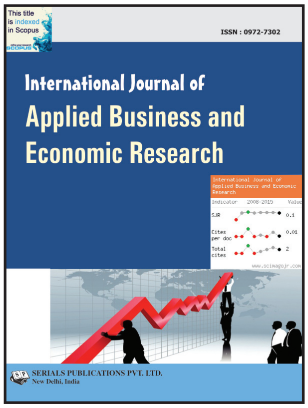

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Fear Estimation–Evidence from BRICS and UK

Bikramaditya Ghosh[1], Corlise Le Roux[2] and Rodica Ianole[3]

[1]*Assoc. Professor, Institute of Management,Christ University, India*
[2]*Asst. Professor, University of Johannesburg, South Africa*
[3]*Assoc. Professor, University of Bucharest, Romania*

ABSTRACT

The paper aims to build a composite Fear Index for the BRICS countries and UK by adding new dimensions to the initial structure, such as overbought/oversold conditions and commodity impacts. The main purpose is to identify the degree in which fear really percolates down to all the market participants, respectively if this generates a certain asset transfer to Gold. The results point out the GMM model as the best fit for explaining the link between the Fear Index and the behaviour of market participants. It also confirms the transfer of assets to a safer asset class during the phases of high volatility on the market.

JEL Classification: C53, C58, G01, G17.

Keywords: VIX, Fear Gauge, Generalized Method of Moments, Reverse Anchoring.

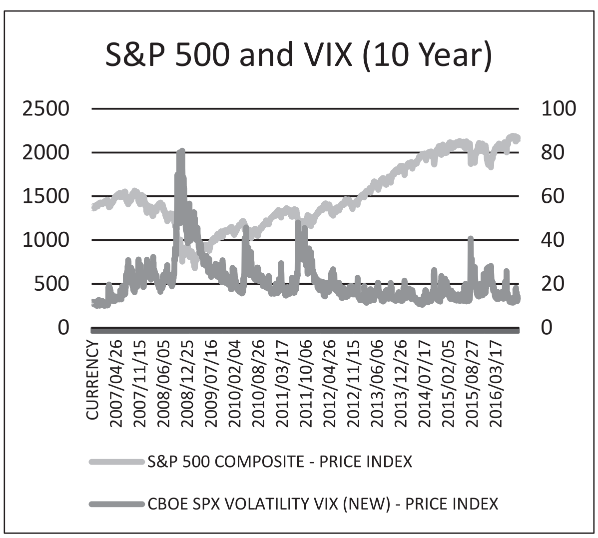
1. INTRODUCTION

"Avoiding danger is no safer in the long run than outright exposure. The fearful are caught as often as the bold" (Keller, n.d.). The Chicago Board of Options Exchange (CBOE) have constructed the CBOE Volatility Index (VIX) for various nations based on the 30-day volatility and market expectation are based from that. The VIX is a market estimate of implied or expected volatility (CBOE, 2016). Popularly it is referred to as the Fear Gauge or Fear Index and investors use it to gauge the overall level of fear that exists within the market. From its initial work in Dow Jones Industrial Average (DJIA) way back in 1993 till date, it got developed in various countries as a measurement of expectation of the market participants as far as the volatility is concerned. It basically tracks the 30 day options volatility from day one till the day of expiration and then as a rolling mode.

Shaikh and Padhi (2015) examined the effects of implied volatility to determine if it could be used as an investor fear gauge as well as if it can be used as a forward-looking expectation of volatility within the future stock market in India. Evidence was found that the India VIX was both a gauge of investor sentiment and a forward-looking index of expected market volatility. Further evidence the VIX being a gauge of investor sentiment and a forward-looking index of expected market volatility is found by Bahadur and Kothari (2016), Bagchi (2012), and Kumar (2012).

