
Source-Niftyindices.com

Fig 9: NIFTY MEDIA SECTOR INDEX



Source-Niftyindices.com

Fig 10: NIFTY REAL ESTATE SECTOR INDEX



Source-Niftyindices.com

Looking at the daily closing index values of two indices, namely Nifty Pharma Index and Nifty Auto Index, it can be observed that there has been a secular decline in index values between the pre-demonetization phase and the post demonetization phase. These two sectoral indices indicate that the event of demonetization has hardly had any impact on the portfolio rebalancing or the equities of these two sectors.

The metal index of NIFTY, however, shows a rising trend pre and post demonetization. A slight increase in volatility post demonetization may be observed. Nifty FMCG Index shows an overall downward trend in both periods which is indicative of the fact that the trend did not get disturbed due to the event of demonetization. However, there seems to be an increase in volatility around the dates of demonetization. Similar observations are made for indices of financial services, private banks and public sector banks (see figures).

Two sectoral indices, namely the media index and the IT index showed a reversal of trend pre and post demonetization. Both indices started rising post demonetization, however, this rise in both cases was accompanied by rising volatility.

Only the real estate sector index showed a break from its trend line in terms of continuing the downward spiral with the trend moving to a different line with a lower intercept.

In order to determine the possibility of a structural break in the trend of index values in the aforementioned sectors, we make use of the fact that the index values move along a trend in the period under consideration across all sectors. If indeed there is a break in the trend, the index values are having a relationship vis-à-vis time and a structural break would show us significant change in this relationship. We employ the Chow test (Chow, 1960) to ascertain the structural breaks in trend and whether these breaks are statistically significant. We do this by ascertaining the trend for the whole period first, i.e. from 1st September to 17th January, and then we look at trends for the two sub-periods, i.e. the period from 1st September 2016 to 8th November 2016 and then from 9th November 2016 to 17th January 2017. For the same set of data, we have calculated the Chow F values for all sectoral indices values as mentioned in the table1.

Table 1: Chow test results

INDEX	F Value
Real Estate Nifty Index	240.3069 (.00000)
FMCG Nifty Index	8.786 (.00032)
Auto Nifty Index	140.457 (.00000)
PSU Bank Nifty Index	28.145 (.00000)
Private Banks Nifty Index	7.092 (.00138)
Pharma Nifty Index	2.14 (.12294)
Metal Nifty Index	2.061 (.13323)
Media Nifty Index	118 (.00000)
IT Nifty Index	118.008 (.00000)
Financial Services Nifty Index	13.652 (.00000)

