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Return and Volatility Spillovers: An Evaluation of India's Demonetization Policy

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Abstract

We investigate the evolution of dynamic interactions among five major financial assets in the Indian economy, which its recent demonetization policy tried to influence. *Spillovers* account for more than 25 percent of the forecast error variance in all the five markets. In terms of total *spillovers*, the banking and the real estate sectors matter the most for the Indian economy. Gold market is responsible for the highest net volatility *spillovers* to other markets. *Spillovers* show major trends and cycles in their time series plots. The US economy transmits shocks directly to the key sectors of the Indian economy and via the gold and the foreign exchange markets. The events such as the election of the National Democratic Alliance government in India and the Indian government's demonetization exercise were contemporaneous to some of the major episodes of return and volatility *spillovers* in the analyzed assets. India's demonetization policy seems to have increased the importance of the IT sector for gold and banking sector volatility shock transmission.

Keywords: demonetization; return; volatility; spillover; asset
JEL: C32; G12; G17

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1. Introduction

The Indian economy is an interesting mix of contradictions. India, with a strongly regulated banking system is considered to be more bank-dependent than market-dependent when it comes to financing[1]. Yet, around 41 percent of its population is still without access to bank accounts[2], thereby deprived of interest-earning deposits. A large population of underbanked and unbanked also makes India rank among the top economies in terms of cash-GDP ratio[3]. Information Technology (IT) and IT Enabled Services is singularly the most important contributor to India's services exports[4]. Moreover, India is also among the top two importers of gold, which is often referred to as a 'barbarous relic.' For the last 10 years, India's gold imports averaged around 8 percent of total imports[5]. For a country with a population of 1.3 billion, India, is expected to have a high demand for residential and commercial real estate. It is estimated that there is an urban housing shortage of around 19.5 million units in India[6]. Yet, top Indian cities are estimated to have seven lakh[7] units of housing stock[8].

Many narratives have been put forward to explain such stark contradictions in the Indian economy, with some being used as prime motive for policy measures. One such instance was on November 8th, 2016 when the Government of India decided to demonetize the INR 500 and INR 1000 denominated notes citing a narrative that tax evasion and money laundering fuels India's love affair with cash, gold and real estate. The ill-gotten cash fuels India's gold demand and artificially props up real estate prices through fake mortgages, thus making these two assets prime vehicles of money laundering. The shock of demonetization was needed to discourage future tax evasion and money laundering, ultimately pushing the Indian population from cash, gold, real estate and other forms of physical assets towards a more bank-based and IT enabled payment and saving habit. While this move naturally provides a fillip to the IT sector, it also discourages gold holding, thereby providing a boost to India's trade balance and strengthening the Indian rupee vis-à-vis other major currencies. The long-run objective of the demonetization

[1] See World Bank, 2016 data on market capitalization of listed domestic companies as percent of GDP.
[2] Census of India, 2011.
[3] See Rogoff (2016).
[4] See the Annual Report, 2016-17 of Ministry of Commerce & Industry, Government of India.
[5] See World Gold Council, 2016.
[6] Ministry of Housing and Urban Poverty Alleviation, Government of India, 2012.
[7] 10 lakh = 1 million
[8] Economic Survey 2015-16, Government of India.

policy was to nudge India towards a digitally driven banking and financial services based economy that accounts for every monetary transaction.

Indeed the issue of corruption is related to the predominance of the Indian banking system and the coexistence of a large fraction of underbanked and unbanked populace. First, we need to understand a fact that if the Indian economy is more bank-dependent, then banks must be able to perform the function of channelizing capital from savers to borrowers better than the capital markets. Berger et al. (2001) for instance, find that banks are better in managing credit risk of informationally opaque small businesses. Moreover, Hsieh and Klenow (2009) find that Indian firms are indeed smaller and inefficient when compared to firms in China and the United States, making banks more relevant in India. However, the natural question that arises next is that if banks are needed to solve the capital allocation problem for the large population of small businesses and consumers in India, then why is still 41 percent of Indian population without a bank account? One potential explanation arises from demand side, which draws on corruption as a motive. Indians apparently intend to stay anonymous for tax purposes and thus prefer informal financial institutions and savings in forms cash, gold and real estate instead of bank deposits and other formal financial assets[9].

The other explanation offered for India's low banking penetration is from the supply side. For that we need to look deeper into the distribution of the underbanked and unbanked in India. The number of branches per 100,000 of population in rural and semi-urban areas is less than half of that in urban and metropolitan areas. Moreover, compared to the urban and metropolitan areas, a large portion of the deposits in rural and semi-urban areas are small.[10] There is also wide income inequality between the urban and the rural India. In 2011-12, the per capita Net Value Added (NVA) for rural areas was INR 40,772 and that for urban areas was INR 1,01,313 at 2011-12 prices[11]. The fixed costs of full service branch banking to low-income rural and semi-urban areas with small deposit base may make branch expansion into these areas economically unviable for Indian commercial banks. Hence, absence of banks may induce the low-income rural and semi-urban populace to rely on informal financial institutions and physical forms of savings, such as cash and gold jewellery, for their liquidity and collaterizability[12]. A couple of

[9] See Schneider (2005) and Rogoff (2016).
[10] Report of the Committee on Medium-term Path on Financial Inclusion, Reserve Bank of India, 2015.
[11] The Central Statistics Office, Government of India.
[12] Source: World Gold Council (2016).

recent papers by Gülseven and Ekici (2016) and Dey and Sampath (2017) show that if interest-earning deposits are not available to a typical investor, the optimal portfolio weight of gold in a typical gold/stock portfolio can be as high as 30 to 50 percent.

There are, however, many other less sinister reasons why economic agents may prefer to invest in gold and real estate. The extant literature finds consistent evidence of gold and real estate being an inflation hedge[13]. Another motive behind investors' demand for gold is its apparent ability to be a hedge against stocks[14]. Gold is also considered as a safe haven asset and a hedge against other currencies, such as the US dollar[15].

In this paper we focus on the five main assets that formed the core of the argument behind India's demonetization policy, namely gold, stock indices representing realty, banking and IT sectors and the rupee-dollar exchange rate. We investigate how the dynamic interactions among these assets have evolved over time and whether the demonetization policy has been able to affect any change in their dynamic interactions. In terms of modelling the dynamic interactions among financial assets, a large body of literature either uses the traditional Multivariate GARCH models or the econometric framework proposed by Diebold and Yilmaz (2012)[16]. In this paper, we use the Diebold and Yilmaz (2012) modeling framework to estimate the dynamic interlinkages between multiple assets. We estimate the degree of influence of the forecast error variance of a particular asset on the forecast error variances of other assets, which are termed as *spillovers*. We find that *spillovers* account for more than 25 percent of forecast error variance over the entire sample. Banking and real estate sectors are the most influential sectors of the Indian economy in terms of *spillovers*. *Spillovers* also vary over time and major domestic and external events seem to be contemporaneous with their significant time variations. India's demonetization policy did seem to have played a role in changing the dynamic interactions of the assets under consideration. We find that the demonetization policy has increased the importance of the IT sector for gold and banking sector volatility shock transmission.

[13] See Fama and Schwert (1977), Hartzell et al. (1987), Beckmann and Czudaj (2013), Batten et al. (2014), Dey (2014), Bampinas and Panagiotidis (2015), and Arnold and Auer (2015) for more details.
[14] See Jaffe (1989), Baur and Lucey (2010), Gülseven and Ekici (2016) and Dey and Sampath (2017).
[15] See for example Capie, Mills, and Wood (2005), Baur and McDermott (2010), Joy (2011), Reboredo (2013) and Reboredo and Rivera-Castro (2014).
[16] See Bauwens et al. (2006), Narayan et al. (2014), Antonakakis and Kizys (2014), Singhal and Ghosh (2016), Subramaniam et al. (2016), Roy and Roy (2017), Mensi et al. (2017) and Dey and Sampath (2017) for more details.

