Dynamic Linkages between Gold and Equity Prices: Evidence from Indian Financial Services and Information Technology Companies

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Abstract

In this paper, we use multivariate GARCH models to analyze dynamic linkages between gold and equity price returns. We model dynamic conditional correlations and volatility spillovers between these assets. Our results indicate that spot gold can be an effective hedge against stock prices. A $1 long position in the NIFTY Financial Services index can be hedged for 12 cents with a short position in spot gold and a $1 long position in the NIFTY Information Technology index can be hedged for 5 cents with a short position in spot gold. Gold also seems to act as a safe haven asset during the Global Financial Crisis period between 2007 and 2009. Our results suggest that crisis or not a prudent investor should allocate around 30 per cent of her investible assets in gold within a gold/stock portfolio. Given that in India around 41% of the population is still without access to banking services and are hence deprived of interest-earning deposits, it is not very surprising to find gold's optimal portfolio weight to be as high as 30 per cent.

Keywords: Spot gold, stock, MGARCH, correlation, volatility spillovers
JEL: G11, G12, C32, C52

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1. Introduction

India is a diverse country with hundreds of languages and many different faiths and beliefs. However, cutting across these linguistic and cultural divisions, for a large section of the Indian population, gold is interconnected with their way of life. For a typical Indian household, gold is often considered as a 'wearable asset'. Moreover, despite significant improvements in financial inclusion, 41% of Indian population in 2011 was still without access to banking services.[1] Between 2009 and 2014, the average annual demand for gold in India was around 895 tonnes, accounting for 26 per cent of world's total physical demand for gold.[2] Also between 2004 and 2015, annual CPI inflation averaged at 7.75% while the bank savings rate and one-year fixed deposits rates averaged around 3.7% and 7.9% respectively.[3] Indeed, the real savings rate and the real one-year fixed deposit rate averaged at - 4% and 0.1% respectively during this time frame. For large sections of the Indian population with no access to formal financial services and even for those with access to banking services, the economic reality of high inflation, eating away all of their real returns made gold an important asset of choice that also provided safety in a volatile and uncertain world. In fact, repeated pan-India surveys find gold investments consistently rank among the top three choices after savings account and insurance products and ahead of investments in stocks and real estate.[4] In addition, formal financial services business relies heavily on information technology; hence, the financial health and stock market performance of these industries is expected to be correlated. In this paper, we model the dynamic linkages between spot gold and equity prices of Indian financial services and information technology companies. We find significant evidence of dynamic conditional correlations and volatility spillovers between the daily returns of these assets.

Literature investigating gold's role as an investment finds consistent evidence of it being an inflation hedge. For some recent study on this topic see Beckmann and Czudaj (2013), Batten et al. (2014), Dey (2014), and Bampinas and Panagiotidis (2015). Funding and profitability of the financial services companies in India depend on the relative attractiveness of their products vis-à-vis gold. However, persistently high inflation rates make the real returns on the deposits and insurance products offered by these companies unappealing for an Indian investor. This is

[1] Census of India, 2011.
[2] Source: World Gold Council (2015).
[3] Source: Reserve Bank of India.
[4] Source: World Gold Council (2016).

likely to be reflected in the financial health and the stock market performance of financial services companies and hence a research agenda to understand the dynamic interplay in the mean and variance of the returns on gold and financial services companies is both relevant and novel in the Indian context.

Another motive behind investors' demand for gold is its apparent ability to be a hedge asset, which Baur and Lucey (2010) define as "an asset that is uncorrelated or negatively correlated with another asset or portfolio on average." A line of research in this literature tries to find the optimal weight for gold in an investment portfolio. Studies by Bruno and Chincarini (2010) and Emmrich and McGroarty (2013) find gold's portfolio weight never to optimally exceed 10%. However, for Turkey Gülseven and Ekici (2016) find that the optimal portfolio weight of gold may go up to more than 50% if interest-earning deposits are not included in the portfolio. In India, given that around 41% of its population is still without access to bank accounts and hence are deprived of interest-earning deposits, the analysis of optimal portfolio weight of gold in a typical gold/stock portfolio in the Indian context is a very fertile area of research that we also intend undertake in this paper.

Gold is also considered as a safe haven asset, which Baur and McDermott (2010) define as "an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g. in times of falling stock markets." Baur and Lucey (2010) find gold to play a role of a safe haven asset for US, UK and German stocks. Moreover, Baur and McDermott (2010) find gold to be a safe haven for US and major European stock markets and not for Australia, Canada, Japan and large emerging markets such as the BRIC countries. Between Nov 30, 2007 and June 30, 2009 world economies suffered one of the most severe financial crises of recent history.[5] There is no research in the Indian context, that we are aware of, which tries to test the safe haven property of gold in a gold/stock portfolio allocation framework. In this paper, we intend to fill that research gap using the period of the Global Financial Crisis (GFC).

Not only is gold a safe haven asset and an asset that can hedge against stocks and inflation, the literature also finds that it can act as a hedge against other currencies, such as the US dollar [see Capie, Mills, and Wood (2005), Joy (2011), Reboredo (2013), Lu and Hamori (2013), and Reboredo and Rivera-Castro (2014)]. Indian information technology companies are

[5] This period is also captured by the St. Louis Fed Financial Stress Index, available at https://fred.stlouisfed.org/series/STLFSI.

one of the major exporter revenue earners of the country. Hence, their profitability and stock market performance is likely to be dependent on the rupee-dollar exchange rate movements. Indeed, logically we would expect spot gold prices to fall and information technology companies' stock prices to rise when dollar appreciates against the Indian rupee. Hence, beyond the structural link between financial services companies and information technology companies, our study including spot gold returns and returns on information technology companies' stocks may also shed some light on the dollar hedging property of gold. Hence, we believe that our research design to investigate the dynamic linkages in mean and volatility of returns on gold and equity prices of Indian financial services and information technology companies is not only unique but also is likely to be fruitful, particularly in the Indian context.