Sudden global collapse will showcase the sudden surge in the volatility index, as investors want to stay with cash and not bothered of less profit even some kind of trading loss as well. International equity demand under such circumstances will nose dive and supply will remain buoyant forcing the VIX to head north. The bigger question here is, whether the sense of fear really percolating down to the bottom of the pyramid and touching the investors in the retail segment. As the understanding of complex indices such as VIX is not plausible among the entire gamut of market participants across the length and breadth of the BRICS nations along with UK, the time lag and understanding deference will create a gap. So, if the investors of all levels simultaneously behave as per the movements of VIX in respective countries, then it could be translated as fear percolation as even and without a lag. The proper justification and utilisation of VIX therefore could be established. The next question is even more critical. If yes then are they staying afloat during such times or shifting their resources to the age old safe heaven called Gold. Gold has been traditionally observed as a crash alternative. So, this study will also throw the light on the movement of yellow metal with respect to the VIX movement which in other term will add the behavioural angel to this study, as loss aversion parameter will come in the forefront. Initially only the BRICS universe was taken into consideration, but later the UK has been added in the fray according to the asymmetric causality found in between BRICS, MIST and UK by Yarovaya and Lau (2016).

Figure 16.1(a) illustrates the relationship between the S&P 500 and the VIX over a ten year period as well as a 1 year period. From a visual perspective the two datasets seem to be moving in an opposite manner, for example when the price of the S&P 500 increases, the VIX decreases.



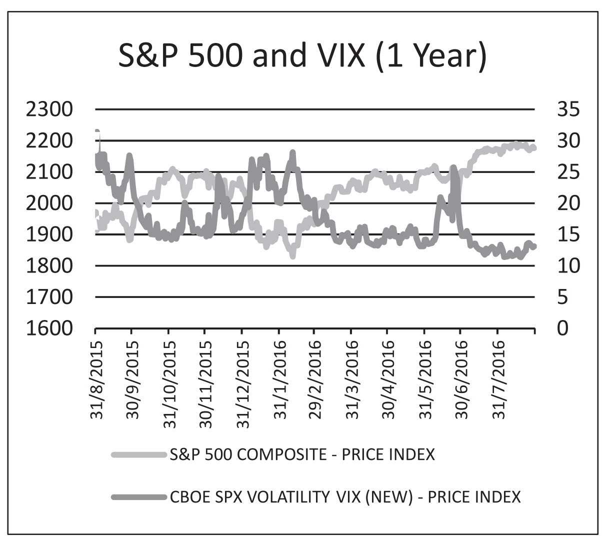


Figure 16.1(a)

Figure 16.1(b) displays the relationship between the VIX and the Gold spot price (in USD) over a ten year period as well as a 3 month period. The same pattern as the S&P 500 and the VIX does not appear in the VIX and Gold price figure, but at times there are opposite movements in the two datasets.

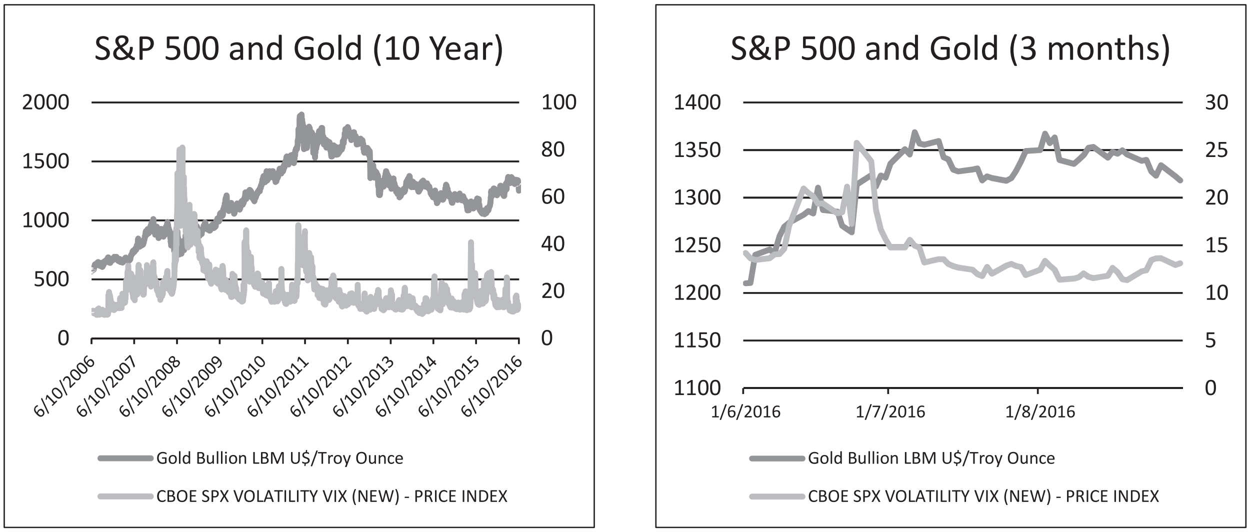


Figure 16.1(b)