We organize our paper in the following manner. In Sections 2 and 3 we describe the data and the empirical strategy in more details. In Section 4 we summarize and interpret our main results and conduct the sensitivity analyses while we provide our conclusions in Section 5.

2. Data

The primary goal of our study is to investigate the evolution of dynamic interactions among a few key financial assets of the Indian economy, which formed the core target assets behind its recent demonetization policy. We focus on three major sectors in India, namely real estate, financial services and information technology, for our analysis. Accordingly, we use NIFTY Realty, NIFTY Financial and NIFTY IT indices respectively. The NIFTY Financial index is comprised of 15 stocks including banks, financial institutions, housing finance and other financial services companies with a base value of 1000. The NIFTY IT index comprises of 10 stocks with a base value of 1000[17] reflecting the performance of IT companies in India. The NIFTY Realty index, designed to reflect the performance of the real estate sector in India, comprises of 10 stocks with a base value of 1000. All indices are computed using free float capitalization method. Beyond these stock indices, we consider two other key assets for the Indian investors, namely gold and exchange rate. For spot gold, we use the data traded on ICE exchange and for gold futures, we use the near month futures data traded on CME exchange. We use the near month futures data of USD/INR traded on National Stock Exchange (NSE) as the exchange rate variable. All data used in our study are in daily frequency and sourced from EIKON, the database provided by Thomson Reuters. The data period ranges from July 19 2010[18] to March 31 2017.

We first compute the continuous compounded daily returns, R_t, as $\ln(p_t/p_{t-1})$. Then we compute the range-based volatility measure of Garman and Klass (1980) (σ_{gk}^2). We additionally use Parkinson (1980) (σ_p^2) range-based volatility measure for checking the robustness of our results. The two volatility measures are formally defined as follows:

$$\sigma_{gk}^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2$$

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[17] Originally from Jan 1 1996 to May 28 2004 the base value was 10 and post May 28, 2004 it was revised to 1000. Weights of each company in the index capped are at 25%.

[18] NIFTY Realty index came into existence from August 30, 2007, however, due to low levels of trading, full data on this index is available only from July 19, 2010.

$\sigma_p^2 = 0.361(H_t - L_t)^2$,

where O_t, H_t, L_t, C_t represent the open, high, low and close of the log prices, respectively, at time t.

3. Empirical Model

Before we delve into our empirical model, we would like to highlight certain stylized facts about our variables of interest, namely, the daily returns (in percentage) and the log volatilities for our five key asset classes: spot gold, the stock indices representing realty, banking and IT sectors and the rupee-dollar exchange rate. All tables and figures reported hereafter use the volatility measure due to Garman and Klass (1980). Later we check the robustness of our results by replacing this volatility measure with the one put forward by Parkinson (1980) and by using gold futures prices instead of the spot gold prices. Tables 1 and 2 present the summary statistics for daily returns and log volatilities our assets. The realty sector delivers the highest daily return together with an expected highest daily volatility. The daily returns and volatilities of spot gold and the banking and IT sectors are similar. The lowest daily return and volatility is observed in the foreign exchange market. The volatility dynamics of our assets also display some degree of persistence.

In Figures 1 and 2 we plot to compare the daily returns and volatilities (in percentage) of our chosen assets. If we consider the real estate market in Figure 1, we observe that over the sample, the daily percentage returns more or less evenly fluctuate within a ± 5 percent band. In the gold, banking and foreign markets, however, we clearly see one main episode of significant deviations in daily returns from their respective sample means. This episode starts with the lowering of the long-term US credit rating by S&P in August 2011 and continues until September 2012 when the US Federal Reserve began QE3. The second episode is visible only in the gold, foreign and IT markets and it begins when spot gold prices plunged the most in 33 years in April 2013[19] and lasts till the end of that year. The daily volatilities in Figure 2 corroborate the same pattern that we find with the daily returns.

[19] This also coincided with rumours of U.S. Federal Reserve slowing quantitative easing and hiking interest rates, resulting in global markets going down and INR depreciating against USD.

Table 1

Summary Statistics for Daily Returns

	Spot Gold	Realty	Banking	IT	FX
Mean	-0.0003	-0.09	0.03	0.01	0.02
Median	0.02	0.05	0.03	0.02	0.00
Maximum	5.43	8.09	9.04	8.92	3.29
Minimum	-10.16	-12.34	-7.15	-12.49	-2.34
Std. Deviation	1.12	2.22	1.52	1.31	0.50
Skewness	-0.76	-0.37	0.05	-0.82	0.38
Kurtosis	7.08	1.80	1.84	9.89	4.67

Table 2

Summary Statistics for Daily Log Volatilities

	Spot Gold	Realty	Banking	IT	FX
Mean	-9.73	-8.38	-9.25	-9.59	-11.75
Median	-9.77	-8.41	-9.31	-9.63	-11.78
Maximum	-5.69	-5.06	-4.40	-4.86	-7.81
Minimum	-14.40	-10.80	-11.72	-12.52	-14.98
Std. Deviation	0.88	0.84	0.91	0.84	1.11
Skewness	0.35	0.18	0.29	0.37	0.21
Kurtosis	1.28	0.17	0.34	0.76	0.02