The empirical model for our study combines a Vector Autoregression model with a multivariate GARCH framework. This empirical strategy of merging a multivariate conditional mean model with a multivariate condition volatility model has found wide acceptance in the empirical literature as evident from the works of Hammoudeh et al. (2009), Arouri (2012), Maghyereh and Awartani (2012), Sadorsky (2012), Andreou et al. (2013), Mensi et al. (2013), Sadorsky (2014), Arouri et al. (2015), Hua and Sanhaji (2015), Wang and Choi (2015) and Singhal and Ghosh (2016). We find the VAR-DCC-GARCH model to be the best fit for our sample. Using this best fit model, our hedge ratios indicate that spot gold can be an effective hedge against stock prices. Moreover, our results on optimal portfolio weights suggest that a prudent Indian investor needs to allocate around 30 per cent of her investible assets in gold within a gold/stock portfolio.

2. Data

The primary data used in our study consists of sectoral index prices of the emerging Indian market and gold spot prices. We use the daily close to close returns of NIFTY Financial Services index (FINANCIAL) and NIFTY Information Technology index (IT) along with gold spot data provided by the Thomson Reuters database. Our data covers the period January 02, 2004 to December 31, 2016. The sectoral indices used in our study are weighted free float indices containing of stocks listed on the National Stock Exchange of India (NSE). The NIFTY Financial Services index comprises of 15 firms including banks, financial institutions, housing finance and other financial services companies with a base value of 1000. The NIFTY

Information Technology index comprising 10 stocks began with a base value of 1000 in Jan 1, 1996 and was later changed to 100 from May 28, 2004. The maximum weight cap for each company in the IT index is set at 25%. The gold spot data used in our study is provided by Thomson Reuters database. This data is dynamically sourced from different markets and consolidated into gold spot prices by Reuters. All the closing prices data used in our study have been extracted from Eikon, the database provided by Thomson Reuters. We compute the continuously compounded daily returns as $100 \times \ln(p_t/p_{t-1})$, where p_t is the daily closing price of an asset.

Fig. 1 depicts the raw time plots of the data series, indicating a high degree of co-movement between FINANCIAL and IT. The GFC period also seems to have adversely affected the stock indices more than the gold spot price. Table 1 summarizes the basic statistical properties of the daily return series. The mean and median value of each series is close to zero, which is also supported by the insignificant values of the Student *t* statistics. The standard deviation of each series is larger than the mean value. The Jarque-Bera statistics suggest rejection of null hypothesis of normality for all the three series. In addition to this, the negative skewness values and kurtosis values greater than three indicate that all the three series are non-normal and asymmetric. We also find that all the daily return series are stationary, corroborated by the strong rejection of null hypothesis of a unit root by the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) test statistics.

Table 2 and Table 3 show the raw correlation coefficients between the daily returns and the volatility measured by squared daily returns, respectively. As expected, there is a high and positive correlation between FINANCIAL and IT and a low, yet positive correlation between spot gold and the stock indices. This reiterates the role gold plays as a hedge asset, which Baur and Lucey (2010) define as "an asset that is uncorrelated or negatively correlated with another asset or portfolio on average." Moreover during the GFC period, the positive raw correlation coefficients between the daily returns and the squared daily returns between FINANCIAL and IT, as shown by Tables 4 and 5, get even stronger while the correlations between the daily returns on spot gold and the stock indices turn negative. This validates yet another attractiveness of gold as a safe haven asset, which Baur and McDermott (2010) define as "an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g. in times of falling stock markets."