The objective of the study is to investigate the degree to which fear filters down to all the market participants involved in investment activities, and whether this fear generates a certain asset transfer to Gold. The period of interest is from December 2011 to the end of August 2016 showing a consolidation phase (post 2008) of the fear index or VIX.

The combination of variables selected for this paper are the daily data for selected momentum oscillators (LT, SIGNAL, and SMI) and William%R which is a momentum indicator for the BRICS countries and UK as well as the international Gold spot price. The momentum oscillators show the momentum continuation or shift within the market, whereas the William%R measures overbought and oversold levels within the market. Gold was included as a variable as it is considered a safe haven asset which provides value during times of distress.

The variables were analysed using thee defined Panel Data Regression methodologies in order to obtain a final composite Fear Index Model. The results of the study showed that fear filtered through to all levels of market participants and their interpretation of fear. That action is observed in the overbuying/oversold zone (W%R) and in Gold. This relates to the objective of the study showing that Gold acts as a universal hedge against fear. The panel behaviour indicated that the BRICS showed a secular movement pattern against fear. The final part of the analysis resulted in the construction of a composite Fear Index Model which combines the commodity (Gold), technical indicators of fear, as well as with the fear gauge (VIX).

The remainder of the paper is structured in the following format. Part 2 provides a review of the current literature available. Part 3 explains the methodology used in the study. Part 4 provides a detailed description of the results and interprets the results and findings of the study. Lastly, part 5, provides the conclusions drawn from the results of the study.

2. LITERATURE REVIEW

The literature review paints a rich framework on how to forecast volatility on the financial markets, both in terms of model technicalities and empirical implications. The interest for measuring and forecasting volatility of both practitioners and research community has greatly increased in the last years, in accordance to its relevance for the economy as a whole but also for many specific fields, from investment to risk management and monetary policy (Poon & Granger, 2003). Fear is a central variable within the 'animal spirits' category (Akerlof & Shiller, 2010), generating a significant influence on investor's behaviour, both at an individual and a collective level. As a negative effect, fear can play multiple roles: in the area of reasoning and judgment, fear is correlated with more pessimism in approaching future events (Lerner & Keltner, 2001), while in the form of anxiety it is associated with initiatives related to uncertainty reduction and risk avoidance (Raghunathan & Pham, 1999). At the level of the market, fear is most commonly conceptualized in the market volatility index (VIX), introduced in 1993 and often labelled as 'the fear gauge' or 'the sentiment index', which is actually measuring the implied volatility of options on the Standard, and Poor's 100 stock index. An important feature is its forward-looking characteristic (Whaley, 2008), thus the orientation towards the investor's expectations on future volatility. Beyond the general depiction offered by the evolution of the index, fear can also be conveyed in a more concrete manner, by looking at the accelerating increases, thus the convexity in the VIX (Low, 2004). Furthermore, Giot (2002) emphasizes the crucial importance of the analysis's horizon: from a short-term perspective, a high level of implied volatility may be also interpreted as a hint for a likely increase in stock indices. Sarwar (2012) examines the relationship between the VIX and stock market returns in BRIC countries, for the period 1993-2007. He points out the existence of a strong negative and contemporaneous relation between VIX and equity returns for China, Brazil and India.