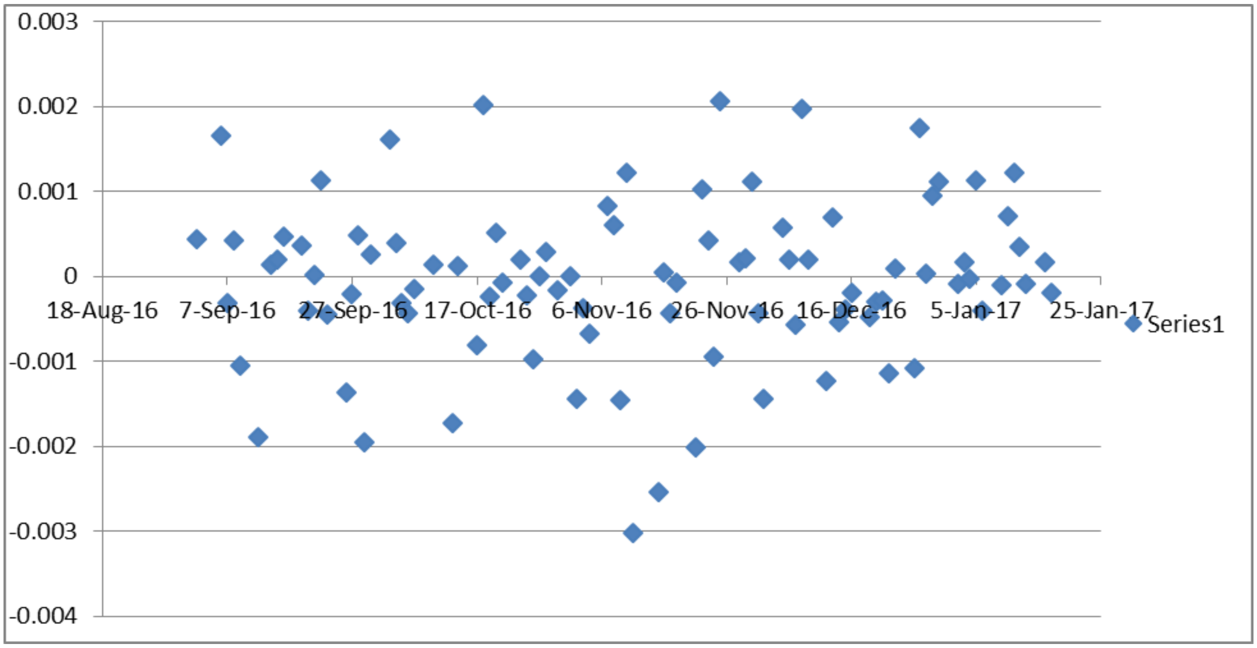
Source- Authors' own calculation

The Chow test results clearly show that eight out of the ten sectors studied underwent a structural break post demonetization. All other sectors (except metal and pharmaceuticals where the trend before the event continued even after the event) saw a new trend emerging while breaking away from the earlier trend. Media and IT sectors not only saw a structural break, but also a reversal of trend post event. Real estate - which did not show any specific trend before demonetization - showed a specific trend post demonetization. Indian equity markets have reacted to demonetization as reflected in the index values in most of the sectors considered.

Hypothesis 2: There is no impact of demonetization on volatility of stock market returns.

In order to explore hypothesis 2, we have considered Nifty index daily returns from 1st September 2016 to 17th September 2017. A plot of returns during the considered period tells us that there may be some changes in volatility in the immediate aftermath of demonetization. As shown in Figure 11, the daily returns seem to be spread everywhere pointing towards increased volatility in the index returns. We divide the period into pre-demonetization (1st September 2016 to 8th November 2016) and post demonetization (9th November 2016 to 17th January 2017) and assess the volatility of the stock market returns in these two periods. For this purpose, we have considered logarithmic returns and estimated the standard deviation of this daily return. The same number is multiplied by the square root of the number of trading days in a year to determine annual volatility. This procedure gave us volatility of 8.6% per annum pre-demonetization and 11.4% per annum post demonetization period. There seems to be a significant shift in volatility post demonetization.

Fig 11: RETURNS: NIFTY INDEX



Source- NSE

In order to assess whether change in volatility of stock index returns is statistically significant, we made use of the Threshold GARCH method (Bollerslev, 1986; Glosten, Jagannathan, & Runkle, 1993). This will provide an insight into volatility changes that may have happened post demonetization. Our earlier analysis of trend of stock price index shows that predominantly, the impact has been negative overall and across most sectors. A TGARCH approach would help us identify whether the negative impact was significant.

It was important to first understand whether there were ARCH effects in the data on stock index returns. An ARCH test done in this regard gave us the following statistics:

As can be seen by the results of Table 2, the ARCH LM statistic is not significant, specifying the fact that there are ARCH effects present in the data. After this confirmation, we conducted a Threshold GARCH, the results of which are shown in Table 3. As can be seen, all coefficients of the variance equation turn out to be significant. The coefficient RESID(-1)^2*RESID(-1)<0, is positive and significant (p=0.0035). This tells us that volatility was significantly affected due to negative shock. The results of the diagnostic tests are given in Table 4 and Figure 12. Diagnostics establish that the data do not have any serial autocorrelation and the residuals are normally distributed. Earlier, we had seen that the standard deviation of logarithmic returns pre and post demonetization was 8.6% and 11.4% respectively. The above GARCH results confirm that this rise in volatility was statistically significant.