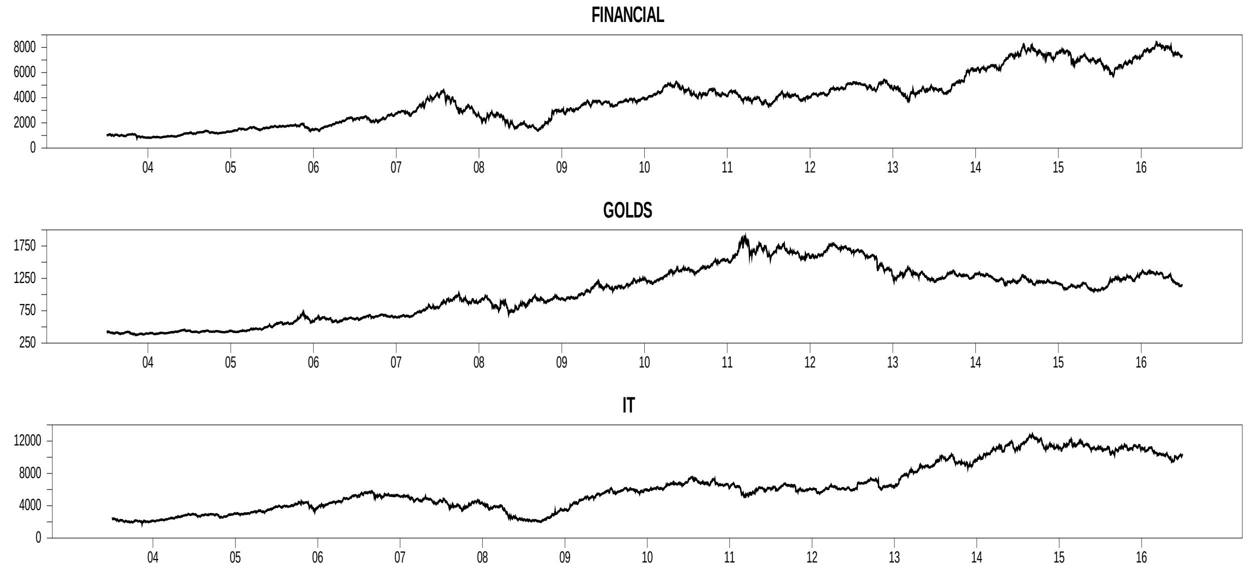

Fig 1. Time Series Plots of FINANCIAL, GOLDS and IT

Table 1

Summary Statistics for Daily Returns

	FINANCIAL	GOLDS	IT
Mean	0.064	0.033	0.047
Median	0.089	0.052	0.060
Maximum	17.807	9.554	11.867
Minimum	-14.413	-8.913	-14.408
Std. Deviation	1.965	1.221	1.743
Skewness	-0.009	-0.299	-0.110
Kurtosis	6.714	5.308	6.436
Student *t*	1.814	1.502	1.504
ADF	-39.520***	-56.609***	-42.423***
Phillips-Perron	-49.887***	-56.618***	-55.770***
Jarque-Bera	5880.400***	3722.163***	5409.388***
Observations	3131	3131	3131

***Significant at 1% level.

Table 2

Correlation between Daily Returns

	FINANCIAL	GOLDS	IT
FINANCIAL	1.000	0.068	0.567
GOLDS	0.068	1.000	0.032
IT	0.567	0.032	1.000

Table 3

Correlation between Squared Daily Returns

	FINANCIAL	GOLDS	IT
FINANCIAL	1.000	0.157	0.608
GOLDS	0.157	1.000	0.136
IT	0.608	0.136	1.000

Table 4

Correlation between Daily Returns during Global Financial Crisis

	FINANCIAL	GOLDS	IT
FINANCIAL	1.000	-0.068	0.690
GOLDS	-0.068	1.000	-0.072
IT	0.690	-0.072	1.000

Table 5

Correlation between Squared Daily Returns during Global Financial Crisis

	FINANCIAL	GOLDS	IT
FINANCIAL	1.000	0.147	0.684
GOLDS	0.147	1.000	0.138
IT	0.684	0.138	1.000

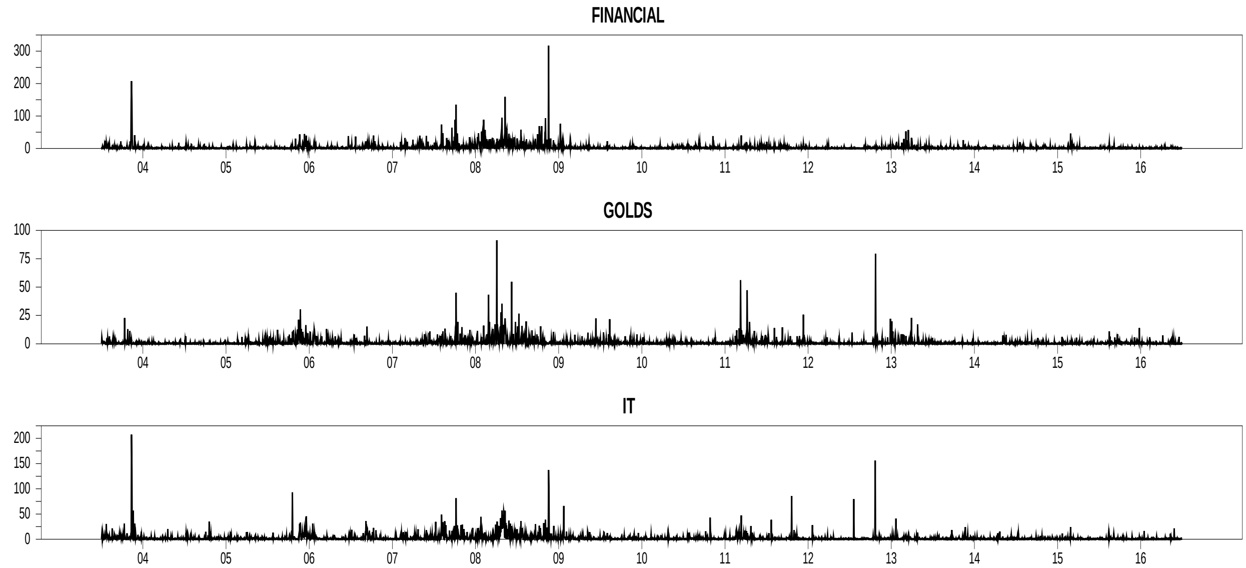

Fig 2. Squared Daily Returns

Finally, based on the information presented in Fig. 2, Table 3 and Table 5, we can conclude that there is prima facie evidence of volatility clustering and volatility spillovers in the asset returns considered in our sample.

3. Empirical Model

In this paper we intend to model the dynamic linkages in conditional mean and volatility between stock returns of financial services and information technology companies and gold spot returns. Given our research goal, using a multivariate GARCH (MGARCH)[6] model, such as the BEKK[7]-GARCH model of Engle and Kroner (1995) or the CCC-GARCH (Constant Conditional Correlation) model of Bollerslev (1990) or the DCC-GARCH (Dynamic Conditional Correlation) model of Engle (2002) seems quite natural. Hence following Sadorsky (2012), we use four MGARCH models – BEKK-GARCH, CCC-GARCH, DCC-GARCH and diagonal-GARCH, where the BEKK-GARCH model is used as a benchmark. In order to reduce the computational burden and avoid convergence issues in the likelihood function, we assume the conditional variance of the CCC-GARCH, DCC-GARCH and diagonal-GARCH models to be

[6] See Bauwens et al. (2006) for a comprehensive survey of MGARCH models.
[7] BEKK refers to Baba, Engle, Kraft and Kroner.