One direction to follow resides in examining the multiple dimensions of the VIX and the different potential correlations between it and the other indicators. Historically, the structure of VIX has encountered some internal transformations (under the shapes of VXO and VXN), generating pertinent questions about what it is actually measuring: fear or just forecasts of future volatility (Arak & Mijid, 2006). The more recent methodology employed by CBOE has managed to settle the debate by introducing a new VIX in 2003 and switching from the initial Standard and Poor's 100 stock index to the 500 version (Wu, 2006). Since 2006 it is even possible to trade VIX options contracts and since 2011 a procedure of VIX-ifing individual stocks is available. The volume of type of trading has increased at a very fast pace given its interesting feature of acting as tail risk hedging strategy (Park, 2016), thus offering protection against potential stock market downturns.

On a concrete level, Sarwar (2012) examines the relationship between the VIX and stock market returns in BRIC countries, for the period 1993-2007. He points out to the existence of a strong negative and contemporaneous relation between VIX and equity returns for China, Brazil and India. In a similar vein, but by employing a quantile regression approach, Mensi and his colleagues (2014) describe the effect of VIX on the BRICs stock market as an asymmetric one and as having a decreased intensity since the 2008 financial crisis. From a larger perspective, spillover effects are also being examined in respect to the fear index and their association is a significant one with respect to the spill over of the US stock market into other markets (the recent paper of Tsai, 2014, discusses this issue for five leading stock markets: the United States, the United Kingdom, Germany, Japan and France).

A second line of action is represented by new developed measures for the investor's fear, either through innovative statistical procedures or through a different conceptualization of fear. With a focus on rare disaster type events, Bollerslev and Todorov (2011) provide such a new index, fundamental on highfrequency data and the principles of the extreme value theory, arguing the central role of jump tail risk in explaining large equity and variance risk premia.

Another approach (Dhaene et. al., 2012) has considered more than one element – volatility in this case – as a significant predictor of fear, creating an enhanced view with three more components – systemic risk, liquidity risk and counterparty risk – under the name of FIX (fear index).

Addressing the reactions to the fear experienced on the financial market, one important question to ask refers to the role of Gold as a shelter or safe haven in times of risk and volatility. Cohen and Qadan (2010) have devoted a careful analysis to the relationship between Gold prices and the fear index, quantified through the VIX score, by employing US data. The correlation obtained is a positive one, suggesting that an increase in Gold prices is linked to higher levels of fear. Furthermore, after a particular threshold registered by the VIX (after 20), the relationship is also a causal one. This result becomes even more interesting if we expand the influences horizon by also including the numerical psychological barriers existing in the formation of daily Gold prices (Aggarwal & Lucey, 2007) and also the findings implying that fluctuations in the VIX drive the returns of Gold contracts (Qadan & Yagil, 2012).

3. DATA AND METHODOLOGY

The total number of observations contained in our dataset is 44352, collected for the period between 12th December 2011 and 30th August 2016 and for all the targeted countries (BRICS and the UK). This phase could well be seen as a mix of post-crash (2008) consolidation phase. It is also associated with global eco-political turmoil, in the Middle Eastdisturbing the equilibrium of normalcy coupled with commodity intensive (crude oil deluge) deterministic phase and observing avalanche breakdown in crude oil prices. The main purpose is to identify the degree in which fear really percolates down to all the market participants, respectively if this generates a certain asset transfer to Gold.

The effect on Fear Gauge or VIX is checked with the following control variables: -William%R (WR), SMI, SIGNAL, LT and GOLD. This structure of Panel data had all the respective variables, mentioned above for respective constituents of BRICS and UK. The control variables (apart from Gold) are technical oscillators, which indicate the trend as well as the strength of the trend. Gold is kept to check the age-old behavioural bias of Heuristic simplification, as the Fear component increase in the market; investors shift their interest from equity to Gold. Invented by Larry Williams, William%R (WR) is a momentum indicator that works exactly inverse of the Fast Stochastic Oscillator. Also referred to as WR, William%R reflects the overbought and oversold conditions for both commodity and equity. William%R oscillates from 0 to −100. Readings from 0 to −20 are considered to be overbought zone, while readings from −80 to −100 are considered to be oversold zone.