Hence, we reject our hypothesis that there has been no change in volatility post demonetization.

Table 2: Test for Arch Effect

Heteroskedasticity Test: ARCH				
F-statistic	1.473407	Prob. F(1,90)		0.228
Obs*R-squared	1.481889	Prob. Chi-Square(1		0.2235
Test Equation:				
Dependent Variable: RESID^2				
Method: Least Squares				
Included observations: 92 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.48E-05	1.50E-05	4.319835	0
RESID^2(-1)	0.127021	0.104644	1.21384	0.228
R-squared	0.016107	Mean dependent v		7.43E-05
Adjusted R-squared	0.005175	S.D. dependent va		r 0.000123
S.E. of regression	0.000123	Akaike info criteri		ɔ -15.1483
Sum squared resid	1.36E-06	Schwarz criterion		-15.0935
Log likelihood	698.8203	Hannan-Quinn crit		e -15.1261
F-statistic	1.473407	Durbin-Watson sta		1.949693
Prob(F-statistic)	0.227985			

Source- Authors' own calculation Table 3: MLARCH

Dependent Variable: NIFTY_RETURNS					
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)					
Sample: 1 93					
Included observations: 93					
Convergence achieved after 36 iterations					
Coefficient covariance computed using outer product of gradients					
Presample variance: backcast (parameter = 0.7)					
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +					

C(5)*GARCH(-1)						
Variable	Coefficien	Std. Error	z-Statistic	Prob.		
C	0.000327	0.000655	0.499628	0.6173		
	Variance Equation					
C	3.00E-05	1.19E-05	2.519814	0.0117		
RESID(-1)^	-0.27563	0.083897	-3.28529	0.001		
RESID(-1)^	0.380297	0.130315	2.918286	0.0035		
GARCH(-1	) 0.648555	0.173614	3.735609	0.0002		
R-squared	-0.00866	Mean dependent v		-0.00047		
Adjusted	R -0.00866	S.D. dependent va		r 0.008629		
S.E. of reg	r 0.008667	Akaike info criteri		) -6.68827		
Sum squa	0.00691	Schwarz criterion		-6.55211		
Log likelih	316.0045	Hannan-Quinn crit		e -6.63329		
Durbin-W	a 2.098693					

Source- Authors' own calculation

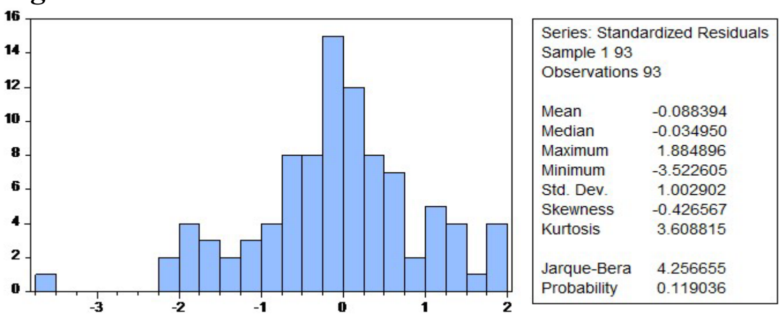
Table 4: Diagnostics for TGARCH

Sample: 1 93						
Included observations: 93						
Autocorre	Partial Correlation		AC	PAC	Q-Stat	Prob*
. |* |	. |* |	1	0.085	0.085	0.7018	0.402
. |. |	. |. |	2	0.001	-0.006	0.7019	0.704
. |. |	. |. |	3	-0.041	-0.041	0.8686	0.833
. |. |	. |. |	4	-0.038	-0.031	1.0138	0.908
. |. |	. |. |	5	0.041	0.047	1.1806	0.947