VARMA-GARCH (1,1) of Ling and McAleer (2003). Our econometric specification thus has two components. First, we have a one period lag Vector Autoregression (VAR) model, which allows for autocorrelations and cross-autocorrelations in returns. Second, we have a MGARCH model, where the CCC, DCC and the diagonal versions are of the Ling and McAleer (2003) type and the last version is the most general in the form of BEKK of the Engle and Kroner (1995) type. The Ling and McAleer (2003) approach of modeling conditional variance is a very convenient way to investigate volatility spillovers that has already seen several applications in the recent commodity price literature, namely Hammoudeh et al. (2010), Chang et al. (2011), Arouri (2012), Sadorsky (2012), Mensi et al. (2013), Sadorsky (2014), and Arouri et al. (2015).[8] We now formally describe our four models and their estimation procedures. The conditional mean of our empirical model is specified as a VAR (1,1) process:

$$r_t = M_0 + Mr_{t-1} + \epsilon_t, \epsilon_t | I_{t-1} \sim N(0, V_t) \tag{1}$$

$$\epsilon_t = D_t v_t, v_t \sim N(0, I_3) \tag{2}$$

where $r_t = (r_{1t}, r_{2t}, r_{3t})'$ is the vector of returns on the financial services stock index, gold spot price and the information technology stock index respectively, $M_0 = (m_{10}, m_{20}, m_{30})'$ is a vector of constant terms in the VAR system, $M = \begin{pmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{pmatrix}$ is a matrix of VAR coefficients, $\epsilon_t = (\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t})'$ is a vector of VAR error terms, I_{t-1} is the market information set at time *t* – 1, $V_t = \begin{pmatrix} h_{11t} & h_{12t} & h_{13t} \\ h_{21t} & h_{22t} & h_{23t} \\ h_{31t} & h_{32t} & h_{33t} \end{pmatrix}$ is the conditional variance-covariance matrix of the VAR error terms, $D_t = diag(h_{11t}^{1/2}, h_{22t}^{1/2}, h_{33t}^{1/2})$ is a diagonal matrix of time-varying standard deviations of ϵ_t, $v_t = (v_{1t}, v_{2t}, v_{3t})'$ is a vector of VAR standardized error terms and I_3 is a (3 x 3) identity matrix.

The conditional variance for the diagonal-GARCH, CCC-GARCH and DCC-GARCH models is assumed as following:

$$H_t = C + A\vec{\epsilon}_{t-1} + BH_{t-1} \tag{3}$$

[8] Also see Chevallier (2012) and Mensi et al. (2014) for a slightly different approach in modeling volatility spillovers by combining the VAR and MGARCH frameworks.

where $H_t = (h_{11t}, h_{22t}, h_{33t})'$, $\vec{\epsilon}_t = (\epsilon_{1t}^2, \epsilon_{2t}^2, \epsilon_{3t}^2)'$, $C = (c_{11}, c_{22}, c_{33})'$ is a vector of constant terms and $A = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{pmatrix}$ and $B = \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{pmatrix}$ are matrices of coefficients that capture the effects of own and cross-asset shocks as well as the effects of own and cross-asset volatilities respectively.

For the Engle (2002) DCC-GARCH model, we can write the conditional variance-covariance matrix as

$$V_t = D_t R_t D_t, R_t = \begin{pmatrix} \rho_{11t} & \rho_{12t} & \rho_{13t} \\ \rho_{21t} & \rho_{22t} & \rho_{23t} \\ \rho_{31t} & \rho_{32t} & \rho_{33t} \end{pmatrix} \tag{4}$$

where $R_t = diag(q_{11t}^{-1/2}, q_{22t}^{-1/2}, q_{33t}^{-1/2}) Q_t \, diag(q_{11t}^{-1/2}, q_{22t}^{-1/2}, q_{33t}^{-1/2})$ is the conditional correlation matrix.

Q_t is a symmetric positive definite conditional covariance matrix of the standardized error vector, v_t, and is defined as follows:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 v_{t-1} v_{t-1}' + \theta_2 Q_{t-1}, Q_t = \begin{pmatrix} q_{11t} & q_{12t} & q_{13t} \\ q_{21t} & q_{22t} & q_{23t} \\ q_{31t} & q_{32t} & q_{33t} \end{pmatrix} \tag{5}$$

$\bar{Q}$ is a (3 x 3) matrix of unconditional correlation matrix of the standardized error vector. The parameters θ_1 and θ_2 are nonnegative scalars such that $\theta_1 + \theta_2 < 1$. The correlation estimator is defined as

$$\rho_{ijt} = q_{iit}^{-1/2} q_{jjt}^{-1/2} q_{ijt} \forall i, j = 1, 2, 3.$$

The DCC-GARCH model is estimated in two steps. First, all the MGARCH parameters are estimated. Then in the second step, the conditional correlations are estimated using the relevant elements of the estimated conditional variance-covariance matrix, V_t.

The CCC-GARCH model of Bollerslev (1990) is a special case of the DCC-GARCH model, where $R_t = R = \bar{Q}, R = \begin{pmatrix} \rho_{11} & \rho_{12} & \rho_{13} \\ \rho_{21} & \rho_{22} & \rho_{23} \\ \rho_{31} & \rho_{32} & \rho_{33} \end{pmatrix}$.

The diagonal-GARCH version of our econometric model is even more restrictive as it assumes $R_t = R = \bar{Q}, R = \begin{pmatrix} \rho_{11} & 0 & 0 \\ 0 & \rho_{22} & 0 \\ 0 & 0 & \rho_{33} \end{pmatrix}$. A simple estimate of R in the CCC-GARCH and the diagonal-GARCH versions of our model is the unconditional correlation matrix of the standardized residuals of the MGARCH model.