The SMI or the stochastic momentum index is a refined version of available stochastic oscillators. It measures the distance of the current closing price from the median of the high as well as low range of price, as developed by William Blau. SIGNAL, as it's described is nothing but a 9 day exponential moving average line (EMA) on the Moving Average Convergence Divergence (MACD) for indicating various buying and selling signals for the investors. Gerald Appel constructed MACD to depict the momentum as well as the trend in late 1970s. If 9 day EMA or SIGNAL is above, 12 day EMA and 26 day EMA, that means the positive momentum is building in the short run, which will keep the up-trend continuous. The shorter EMA holds the key, as its divergence from the longer EMA, will determine the trend. LT or Line of Trade Price is nothing but trading day end price of either the bourse or the specific stock. In this case it is the trading day end price of the base bourse on which CBOE VIXhas been calculated and constructed for the respective countries under consideration.

Three defined Panel Data Regression methodologies are used in this study. Firstly the Fixed Effect, secondly the Random Effect and lastly the Generalized Method of Moments have been used to choose a comparatively better and accurate model to choose from. Both Cross Section as well as Period has been kept fixed for the Fixed Effect Model. Both Cross Section as well as Period has been kept random for the Random Effect Model. Cross Section has been kept random and Period has been kept fixed for the Generalized Method of Moments Model.

Panel Data Regression (Fixed and Random Effects)

Time series and cross-sectional data get combined to form Panel Data, where similar universe of countries or companies are recorded with time and phenomena. Sometimes the presence of lagged dependent variables too becomes an accurate estimator. Panel Data Regression, both in Random Effect and Fixed Effect has the same basic equation to follow:

$$y_{it} = a + bx_{it} + \in_{it} \tag{1.0}$$

Where y and x are variables, "a" and "b" are coefficients and i, t are indices for individuals and time. $\in$ as an error term is the only part that changes between a Fixed effect and Random effect. For Fixed Effect it varies in non-stochastic manner with reference to either i or t, where as in Random Effects it varies in stochastic manner with reference to either i or t.

Generalized Method of Moments (GMM)

According to Hansen & Singleton (1982) Generalized Method of Moments (GMM) generally combines observed financial or economic data with the information in population moment (moments such as mean, variance, Skewness and kurtosis) conditions to produce estimates of the hidden or unknown parameters of this financial/economic model. GMM estimator makes the model robust by removing the unnecessary assumptions. Moments are defined as measures which in turn describes the shape of the distribution. The more moments that GMM uses the more standard deviation reduces and getting it close to the true value.

Where L moment conditions with K dimensional parameters that β should satisfy. So the vector L >= K is written as below.

$$E = (m(y_t, \beta)) = 0 \tag{1.1}$$

When it is represented as per orthogonality condition between the residuals of the equation and the set of K instruments called as Z_t.

$$E = (Z_t U_t(\beta)) = 0 \tag{1.2}$$

Generalized method of moments is the estimation of β, which has to be minimised gradually.

Hausman Test

Under the condition that there is no correlation between the regressors and the effects both FE and RE are found to be consistent, however FE is inefficient. But if the correlation is present between the regressors and the effects then FE is consistent and RE is inconsistent. So, the covariance of an efficient estimator with its difference from an efficient estimator should be zero. Where, β_0 is the FE estimator and β_1 is the RE estimator.

$$H = (\beta_1 - \beta_0) + (\mathrm{Var}(\beta_0) - \mathrm{Var}(\beta_1)) + (\beta_1 - \beta_0) \tag{1.3}$$

4. RESULTS AND DISCUSSIONS

The first model uses the Panel Least Squares, with the Fixed Effects, including six cross-sections for the horizon of 12th December 2011 to 30th August 2016, comprising of 1232 periods and a total number of 7392 observations. The coefficients obtained for the independent variables chosen to explain the variance of the VIX are illustrated in Table 16.1.