.*|. |	.*|. |	6	-0.09	-0.1	2.0017	0.92
. |. |	. |. |	7	-0.059	-0.046	2.3569	0.937
. |. |	. |. |	8	-0.005	0.006	2.36	0.968
. |* |	. |* |	9	0.077	0.074	2.9807	0.965
.*|. |	.*|. |	10	-0.1	-0.13	4.043	0.945
. |. |	. |. |	11	0.006	0.032	4.0465	0.969
. |. |	. |. |	12	0.033	0.035	4.1649	0.98
. |. |	. |. |	13	-0.005	-0.026	4.1682	0.989
. |. |	. |. |	14	0.066	0.05	4.6533	0.99
.*|. |	.*|. |	15	-0.114	-0.098	6.1363	0.977
. |. |	. |. |	16	-0.034	-0.028	6.2689	0.985
. |. |	. |. |	17	-0.055	-0.061	6.625	0.988
. |* |	. |* |	18	0.146	0.168	9.151	0.956
. |. |	. |. |	19	0.031	-0.001	9.2655	0.969
. |* |	. |* |	20	0.127	0.132	11.225	0.94
. |. |	. |. |	21	0.049	0.018	11.516	0.952
. |. |	. |. |	22	-0.028	-0.021	11.616	0.965
.*|. |	.*|. |	23	-0.117	-0.165	13.345	0.944
.*|. |	. |. |	24	-0.086	0.005	14.288	0.94
.*|. |	.*|. |	25	-0.104	-0.127	15.692	0.924
.*|. |	.*|. |	26	-0.108	-0.085	17.233	0.902
. |. |	. |. |	27	0.031	0.039	17.361	0.922
.*|. |	. |. |	28	-0.078	-0.057	18.192	0.921
. |. |	. |. |	29	0.057	0.041	18.639	0.93
. |. |	. |. |	30	0.043	0.024	18.901	0.942
.*|. |	.*|. |	31	-0.08	-0.087	19.805	0.94
. |. |	.*|. |	32	0.003	-0.067	19.807	0.955
. |. |	. |. |	33	0.012	0.044	19.828	0.966
. |. |	. |. |	34	0.026	-0.001	19.933	0.974
.*|. |	.*|. |	35	-0.096	-0.082	21.349	0.966
.*|. |	.*|. |	36	-0.112	-0.116	23.286	0.95

Source- Authors' own calculation

Fig 12: Distribution of residuals for TGARCH



Source- Authors' own calculation

Hypothesis 3: The liquidity in the market has no impact on the stock index.