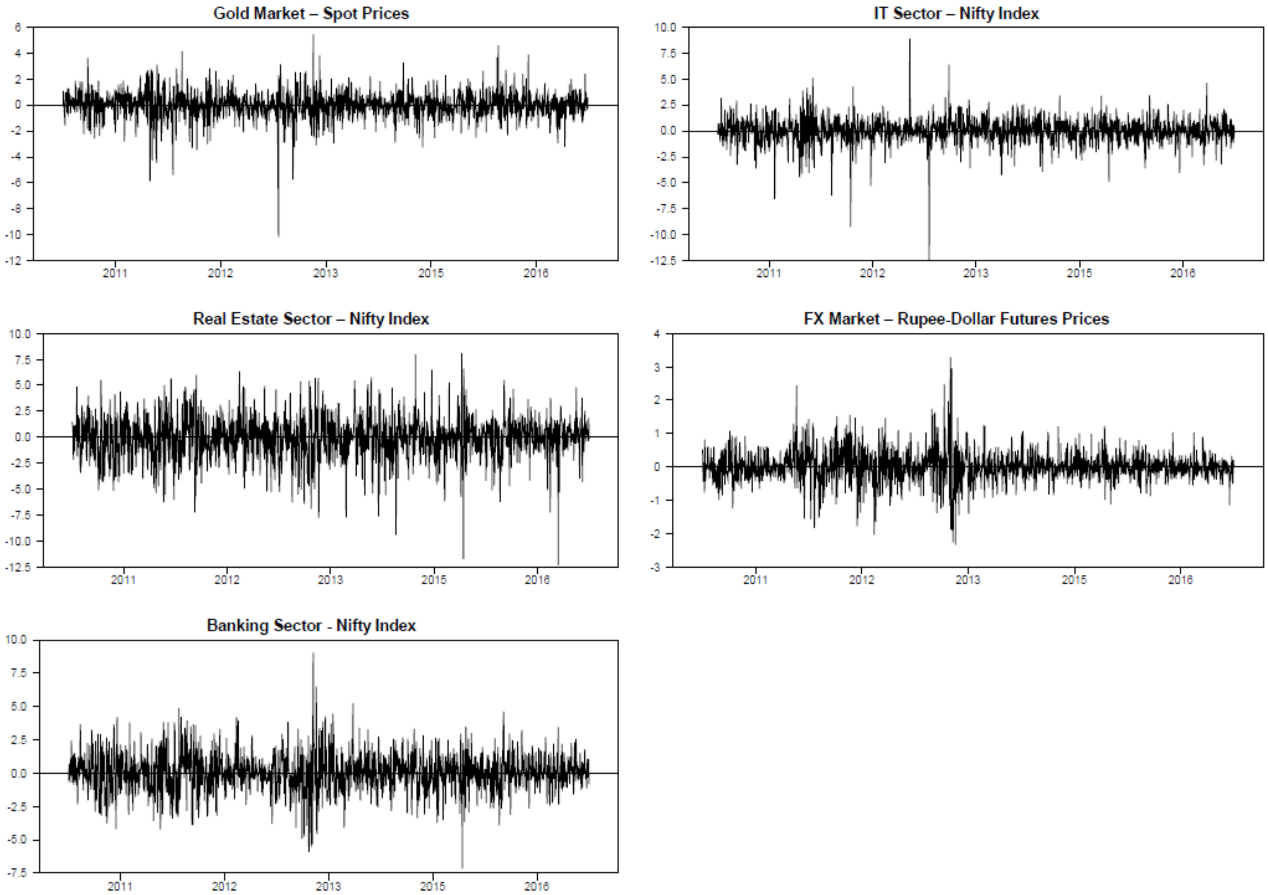

Figure 1. Daily Returns, Percent

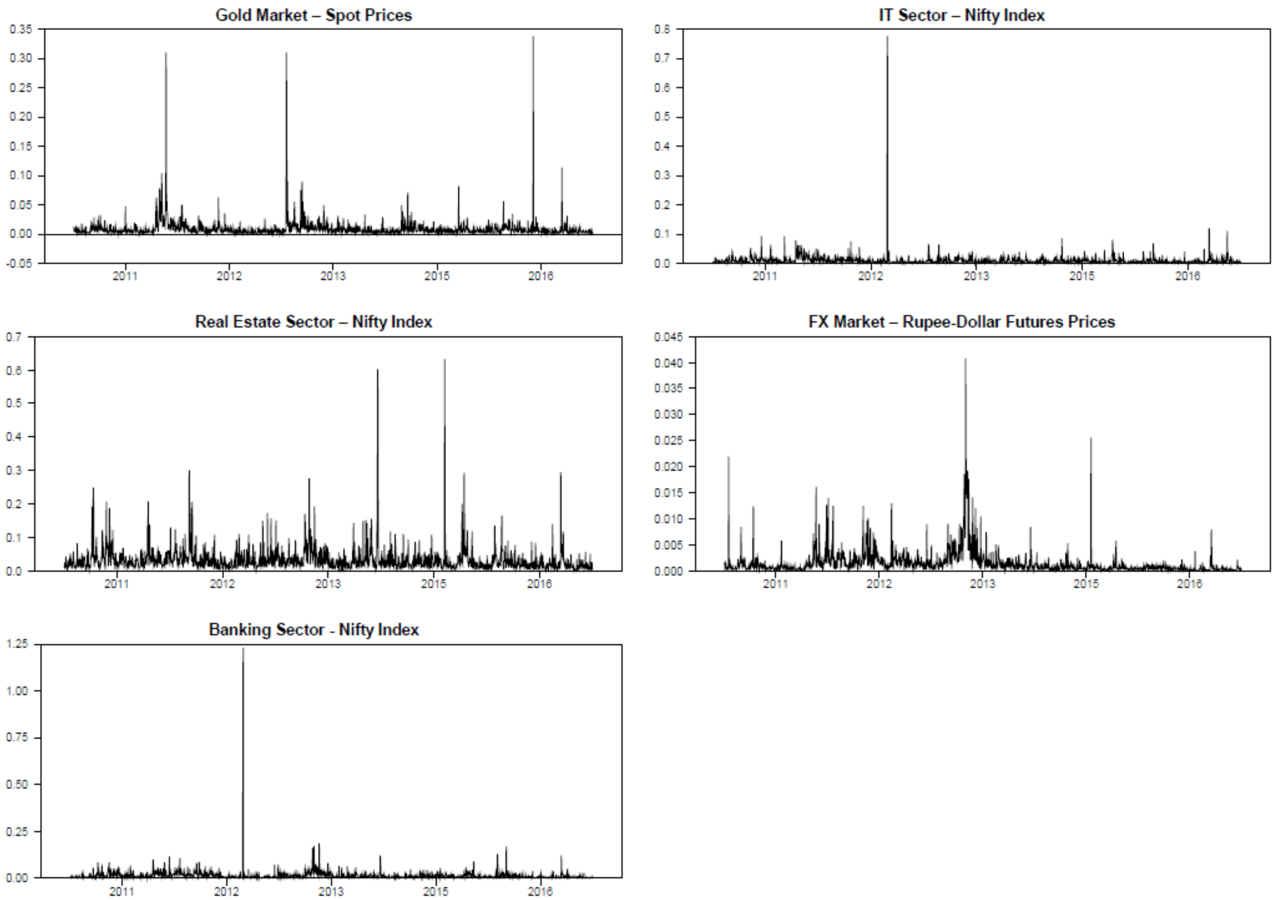

Figure 2. Daily Volatilities, Percent

3.1 VAR Model

Following the empirical strategy put forward by Diebold and Yilmaz (2012), we use an N-variable covariance-stationary *VAR* (p) model given by $X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim iid\ (0, \Sigma)$. The *VAR* model has a moving average representation as $X_t = \sum_{i=0}^{\infty} \mathrm{A}_i \epsilon_{t-i}$, where $A_i = \sum_{j=1}^{p} \Phi_j A_{i-j}$, with A_0 as an $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$. Using the moving average coefficients, we calculate the variance decompositions that segregate the forecast error variances of each variable into parts that are attributable to the various shocks. We take a generalized approach that allows for correlation of shocks using the historically observed distribution of the errors.

3.2 Variance Shares

The fractions of the *H*-step-ahead error variances in forecasting X_i that are due to shocks to X_i, for *i* = 1, 2, . . . , *N* are defined as *own variance shares* and *cross variance shares* or *spillovers* are the fractions of the *H*-step-ahead error variances in forecasting X_i that are due to shocks to X_j, for *i*, *j* = 1, 2, . . . , *N*, such that $i \neq j$. The *H*-step-ahead forecast error variance decompositions, for *H* = 1, 2 . . . are given by:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \Sigma e_j)^2}{\sum_{h=1}^{H-1}(e_i' A_h \Sigma A_h' e_i)}, \tag{1}$$

where σ_{jj} is the standard deviation of the error term for the *j*th equation and e_i is the *N*×1 selection vector, with one in the *i*th element and zeros elsewhere. We normalize the variance decompositions as:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\theta_{ij}(H)} \tag{2}$$

such that $\sum_{j=1}^{N}\tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H) = N$.