As a benchmark, we now consider the BEKK-GARCH version of our model, where the VAR (1,1) system outlined in equations (1) and (2) is augmented by a conditional variance-covariance matrix defined as follows:

$$V_t = C^{*\prime}C^* + A'\varepsilon_{t-1}\epsilon'_{t-1}A + B'V_{t-1}B \tag{6}$$

where $C^{*\prime} = \begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix}$ is a lower triangular matrix of constant terms, ε_t, A and B are defined as before.

All the four MGARCH models are estimated by Quasi-Maximum Likelihood Estimation (QMLE) procedure using the BFGS algorithm. The associated *t* statistics are calculated using a robust estimate of the variance-covariance matrix.

4. Empirical Results

In this section we report and discuss the empirical results of our MGARCH model estimations. The most general BEKK-GARCH model is used as a benchmark against the CCC-GARCH, DCC-GARCH and diagonal-GARCH models. Table 6 reports the main estimation results of all the models considered in this paper. Among the VAR estimates, we observe that there are strong positive autoregressive effects in the returns of stock indices, as shown by statistically significant positive values of m_{11} and m_{33} in all the four models. However, the same is not true for gold spot returns. In the cross-mean effects, we have only the negative effect of a one period lag FINANCIAL return on the current IT return (m_{31}) to be significant and that too across all models. A strong domestic economic performance which triggers a higher financial services sector return, may also cause Indian rupee to appreciate against dollar; thereby adversely affecting the profitability and stock market performance of the more export-dependent information technology sector.

Coming to the variance equation estimates, among the short-term volatility persistence measures (α_{ij}), we have the own ARCH effects (α_{ii}) to be significant and positive across all the models. There is evidence of positive short-term volatility spillovers from IT to FINANCIAL (α_{13}) in the BEKK-GARCH model and from FINANCIAL to IT (α_{31}) in the other three

MGARCH models. We also find significant short-term volatility spillovers from IT to gold spot return (α_{23}) in all the four models. Except for the BEKK-GARCH model, these IT-GOLDS short-term volatility links are all positive.

The long-term volatility persistence measures, given by the (β_{ij}) estimates or the GARCH effects, consistently show strong positive own conditional volatility effects (β_{ii}) in all the four models. There is also evidence of positive long-term volatility spillovers from IT to FINANCIAL (β_{13}) and vice-versa (β_{31}) and from FINANCIAL to gold (β_{21}) only in the CCC-GARCH model. Finally, we also find significant long-term volatility spillovers from IT to gold (β_{23}) in the BEKK-GARCH and the CCC-GARCH models. In a reversal of the earlier result on short-term volatility spillovers, we find that for the BEKK-GARCH model this effect is positive and for the CCC-GARCH model it is negative.

For the CCC-GARCH model, only the correlations between gold spot returns and the FINANCIAL returns (ρ_{21}) and that between IT and FINANCIAL returns (ρ_{31}) are significant and they are both positive. Among these two correlations, the one between IT and FINANCIAL returns is almost 5 times larger than the correlation between GOLDS and FINANCIAL. Hence, this indicates that gold prices are important for the financial service industry stock price returns, but not as important as the information technology industry stock price returns.

In the DCC-GARCH model, the estimated θ_1 and θ_2 coefficients are positive and significant and their sum is less than one, implying that the dynamic conditional correlations are not explosive in nature.

By comparing our various MGARCH models based on the AIC and SIC criteria, we find that the DCC-GARCH model is the most suitable model for our sample, with the BEKK-GARCH model as the second best. It is worth noting that the residual diagnostics results shown in Table 7 clearly point towards white noise standardized errors in all the models, as the Q-statistics for the standardized residuals show no evidence of serial correlation and GARCH effects.

4.1 Robustness

As a robustness check, we also estimated our MGARCH models using the NIFTY Bank index (BANK) and the 3-month gold future prices (GOLDF). Residual diagnostics of our models using these alternative series indicated that there are evidences of serial correlations or GARCH