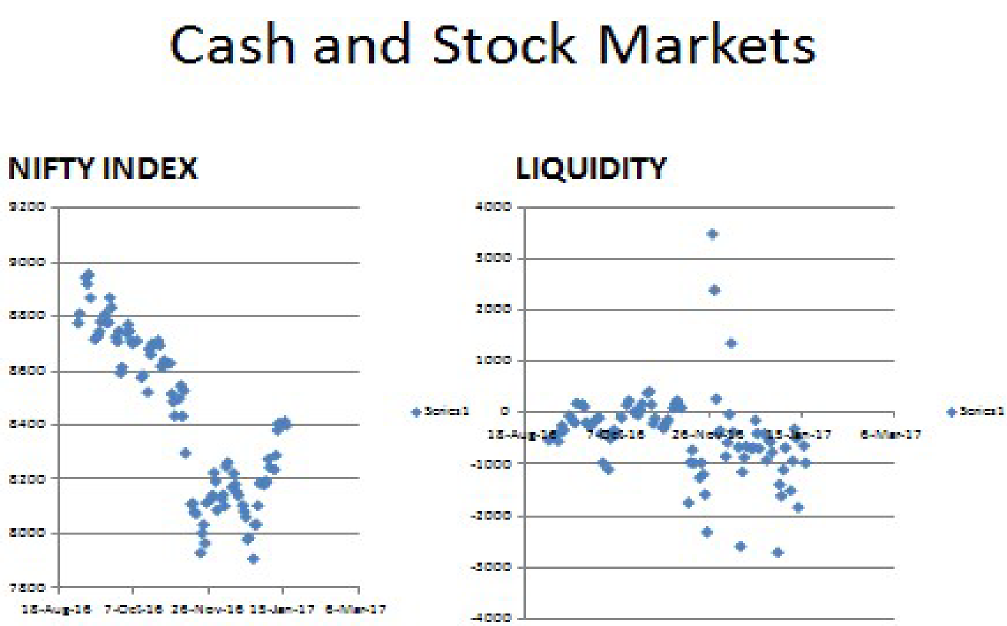
For this purpose, we looked at injection and withdrawal of liquidity in the money market through the liquidity adjustment facility of the Reserve Bank of India. We considered the same period as before and looked at daily characteristics before and after demonetization. Hence, our data ranges from 1st of September 2016 to 17th January 2017. We removed data worth two days from this series because while the LAF (Liquidity Adjustment Facility) was functional on those days, the stock markets were closed. This has ensured daily correspondence, i.e., we have data of daily stock returns as well as daily liquidity data. A look at index returns during this period and the liquidity correspondingly reveals some amount of coincidence. In order to establish any coincidence between the two, we need to check whether stock market returns are caused by liquidity in the market. For this purpose, we use the Granger causality technique (Granger, 1969). In conformity to this technique, we have established that the data for stock index values are stationary at the first difference levels. Since we are considering stock index returns, it is automatically established that the return series is stationary. Unit root test was conducted on the stock index data to arrive at the aforementioned conclusion. Adopting a similar approach for testing unit root for data series on liquidity, we found that the data were stationary at the level and did not require going for differencing. After having established that both data series are stationary, we checked the Granger causality between them. We found that at the 12th lag, liquidity Granger caused stock index returns. The results of the test are given in Table 5 (see also Figure 13).

Table 5: Causality Test

Pairwise Granger Causality Tests			
Sample: 1 93			
Lags: 12			
Null Hypothesis:	Obs	F-Statistic	Prob.
RETURNS does not Granger Cause LIQUIDITY	81	0.89057	0.5613
LIQUIDITY does not Granger Cause RETURNS		2.17543	0.0257

Source- Authors' own calculation

Fig 13: Stock Market and Cash Market Distribution



Source- NSE and RBI

In light of aforementioned results, we reject our third hypothesis that liquidity does not cause stock returns. We also found that it is not true vice versa i.e., stock returns doe not cause liquidity, both of which confirms with the theory and common understanding. It may thus be concluded that demonetization had a significant impact on stock index returns.

Robustness Test

The study conducts a number of post hoc tests to ascertain the results through the methods of sentiment and text analytics. We use news analytics to gauge the impact of news and media on sentiments and its overall impact on stock market. It is well established in the literature that information and availability of information plays a crucial role in the determination of stock price movements and therefore in the case of such unexpected events(demonetization), it is necessary to capture this aspect too.