3.3 Total Spillovers

The total *spillover* index, which measures the contribution of *spillovers* of volatility shocks across five assets to the total forecast error variance, is given by:

$$S(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N}\tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N}\tilde{\theta}_{ij}(H)}{N} \times 100 \tag{3}$$

3.4 Directional Spillovers

The directional volatility *spillovers* received by market *i* *from* all other markets *j* is defined as

$$S_{i.}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\tilde{\theta}_{ij}(H)}{N} \times 100 \tag{4}$$

Similarly, the directional volatility *spillovers* transmitted by market *i* *to* all other markets *j* is given by:

$$S_{.i}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\tilde{\theta}_{ji}(H)}{N} \times 100 \tag{5}$$

3.5 Net Spillovers

The difference between the gross volatility shocks transmitted *to* and received *from* all other markets or the net volatility *spillovers* is defined as:

$$S_i(H) = S_{.i}(H) - S_{i.}(H) \qquad (6)$$

3.6 Net Pairwise Spillovers

Finally, we obtain the net pairwise volatility *spillovers* between markets *i* and *j* as the difference between the gross volatility shocks transmitted *from* market *i* to market *j* and those transmitted *from* market *j* to market *i*. We define these net pairwise volatility *spillovers* as:

$$S_{ij}(H) = \left(\frac{\tilde{\theta}_{ji}(H)}{\sum_{i,k=1}^{N}\tilde{\theta}_{ik}(H)} - \frac{\tilde{\theta}_{ij}(H)}{\sum_{j,k=1}^{N}\tilde{\theta}_{jk}(H)}\right) \times 100$$

$$= \left(\frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{N}\right) \times 100 \qquad (7)$$

4. Results and Discussion

We report all our results based on a *VAR* model of order 4 and generalized variance decompositions of 10-day-ahead volatility forecast errors. We later check the robustness of these results by varying the *VAR* lag-length from 2 to 6 days. We also see how sensitive our results are to changes in forecasting horizon by varying it from 5 to 10 days.

4.1 Full Sample Return and Volatility Spillovers

Tables 3 and 4 are the *spillover* tables. The *ij*th entries of these tables are the estimated contributions to the forecast error variances of market *i* coming from shocks to market *j*. The labels ‘Contribution to Others’ and ‘Contribution from Others’ are the off-diagonal column sums and row sums representing the ‘to’ and ‘from’ directional *spillovers*. The Total *Spillover* Index is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals), expressed as a percentage. From Table 3, we can observe that the gross return *spillovers* to others from the banking sector is the highest, at 51 percent, followed by the realty sector, with the return *spillovers* to others explaining about 44.8 percent of the forecast error variance. The gross return *spillover* from others to the banking sector is also the highest, again followed by the realty sector. As for the

Table 3

Return *Spillover* Table, All Five Assets

	Spot Gold	Realty	Banking	IT	FX	Contibution from Others
Spot Gold	92.87	0.53	0.48	0.29	5.82	7.1
Realty	0.42	57.66	28.43	5.32	8.17	42.3
Banking	0.25	27.06	55.41	6.02	11.27	44.6
IT	0.47	7.56	8.24	81.08	2.66	18.9
FX	4.62	9.61	13.89	2.06	69.82	30.2
Contribution to Others	5.8	44.8	51.0	13.7	27.9	Total *Spillover*
Contribution Including Own	98.6	102.4	106.4	94.8	97.7	Index (143.2/500) : 28.6%

gross volatility *spillovers*, given in Table 4, we again find that the relative importance of the banking and the realty sectors for the Indian economy. Moreover for the entire sample, the gold market is the least important market with respective to return and volatility *spillovers*.

Now, if we consider the net *spillover*s, we find that the largest net return *spillover* is from the banking sector to others (51 – 44.6 = 6.4%), while, interestingly, the gold market is responsible for the highest net volatility *spillovers* to other markets (13.6 – 8.5 = 5.1%). Similarly, the net return and volatility *spillovers* from other markets is highest to the IT sector (13.7 – 18.9 = – 5.2% and 21.2 – 27.7 = – 6.5%, respectively).

The Total *Spillover* Index is given at the lower right-hand corner of Tables 3 and 4. These indices show that, on average, across our entire sample, 28.6 percent of the return forecast error variance and 25.3 percent of the volatility forecast error variance in all five markets come from *spillovers*. If we sum up the results from both Tables 3 and 4, we see that both the total and directional return and volatility *spillovers* over the full sample period are quite substantial.

Table 4

Volatility *Spillover* Table, All Five Assets

	Spot Gold	Realty	Banking	IT	FX	Contribution from Others
Spot Gold	91.46	0.36	4.10	1.88	2.21	8.5
Realty	0.87	66.66	18.36	7.29	6.83	33.3
Banking	4.33	17.00	62.57	9.24	6.85	37.4
IT	3.9	7.94	12.45	72.33	3.38	27.7
FX	4.47	5.20	7.22	2.82	80.29	19.7
Contribution to Others	13.6	30.5	42.1	21.2	19.3	Total *Spillover*
Contribution Including Own	105.0	97.1	104.7	93.6	99.6	Index (126.7/500) : 25.3%

4.2 Rolling-sample Return and Volatility Spillovers

Although the *VAR* model over the entire sample gives us a good idea about the overall importance of the five assets for the Indian economy, we now wish to highlight the major trends and cycles in the *spillovers* among these assets. In order to achieve that, we estimate the return and volatility spillovers using 200-day rolling samples and plot the time series of the total *spillover* indices in Figures 3 and 4.

If we consider the total return *spillover* index in Figure 3, we can clearly identify several major and minor trends and cycles in the total return *spillover* index. Starting from a value of 38 percent, the first major cycle starts from June 2011, which interestingly coincides with the end of QE2 in the US, and continues till May 2012. Next we have a minor cycle that starts in May 2012 and ends in August 2012. Starting September 2012, which is also the start date of QE3, we then see a major downward trend in the total return *spillover* index that continues till August 2013. This is followed by a minor cycle between August 2013 and November 2013 and a major cycle between November 2013 and May 2014. The last two cycles coincides with the end of the United Progressive Alliance government in India, the general elections in India and the swearing in of the National Democratic Alliance government in May 2014. This is followed by a minor downward trend in total return *spillover* from May 2014 onwards till March 2015. Finally, we see the beginning of a very long cycle starting with a low of 20 percent in March 2015, reaching