Table 6

MGARCH Parameter Estimates

	BEKK			CCC			DCC			Diag		
	Coeff	t	Sig	Coeff.	t	Sig	Coeff	t	Sig	Coeff	t	Sig
Mean												
m_{10}	0.13	5.15	0.00	0.10	4.39	0.00	0.09	3.28	0.00	0.11	4.07	0.00
m_{11}	0.10	5.01	0.00	0.11	6.19	0.00	0.11	6.17	0.00	0.11	5.19	0.00
m_{12}	-0.01	-0.21	0.84	-0.04	-1.64	0.10	-0.02	-0.68	0.50	-0.03	-1.21	0.23
m_{13}	0.01	0.44	0.66	-0.01	-0.41	0.68	-0.01	-0.66	0.51	0.00	0.06	0.96
m_{20}	0.02	0.84	0.40	0.03	1.49	0.14	0.02	1.27	0.20	0.03	1.40	0.16
m_{21}	0.01	0.64	0.52	0.02	1.15	0.25	0.02	1.25	0.21	0.02	1.22	0.22
m_{22}	-0.01	-0.35	0.73	-0.01	-0.27	0.79	-0.00	-0.15	0.88	-0.01	-0.23	0.82
m_{23}	0.03	1.19	0.23	0.00	0.03	0.97	0.00	0.14	0.89	0.00	0.13	0.90
m_{30}	0.11	4.31	0.00	0.08	3.84	0.00	0.08	3.28	0.00	0.07	3.03	0.00
m_{31}	-0.05	-3.32	0.00	-0.05	-2.62	0.01	-0.05	-2.80	0.01	-0.04	-2.54	0.01
m_{32}	-0.03	-1.36	0.17	-0.04	-1.86	0.06	-0.03	-1.04	0.30	-0.04	-1.39	0.17
m_{33}	0.06	3.48	0.00	0.05	2.63	0.01	0.06	2.72	0.01	0.05	2.49	0.01
Variance												
c_{11}	0.25	4.19	0.00	0.03	1.01	0.31	0.05	0.52	0.60	-0.01	-0.11	0.91
c_{21}	-0.06	-2.20	0.03									
c_{22}	0.07	1.86	0.06	0.12	8.42	0.00	0.06	2.35	0.02	0.09	1.14	0.25
c_{31}	-0.00	-0.03	0.98									
c_{32}	0.21	1.07	0.29									
c_{33}	0.45	8.79	0.00	0.37	11.66	0.00	0.25	3.35	0.00	0.27	2.08	0.04
α_{11}	0.26	11.24	0.00	0.08	6.21	0.00	0.07	2.62	0.01	0.08	5.82	0.00
α_{12}	-0.00	-0.08	0.94	0.04	1.65	0.10	0.03	1.10	0.27	0.04	1.73	0.08
α_{13}	0.13	3.11	0.00	-0.01	-0.57	0.57	0.01	0.18	0.86	-0.01	-0.68	0.50
α_{21}	-0.03	-0.95	0.34	0.00	0.47	0.64	0.00	0.57	0.57	0.00	0.19	0.85
α_{22}	0.18	8.60	0.00	0.05	5.68	0.00	0.05	5.15	0.00	0.05	5.01	0.00
α_{23}	-0.09	-2.04	0.04	0.03	5.59	0.00	0.03	2.08	0.04	0.03	2.19	0.03
α_{31}	0.01	0.32	0.75	0.04	2.73	0.01	0.03	1.89	0.06	0.04	2.56	0.01
α_{32}	0.04	1.14	0.25	0.04	1.83	0.07	0.04	1.50	0.13	0.05	1.49	0.14
α_{33}	0.31	7.88	0.00	0.11	4.26	0.00	0.12	3.64	0.00	0.11	2.35	0.02
β_{11}	0.95	44.28	0.00	0.82	21.26	0.00	0.90	6.96	0.00	0.80	7.30	0.00
β_{12}	0.01	1.58	0.11	-0.01	-0.32	0.75	-0.01	-0.15	0.88	-0.01	-0.23	0.82
β_{13}	0.01	0.32	0.75	0.11	2.05	0.04	0.01	0.06	0.95	0.15	0.91	0.36
β_{21}	0.02	1.30	0.19	0.08	23.79	0.00	0.04	0.85	0.39	0.10	0.81	0.42
β_{22}	0.98	208.09	0.00	0.94	49.22	0.00	0.95	47.84	0.00	0.94	26.14	0.00
β_{23}	0.03	2.09	0.04	-0.17	44.70	0.00	-0.09	-1.40	0.16	-0.18	-0.95	0.34
β_{31}	0.01	0.29	0.77	0.18	8.06	0.00	0.12	1.54	0.12	0.21	1.27	0.21
β_{32}	-0.04	-1.76	0.08	-0.00	-0.09	0.93	0.02	0.17	0.87	-0.01	-0.08	0.94
β_{33}	0.87	32.03	0.00	0.47	15.70	0.00	0.59	4.71	0.00	0.46	1.79	0.07
ρ_{21}				0.09	4.79	0.00						
ρ_{31}				0.49	32.14	0.00						
ρ_{32}				0.03	1.62	0.11						
Θ_1							0.016	3.52	0.00			
Θ_2							0.980	147.45	0.00			
Obs	3130			3130			3130			3130		
Log L	-16132.5			-16141.9			-16047.9			-16572.4		
AIC	10.331			10.337			10.277			10.610		
SIC	10.349			10.355			10.293			10.626		

Models are estimated using robust QMLE procedure, with the following order of variables: FINANCIAL, GOLDS and IT. Here, m_{21} represents the effect of a one period lag FINANCIAL index returns on current period gold spot returns, c denotes the constant terms, and α_{ij} and β_{ij} represent the short-term and long-term volatility spillovers.

effects in the standardized residuals of some of these models. Moreover, for each MGARCH model, the set of variables consisting of FINANCIAL, GOLDS and IT produced the lowest values of AIC and SIC. Further, using this chosen set of variables and the two information criterion, we have already shown that the VAR-DCC-GARCH model is the most suitable in explaining the variations in conditional mean and variance. Based on these results, we now construct the dynamic conditional correlations, optimal hedge ratios and portfolio weights using the VAR-DCC-GARCH model for FINANCIAL, GOLDS and IT.

Table 7

Diagnostic Tests for Standardized Residuals

	BEKK			CCC			DCC			Diag		
	FIN.	GOLDS	IT	FIN.	GOLDS	IT	FIN.	GOLDS	IT	FIN.	GOLDS	IT
Resid												
Q(20)	22.0	11.3	23.7	22.4	11.3	27.7	21.1	11.4	25.8	20.59	11.21	25.88
p	0.3	0.9	0.3	0.3	0.9	0.1	0.4	0.9	0.2	0.42	0.94	0.17
Resid^2												
Q(20)	21.4	16.8	7.6	16.4	20.6	7.2	16.5	20.7	6.6	12.31	20.55	7.14
p	0.4	0.7	1.0	0.7	0.4	1.0	0.7	0.4	1.0	0.91	0.42	1.0

4.2 Dynamic Conditional Correlations

The dynamic conditional correlations are plotted in Fig. 3. It is evident from the plots of ρ_{12}, ρ_{13} and ρ_{23} that the conditional correlations are stationary and there is quite a bit of variability in their values over the time period of our sample. The dynamic correlations between FINANCIAL and IT (ρ_{13}) are always positive with a sample mean of 0.52. It is therefore clear that an investor has very little scope for portfolio diversification between these two assets. On the other hand, the dynamic conditional correlations between FINANCIAL and GOLDS (ρ_{12}) vary from a low of -0.41 to a high of 0.44 and those between GOLDS and IT (ρ_{23}) range from -0.35 to 0.45. Hence, the periods of negative pairwise correlations between GOLDS and the other stock indices considered in our study provide opportunity for meaningful portfolio diversification for an investor.