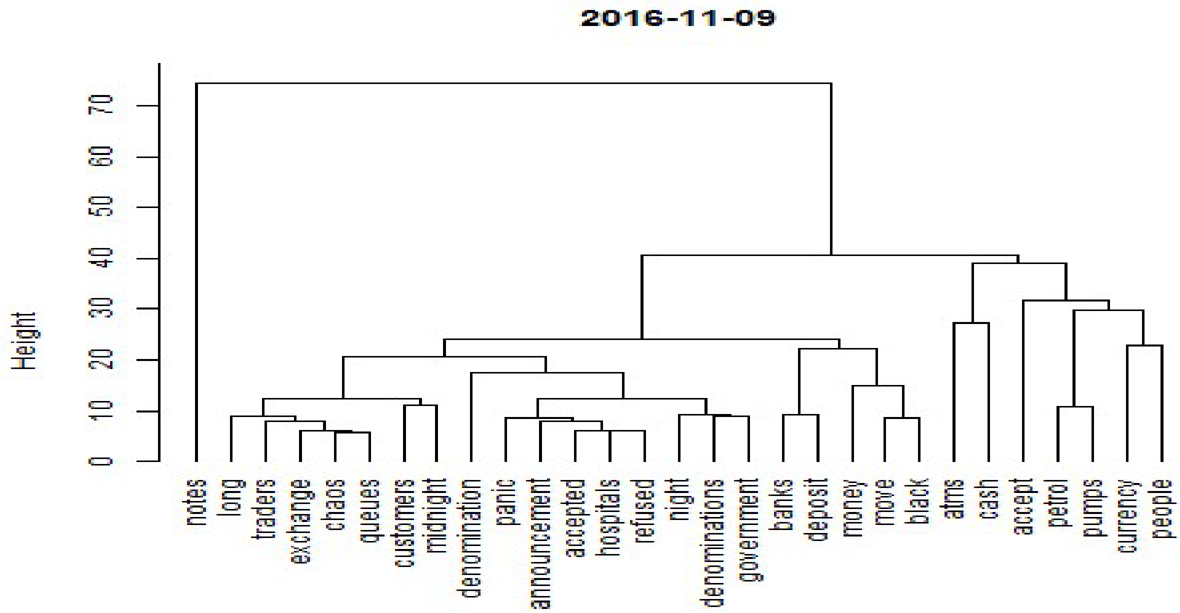
To assess the impact of news items on public sentiment during the demonetization phase, we collected news articles published in leading English newspapers in India. Demonetization was announced late in the evening on 8th Nov 2016, therefore, we collected news articles from 9th Nov 2016 to 25th Jan 2017 (frequency of news articles on demonetization reduced significantly after 25th Jan 2017). News articles were collected using web scraping effort. We collected and analyzed 510 published news items during the mentioned period. We removed stop words from our analysis. Then we followed natural language processing to identify bag-of-words from the title and content of the news article. Initial screening of news articles resulted in word clouds and dendograms using k-means cluster analysis. These word clouds and dendograms provided insights into variety of words, frequency of words followed and clustering of those words with one another. Figure 14 exhibits word cloud based on the evaluation of news articles circulated on 9th Nov 2016.

Fig 14: Word Cloud 2016-11-09

Source- Authors' own calculation using R

Fig 15: Dendogram of News Articles

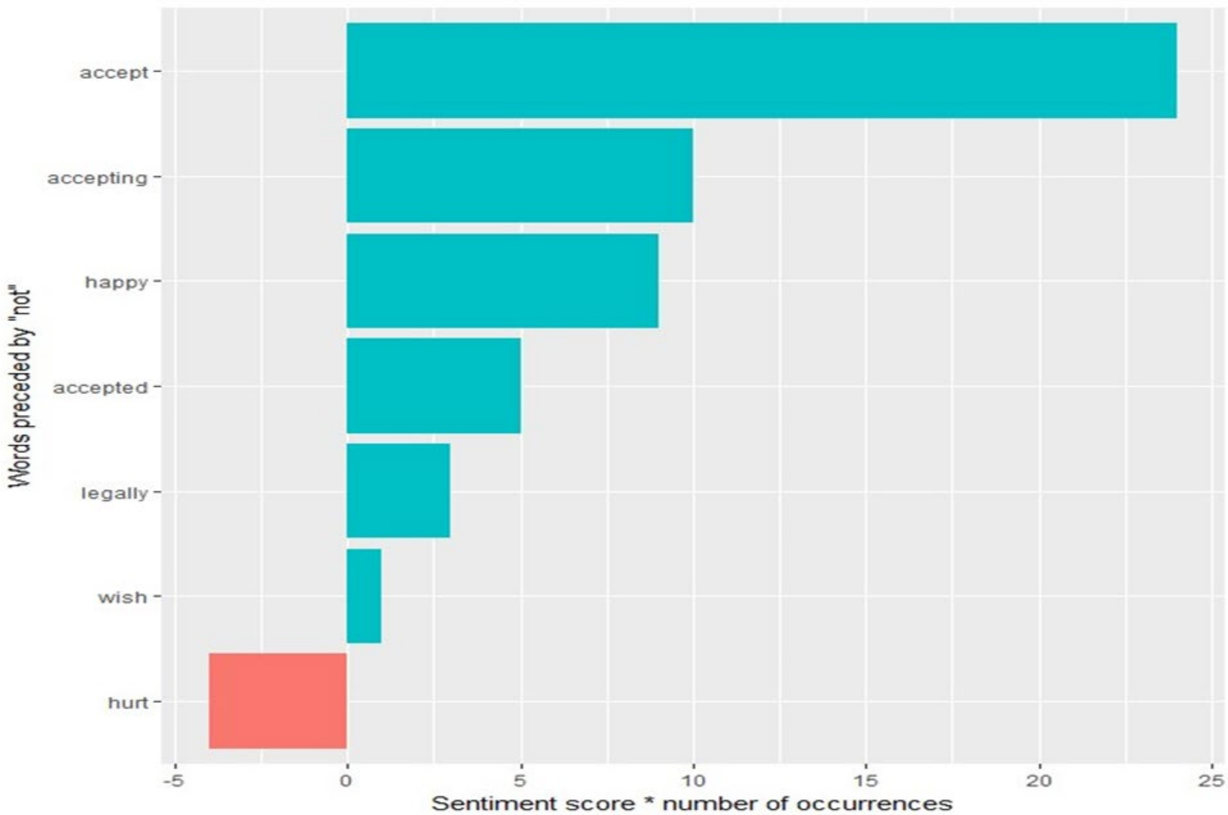
Source- Authors' own calculation using R