Figure 3. Total Return *Spillovers*, Five Asset Classes

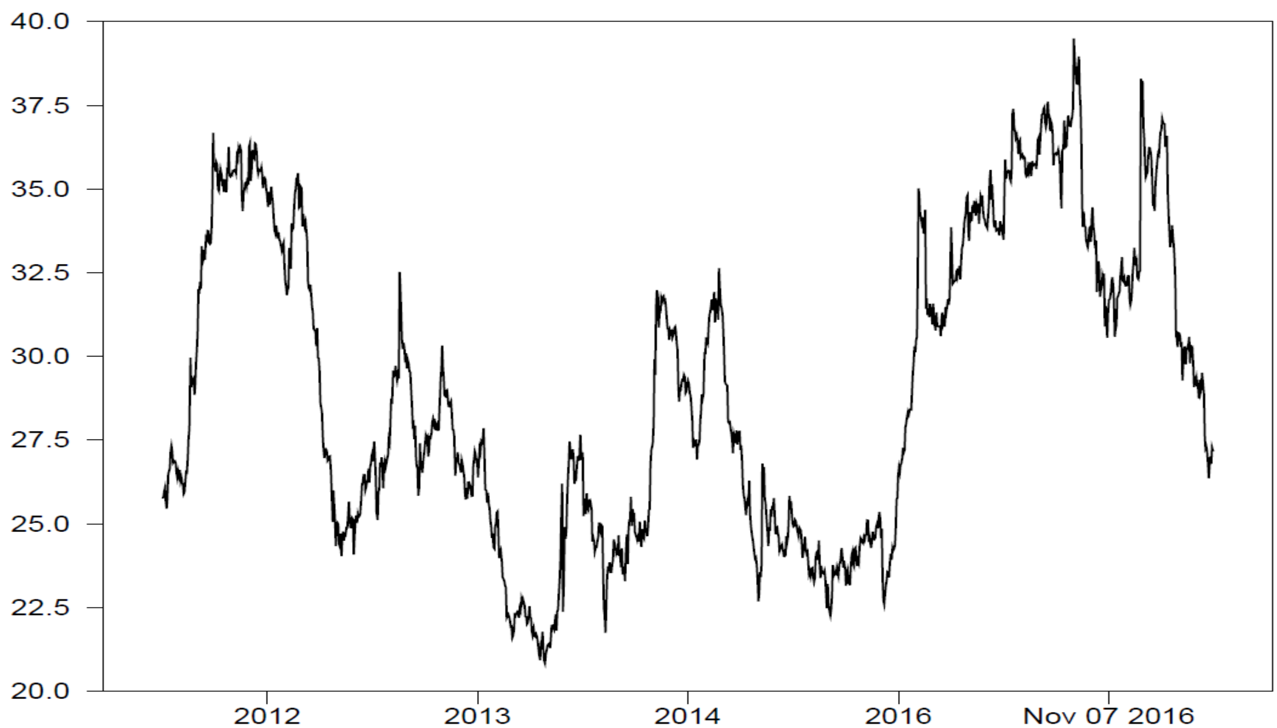

Figure 4. Total Volatility *Spillovers*, Five Asset Classes

a peak of 44 percent on June 23 2016, the Brexit referendum date, and continuing till the end of the sample in March 2017.

Unlike the total return *spillover* series in Figure 3, the total volatility *spillover* index in Figure 4 shows no major or minor trends in the data. There are of course several major and minor volatility *spillover* cycles. The first major cycle starts in June 2011 and continues till May 2012. This was followed by another major cycle from May 2012 till August 2013. Then there was a minor cycle during the end of the United Progressive Alliance tenure (between August 2013 and November 2013), followed by a major cycle (between November 2013 and May 2014) covering the general election and the formation of the National Democratic Alliance government. We again see a long cycle in volatility *spillovers* starting from a low value of 22 percent in March 2015, reaching as high as 39 percent on June 23 2016 (the Brexit referendum date) and then coming down to 30 percent in September 2016. Finally, we see a small cycle in volatility *spillovers* starting November 8 2016 till the end of the sample in March 2017. It is worth again noting that November 8 2016 marked the Indian government's decision to demonetize 86 percent of the currency in circulation in the Indian economy.

4.3 Rolling-sample Net Return and Volatility Spillovers

Each point in the panel of graphs in Figures 5 and 6 represent the difference between the gross shocks transmitted from market *i* to other markets and those transmitted from other markets to market *i*. Hence, a positive value indicates that market *i* has been a net contributor of shocks to other markets and a negative value means that market *i* has been a net receiver of shocks from other markets. The panels in Figures 7 and 8 represent similar measures between a pair of markets *i* and *j*.

First things we observe in Figures 5 and 6 are that in several episodes in our sample the net return and volatility *spillovers* exceeded 10 percent. There have been times when net return *spillovers* exceeded 15 percent and net volatility *spillovers* exceeded 25 percent. If we dig deeper into the specific markets in Figure 5, we see that gold market has been primarily a receiver of return shocks from other asset markets. The periods where its contribution to net return *spillovers* exceeded 3 percent include September 2012 to October 2012 (the beginning of QE3 in the US), February 2013 to April 2013 (prelude to the gold price crash in mid-April), September

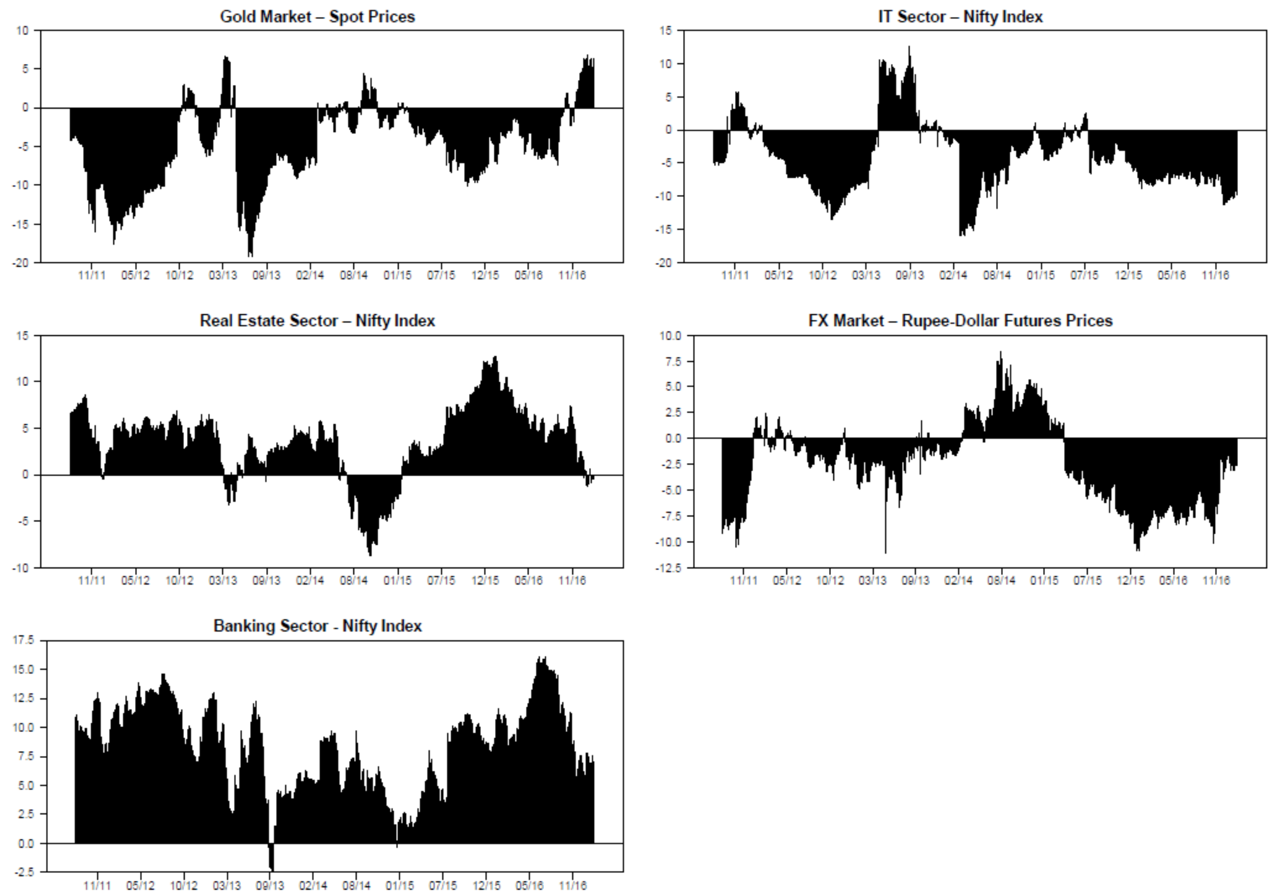

Figure 5. Net Return *Spillovers*, Five Asset Classes

2014 to November 2014 (the end of QE3 in the US) and January 2017 to March 2017. From the pairwise net *spillover* panels in Figure 7 we find that the return *spillovers* from the gold market are primarily transmitted through the foreign exchange market.