In general, the dynamic conditional correlation estimates indicate that gold acts as an equity-hedge for an Indian investor. Moreover, since a positive stock market performance of the export-dependent information technology companies is often related to a strong dollar vis-à-vis the Indian rupee, the negative GOLDS and IT return correlations may also capture the dollar-hedging capability of gold in the Indian context.

In fact if we consider only the GFC period, we find that the dynamic conditional correlations between FINANCIAL and IT are much larger, with a mean of 0.67. Whereas the dynamic conditional correlations between FINANCIAL and GOLDS and those between GOLDS and IT are mostly negative with a mean value of -0.06 and -0.07 respectively. This indicates that during periods of crisis the diversification benefits of gold in a portfolio become even stronger for an investor; therefore, providing the much needed safety.

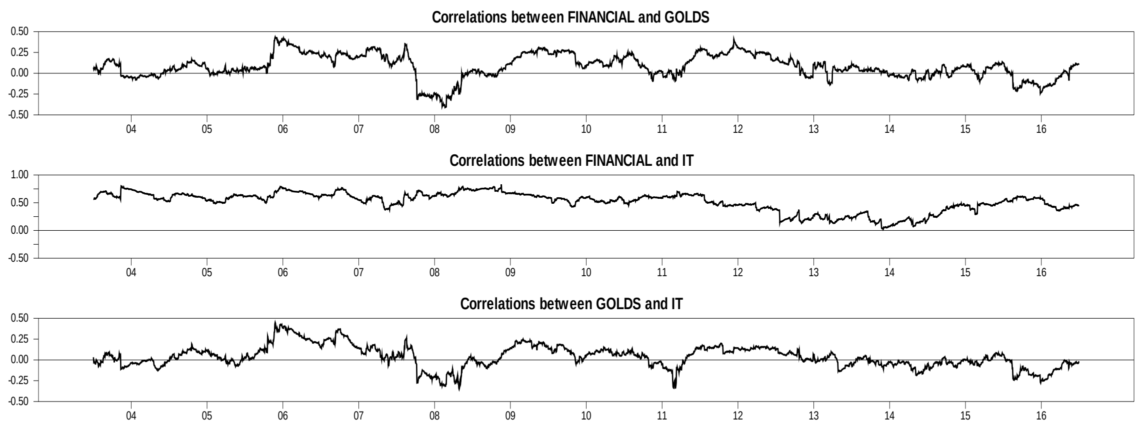

Fig 3. Time-varying Conditional Correlations from the DCC Model

5. Hedging

Using the Kroner and Sultan (1993) methodology we now construct the long/short hedge ratios of our assets. The hedge ratio between an asset *i* and asset *j* is defined as

$$\beta_{ijt} = \frac{h_{ijt}}{h_{jjt}}$$

We plot the dynamic hedge ratios from the VAR-DCC-GARCH model in Fig. 4. We notice that the pairwise hedge ratios, where spot gold is an asset under consideration are more volatile and turn particularly negative during the GFC period. On the other hand, the FINANCIAL/IT hedge ratios are more stable and are all positive. The average value of the hedge ratio between FINANCIAL and GOLDS is 0.12 while the average hedge ratio value between FINANCIAL and

IT is 0.57. The average value of the hedge ratio between GOLDS and IT is 0.03. This means that a $1 long position in FINANCIAL can be hedged for 12 cents with a short position in spot gold. Moreover, a $1 long position in spot gold can be hedged for 3 cents with a short position in IT. The cheapest average hedge is the long GOLDS and short IT while the most expensive average hedge at 57 cents is the long FINANCIAL and short IT.

If we take the average hedge ratios during the GFC period, we find that a $1 long position in FINANCIAL can be hedged for 11 cents with a long position in spot gold while a $1 long position in IT can be hedged for 9 cents with a long position in spot gold. This again reiterates, gold's role as a haven asset in times of financial crisis. Just by holding some gold in their portfolio a typical Indian investor can withstand the financial crisis better.

6. Portfolio Weights

We now use the conditional volatility measures from the DCC-GARCH model to construct optimal portfolio weights following Kroner and Ng (1998). The goal of an investor is to minimize the risk of her portfolio for a given expected return. Given that objective, the optimal weight of an asset *i* in a one-dollar portfolio consisting of asset *i* and asset *j* is given by

$$w_{ijt} = \frac{h_{jjt} - h_{ijt}}{h_{iit} - 2h_{ijt} + h_{jjt}}$$

Without the possibility of short-selling, following restrictions are imposed on the optimal portfolio weights:

$$w_{ijt} = \begin{cases} 0, & if\ w_{ijt} < 0 \\ w_{ijt}, & if\ 0 \leq w_{ijt} \leq 1 \\ 1, & if\ w_{ijt} > 1 \end{cases}$$

The portfolio weights are summarized in Tables 10 and 11. Table 10 provides the summary statistics of the portfolio weights for the full sample while Table 11 focuses on only the GFC period. Considering the full sample, the average optimal weight for the GOLDS/FINANCIAL portfolio is 0.28, which implies that for a $1 portfolio, 28 cents should be invested in spot gold and 72 cents should be invested in FINANCIAL. The average optimal weight for the IT/FINANCIAL portfolio suggests that 40 cents should be invested in IT and 60 cents should be invested in FINANCIAL. Lastly, the average optimal weight for the IT/GOLDS portfolio implies that 68 cents should be invested in IT and 32 cents should be invested in spot gold.