This word cloud represents reaction of media on the announcement of demonetization. Figure 15 exhibits dendogram based on k-mean clustering of words. The word cloud and dendogram exhibit certain negative words such as "panic", "chaos", "refused", and "queues".

However, these analyses provide only an overview of the scenario. To understand the deeper meaning of text analytics, we conducted sentiment analysis of news articles. Sentiment analysis is done by analyzing frequency of words preceded by 'not'. Results of sentiment analysis are presented in Figure 16.

Fig 16: Sentiment Analysis



Source- Authors' own calculation using R

Preliminary analysis of 510 news articles through bag-of-words, word cloud and cluster analysis indicate high frequency of negative words and negative media coverage of the announcement which led to overall negative sentiment of the general public. Overall text analytics exhibit a distressed tone of the media coverage which affected the sentiment of the public at large and may have resulted in structural breakdowns in price and liquidity movements of the market.

Conclusion

This study analyses the impact of demonetization as an unexpected shock on the Indian stock market and examines, through news analytics, how public sentiments were moved during the event. This paper presents a novel method to integrate time series analysis of an event and sentiments through media coverage.

The contribution of this study can be summarized as follows: First, it examines, through time series analysis, the impact of demonetization as an unexpected event on stock market movement. Time series analysis evaluates the impact on overall stock market movements and on sectoral indices, liquidity shocks in the emerging Indian economy due to demonetization. Second, this study integrates time series analysis with robustness tests and follows text analytics, news analytics and sentiment analytics to gauge public sentiment (influenced by media coverage) during the event. These evaluations validate negative movements in the market and most of the sectors due to the negative sentiment of people about demonetization.

A limitation of this research is that it assesses market movements during the demonetization event, however, stock market movements are affected by many factors and it is difficult to explicitly gauge market movements solely ascribed to demonetization. To overcome this limitation, future research may follow multiple phases of announcement of events with greater frequency. Researchers may also track price movements day-wise and associate them with the timing of announcement of event and the reaction time of investors.

The study only gauged the direction of public sentiment (negative or positive) and stock market movements (up or down). However, market makers and investors would prefer to understand the degree of movement of the stock market. Future studies may evaluate the degree of association between sentiments during event and market movement on daily data of market. Another limitation of this study is that only historical price movements and public sentiment driven by news articles were considered for analysis. Future research may aim to integrate more channels of investor sentiment such as social media and other macro-economic factors.

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