The net return *spillover* panels in Figure 5 also suggest that banking and realty sectors are overall the main source of shocks that get transmitted to the other markets, with banking sector undoubtedly being the prime mover.

Similar to the gold market in Figure 5, we find that the IT and the foreign exchange markets are also mainly receivers of return shocks from other markets. The only major episode of net return *spillovers* originating from the IT sector is between April 2013 and December 2013.

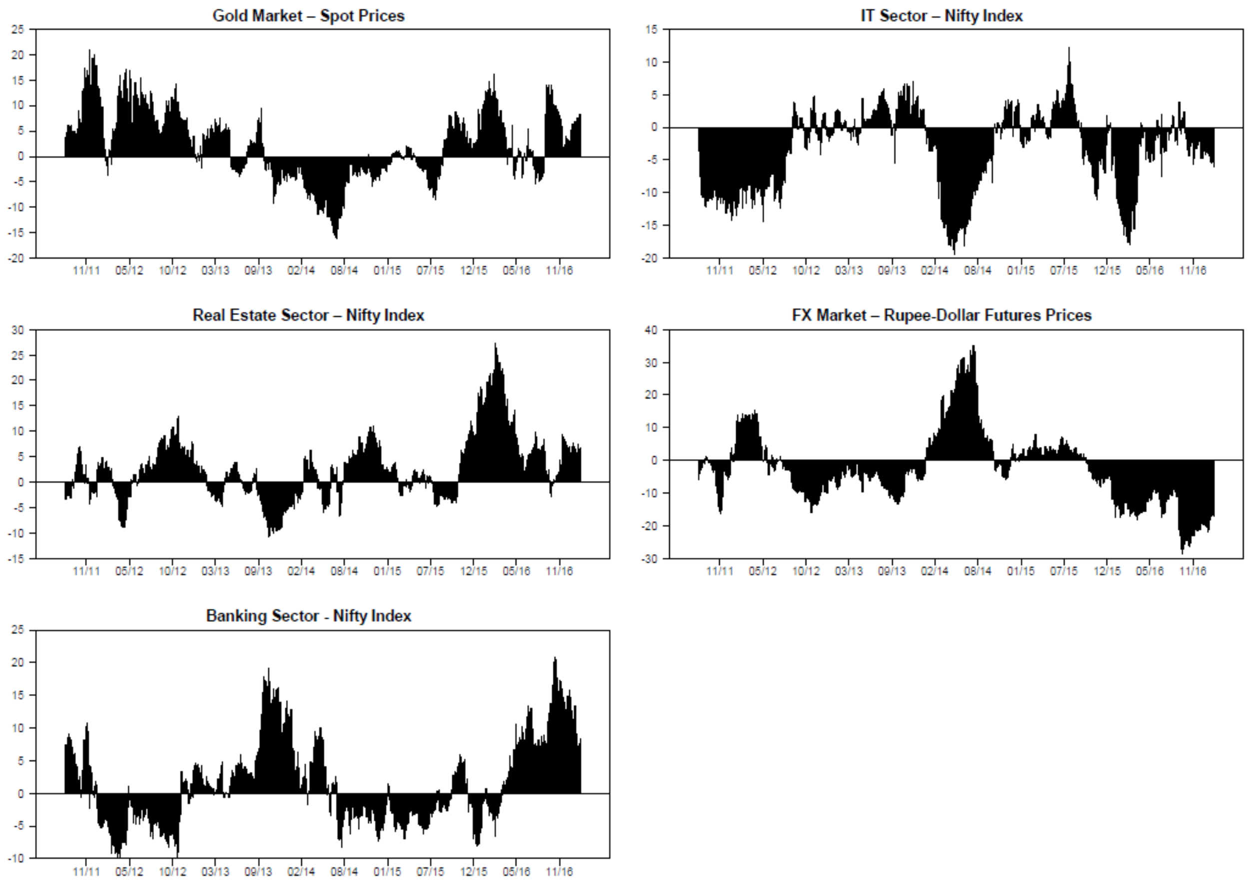

Figure 6. Net Volatility *Spillovers*, Five Asset Classes

This period includes the gold price crash in mid-April and a steep depreciation of the Indian rupee vis-à-vis US dollar between the months of April and August of 2013.[20] Although, looking closely at the pairwise net *spillover* panel between IT and the exchange market in Figure 7, we see that the IT sector at that time was just transmitting the shocks coming from the rupee-dollar exchange rate market.

From Figure 5 we see that the foreign exchange market was a net contributor of return *spillovers* to other markets during February 2014 and to April 2015. The year 2014 marked a strong recovery of the US economy[21] and the dollar vis-à-vis all the major currencies of the

[20] Between 01 April 2013 and September 02, 2013, the Indian rupee depreciated against the dollar by almost 22%, coinciding with rumours of US Federal Reserve reducing quantitative easing and hiking interest rates.
[21] The third quarter growth rate of the US real GDP was indeed the strongest in 11 years.