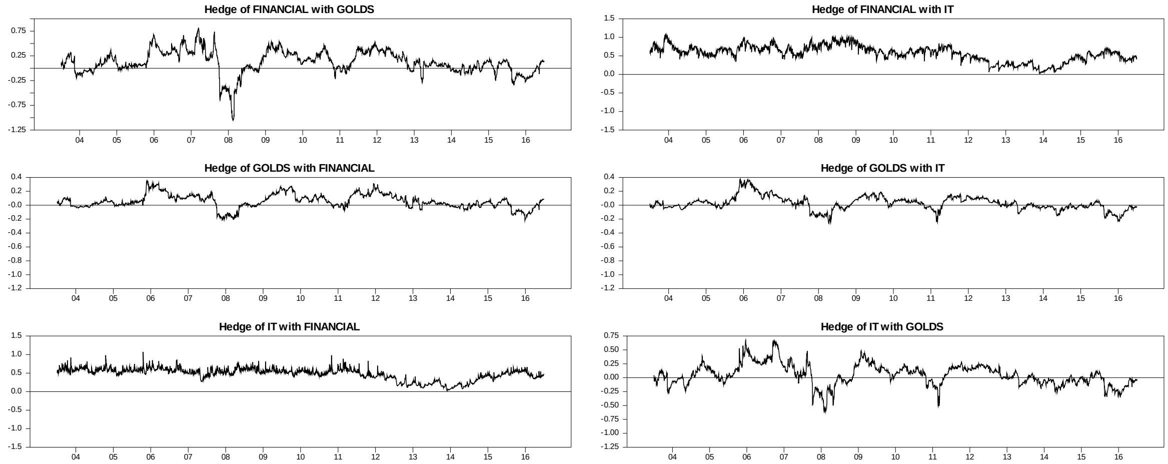

Fig 4. Time-varying Hedge Ratios from the DCC Model

Table 8

Hedge Ratio Summary Statistics

	Mean	St. Dev.	Min	Max
FINANCIAL/GOLDS	0.12	0.24	-1.06	0.81
FINANCIAL/IT	0.57	0.21	0.02	1.09
GOLDS/FINANCIAL	0.06	0.10	-0.22	0.36
GOLDS/IT	0.03	0.10	-0.27	0.38
IT/FINANCIAL	0.48	0.16	0.02	1.07
IT/GOLDS	0.05	0.19	-0.61	0.67

Table 9

Hedge Ratio Summary Statistics during Global Financial Crisis

	Mean	St. Dev.	Min	Max
FINANCIAL/GOLDS	-0.11	0.35	-1.06	0.74
FINANCIAL/IT	0.80	0.13	0.43	1.03
GOLDS/FINANCIAL	-0.04	0.10	-0.20	0.19
GOLDS/IT	-0.05	0.09	-0.27	0.14
IT/FINANCIAL	0.56	0.08	0.38	0.83
IT/GOLDS	-0.09	0.22	-0.61	0.48

Table 10

Portfolio Weights Summary Statistics

	Mean	St. Dev.	Min	Max
GOLDS/FINANCIAL	0.28	0.09	0.03	0.60
IT/FINANCIAL	0.40	0.14	0.00	1.00
IT/GOLDS	0.68	0.09	0.42	0.91

Table 11

Portfolio Weights Summary Statistics during Global Financial Crisis

	Mean	St. Dev.	Min	Max
GOLDS/FINANCIAL	0.27	0.09	0.06	0.45
IT/FINANCIAL	0.24	0.15	0.00	0.72
IT/GOLDS	0.67	0.09	0.51	0.89

The average optimal weights during the GFC period remained about the same for the GOLDS/FINANCIAL and the IT/GOLDS portfolios while for the IT/FINANCIAL portfolio it seems that an investor should have realigned her portfolio in such a way that she should have invested 24 cents in IT and 76 cents in FINANCIAL.

In general, our results on gold's portfolio weight vis-à-vis stocks, suggest that crisis or not a prudent investor should allocate around 30 per cent of her investible assets in gold. This is in line with the results that Gülseven and Ekici (2016) find for Turkey, where the optimal portfolio weight of gold goes higher than 50% if interest-earning deposits are not included in the portfolio. Given that in India around 41% of the population is still without access to bank accounts and hence are deprived of interest-earning deposits, gold's optimal portfolio weight of 30 per cent is therefore not very surprising.

7. Conclusion

In this paper, we use multivariate GARCH models to analyze dynamic linkages between gold and equity prices returns. We model dynamic conditional correlations and volatility spillovers between these assets. We also estimate and compare BEKK-GARCH, CCC-GARCH, DCC-GARCH and diagonal-GARCH models within a VAR framework. Based on several information criteria, we find the VAR-DCC-GARCH model to be the best fit for our sample. Our results show that spot gold can be an effective hedge against stock prices of financial services and information technology companies. A $1 long position in the NIFTY Financial Services index can be hedged for 12 cents with a short position in spot gold and a $1 long position in the NIFTY Information Technology index can be hedged for 5 cents with a short position in spot gold. During the Global Financial Crisis period between 2007 and 2009, gold seems to play a role of a safe haven asset as the dynamic conditional correlations between spot gold returns and equity indices returns turn negative. In the crisis period an investor with a $1 long position in the NIFTY Financial Services index can hedge her exposure for 11 cents with a long position in spot gold.

The analysis of optimal portfolio weights indicates that stocks should outweigh gold assets. Indeed a prudent investor should always optimally allocate around 30 per cent of her investible assets in gold within a gold/stock portfolio. In India, where around 41% of its population is still without access to banking services and hence are deprived of interest-earning deposits, it is not very surprising to find gold’s optimal portfolio weight to be as high as 30 per cent.

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