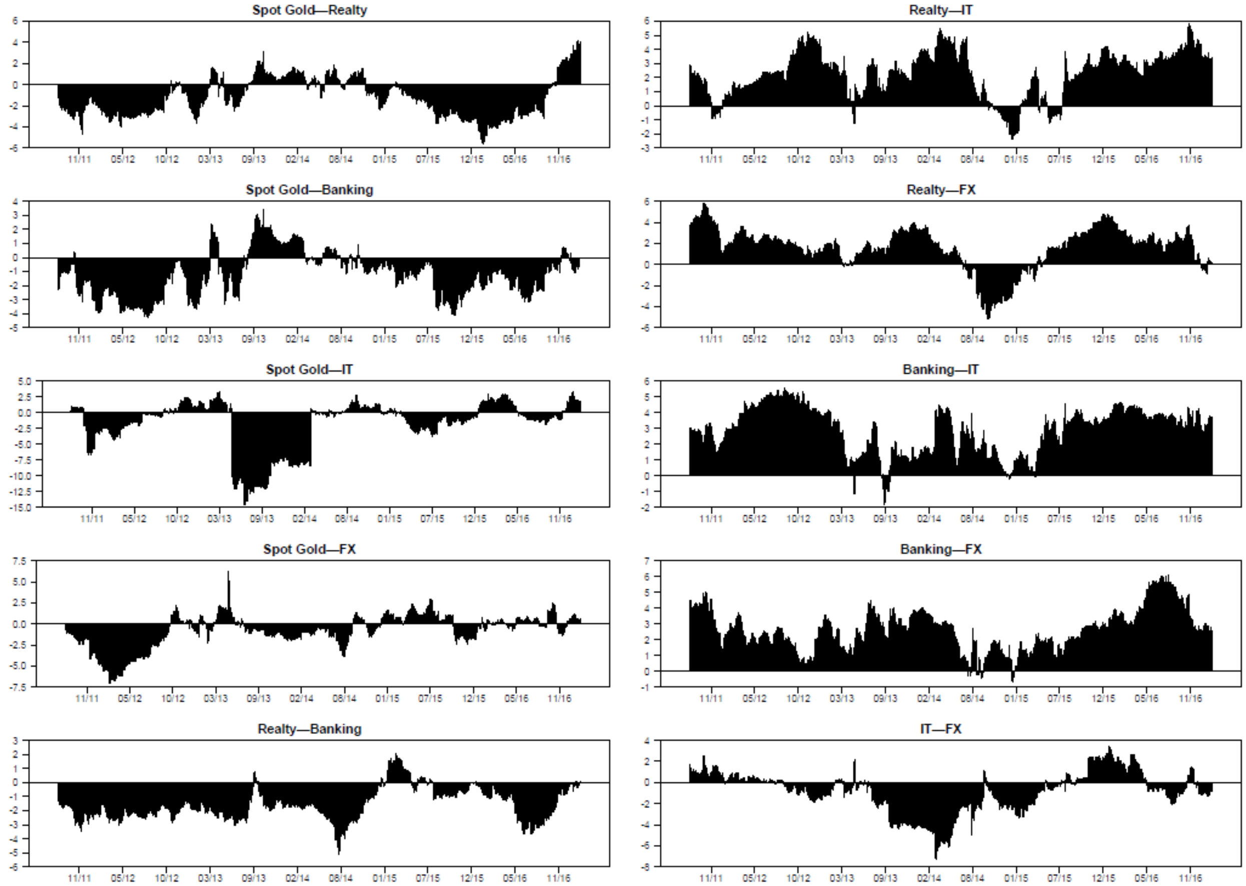

Figure 7. Net Pairwise Return *Spillovers*

world; hence this period can be seen as a time where the Indian economy was largely affected by external shocks originating from the rupee-dollar foreign exchange market. Moreover, from Figure 7 we observe that the majority of the return *spillovers* from the exchange market spread first to the IT sector[22] and then to the realty sector.

Now coming to the net volatility *spillovers* among these markets in Figure 6, first, we observe that these *spillovers* to be an order of magnitude higher than the net return *spillovers*. Second, none of the markets can be seen to be either purely net receivers from or net givers to other markets. Three major episodes when volatility shocks from the gold market spilled over to other asset markets are: during June 2011 to April 2013, between September 2015 and June 2016 and after November 2016. The first episode begins just after the end of QE2 in the US and it

[22] One of the major sectors in India that is affected by exchange rate movements, as most of sales from IT services are denoted in USD.

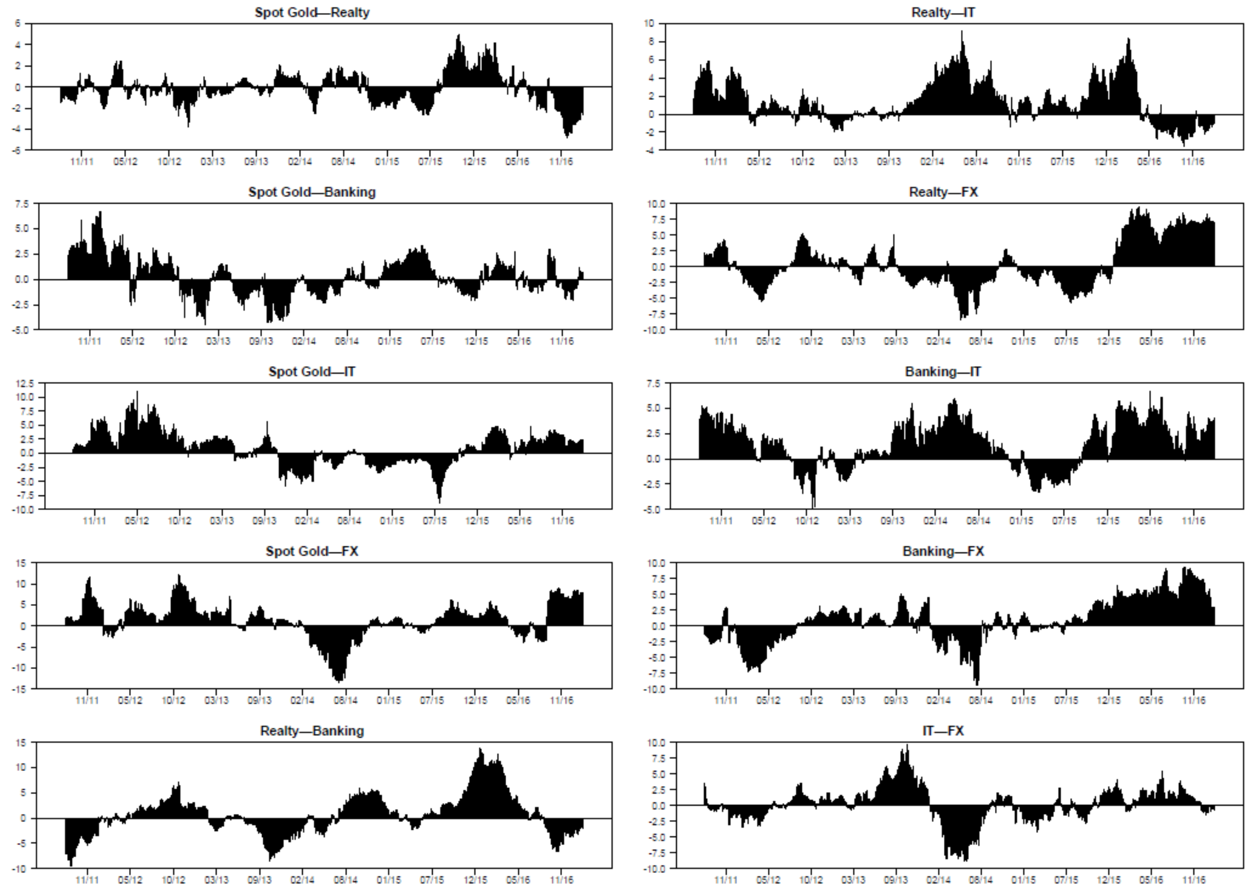

Figure 8. Net Pairwise Volatility *Spillovers*

includes the event of US long-term credit rating downgrade, the Operation Twist period and the gold price crash of mid-April 2013. The second episode includes the US Federal Reserve's historic decision to raise interest rates for the first time in 9 years in December 2015 till the Brexit referendum results in June 2016. Finally, the third episode starts with the Indian government's decision to demonetize 86 percent of the currency in circulation in the Indian economy and continues till the end of our sample. Similar to the return *spillovers*, the panels of Figure 8 suggest that the volatility *spillovers* from the gold market primarily transmits through the foreign exchange market. However post India's demonetization exercise, the volatility *spillovers* from the gold market were first transmitted to the IT sector and then it spread to the exchange market.

From Figure 6 we see that the realty sector was a major net transmitter of volatility shocks from the period stretching the Federal Reserve rate hike event in December 2015 right up to the India's demonetization exercise in November 2016. Figure 8 panels suggest that the bulk of the volatility spillovers from the realty market during that time went first to the banking sector and then to the IT sector.

Similarly, we see two major episodes when the banking sector was the net volatility transmitter to other sectors. First, was during April 2013 and July 2014 – a period that included the gold price crash of April 2013 and the swearing in of National Democratic Alliance government in India in May 2014. The second episode started with the Brexit referendum result of June 2016, included India's demonetization exercise and continued till the end of the sample. During the 2013-2014 episode, the shock transmission from the banking sector mainly went first to the realty sector and then to the IT sector. However, during the second episode the volatility *spillovers* from the banking sector went first to the IT sector and then to the realty sector. Hence, our results seem to suggest that post Brexit and India's demonetization exercise, the IT sector played a greater role in transmitting banking sector volatility shocks than the realty sector. This reinforces our earlier finding of increased importance of the IT sector in transmission of gold market volatility shocks post India's demonetization. To sum up, our results indicate that the Indian government's demonetization policy has increased the importance of the IT sector for the Indian economy.

4.4 Robustness and Sensitivity Analysis

All our reported results are based on a *VAR* model of order 4 and generalized variance decompositions of 10-day-ahead volatility forecast errors. We also use spot gold prices for our return and volatility calculations. Moreover, our volatility measure is due to Garman and Klass (1980). We intend to see how sensitive our results and conclusions are to choice of variables and model structure. First, we find that our results are robust to changes in the volatility measure from Garman and Klass (1980) to the one put forward Parkinson (1980). Second, replacing our spot gold price variable with gold futures prices also made no perceptible difference in our results and conclusions. Third, we vary our *VAR* model lag structure from 2 to 6 and plot the minimum, maximum and the median values of the total return and volatility *spillovers* coming out of the 200-day rolling window regressions in Figures R1 and R2. Both the figures show that

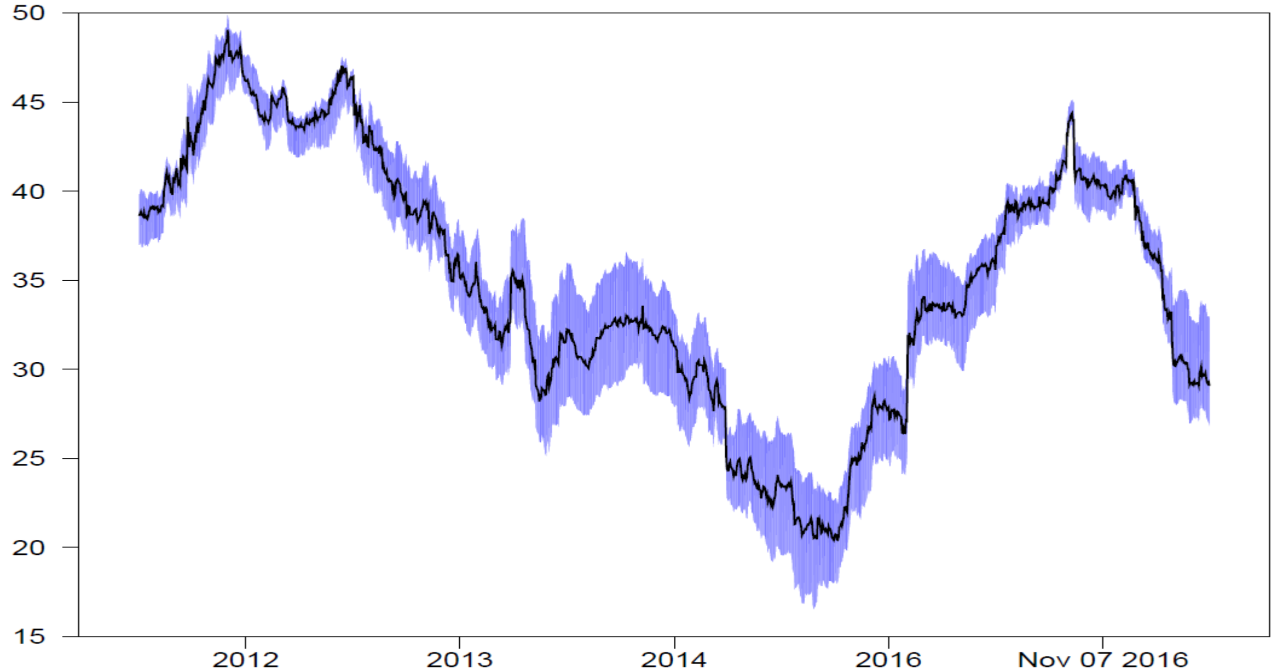

Figure R1. Sensitivity of the Total Return *Spillovers* to VAR Lag Structure

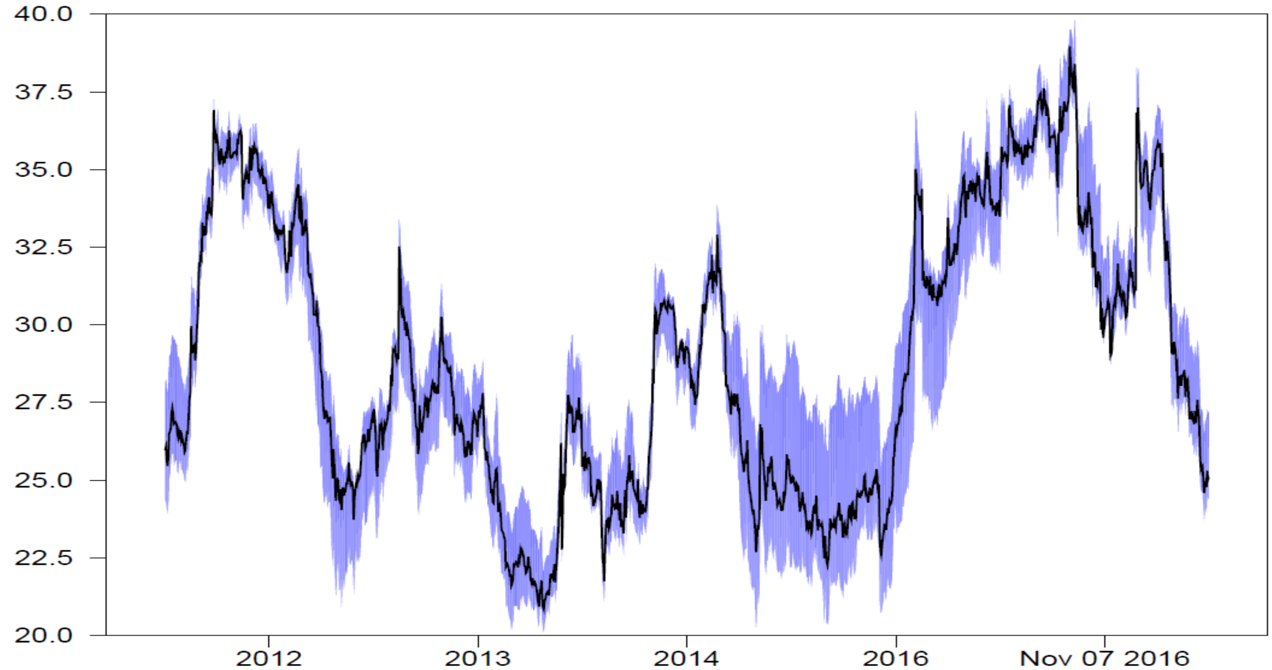

Figure R2. Sensitivity of the Total Volatility *Spillovers* to VAR Lag Structure the total *spillover* plot is not very sensitive to the choice of number of lags in our *VAR* model. Finally, we do a similar sensitivity analysis by varying our forecasting horizon between 5 to 10 days. We find that the total *spillover* plots show almost no sensitivity to changes in the forecasting horizon of our *VAR* model.

5. Conclusion

In this paper we investigate the evolution of dynamic interactions of five major financial assets in the Indian economy, which were the main target assets behind its recent demonetization policy. *Spillovers* account for more than 25 percent of the forecast error variance in all the five markets. When we break down the *spillovers* in terms of sectors, we clearly find the importance of the banking and the real estate sectors for the Indian economy. Moreover, the gold market is responsible for the highest net volatility *spillovers* to other markets.

Spillovers, however, vary over time, as it is evident from the major trends and cycles in their time series plots. Both external and internal events have contributed to the changing dynamics of both return and volatility *spillovers*. As expected, the performance of the US economy and the actions taken by the US Federal Reserve spills over to the Indian economy via the gold and the foreign exchange markets as well as directly to the key sectors considered in this paper. Among the domestic events, the election of the National Democratic Alliance government in India in May 2014 and the Indian government's decision to demonetize 86 percent of the currency in circulation in the Indian economy clearly stand out. India's demonetization policy seems to have increased the importance of the IT sector for gold and banking sector volatility shock transmission.

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