Panel LS (Cross-sectional Fixed Effects)

Table 16.1

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*	*Occurrence*
C	25.58722	0.54269	47.14889	0	
WR	–0.004447	0.005592	–0.795161	0.4266	57.34%
SMI	–0.006729	0.007026	–0.957689	0.3383	66.17%
SIGNAL	0.004518	0.005104	0.885144	0.3761	62.39%
LT	–0.000592	2.52E-05	–23.49787	0	100.00%
GOLD	0.000231	1.01E-05	22.78904	0	100.00%

Table 1.1

R-squared	0.76747	Mean dependent var	23.80421
Adjusted R-squared	0.720549	S.D. dependent var	10.04661
S.E. of regression	5.310958	Akaike info criterion	6.329514
Sum squared resid	173468.6	Schwarz criterion	7.490219
Log likelihood	–22151.89	Hannan-Quinn criter.	6.728381
F-statistic	16.35636	Durbin-Watson stat	0.102352
Prob (F-statistic)	0		

Fixed Effect Panel Data Regression has clearly showed that Gold and LT (Line of Trade Prices) are the two defining parameters with a precision of about 72% accuracy (by Adjusted R squared). AIC, SC and HQ as we know consider the log likelihood factor and subsequently define a definite penalty on that depending on the number of variables under estimation. Generally the values are found to be quite close to each other. Since BIC or SC penalises free parameters more strongly, so it is considered to be a better measure over AIC. Durbin Watson Figure 16.being closer to zero signifies that there is positive auto-correlation in this complex Panel.

Pedroni Residual Cointegration Test

The analysis is strengthened by the implementation of a Pedroni Residual Cointegration Test. As usual, the null hypothesis refers to the lack of cointegration, while the trend assumption is a deterministic intercept. The technical coordinates are a user-specified lag length of 1 and the underlying method is based on a Newey-West automatic bandwidth selection and Bartlett kernel.

Table 2

Alternative hypothesis: common AR coefs. (within-dimension)	*Statistic*	*Prob.*
Panel v-Statistic	4.601112	0.0015
Panel rho-Statistic	–8.937809	0
Panel PP-Statistic	–7.186029	0
Panel ADF-Statistic	–5.463669	0

Table 2.1

Alternative hypothesis: individual AR coefs. (between-dimension)	*Statistic*
Group rho-Statistic	–16.53364
Group PP-Statistic	–9.527061
Group ADF-Statistic	–6.465451

Pedroni Tests are used as a second step for finding cointegration originating from a static relationship within the residuals. Here, as the Panel Data Regression is done on Fixed Effects, so this suits Pedroni Test to follow. Again in Pedroni Test, it is once again proved that the Null Hypothesis has been rejected, thus there is a trace of cointegration found, even in such a complex Panel. The detailed tests under this umbrella, i.e. PP, Rho and ADF too have very low to zero P value signifying that Null Hypothesis will be rejected. This is re- confirming the presence of cointegration in this Panel. Co-integration in such complex Panel indicates at the possibilities of construction of an advanced model, combining the cointegrated variables, which in turn will increase the efficiency of the established CBOE VIX model.

The second model uses the Panel Estimated Generalized Least Squares, with the Random Effects, including six cross-sections for the horizon of 12th December 2011 to 30th August 2016, comprising of 1232 periods and a total number of 7392 observations. The coefficients obtained for the independent variables chosen to explain the variance of the VIX are illustrated in table 3.

Panel EGLS (Cross-sectional Random Effects)

Table 3

Wansbeek and Kapteyn estimator of component variances

Variable	*Coefficient*	*Std. Error*	*Prob.*	*Occurrence*
C	25.56274	0.54236	0	
WR	–0.004433	0.005592	0.428	57.20%
SMI	–0.006721	0.007026	0.3389	66.11%
SIGNAL	0.004499	0.005104	0.3781	62.19%
LT	–0.00059	2.52E-05	0	100.00%
GOLD	0.00023	1.01E-05	0	100.00%

Table 3.1

Weighted Statistics			
R-squared	0.494347	Mean dependent var	23.80421
Adjusted R-squared	0.392805	S.D. dependent var	6.81567
S.E. of regression	5.310954	Sum squared resid	173609.4
F-statistic	4.868424	Durbin-Watson stat	0.102278
Prob(F-statistic)	0		

Panel Generalized Method of Moments (GMM)

The third model uses the Panel Generalized Method of Moments (GMM), with the Random Effects, including six cross-sections for the horizon of 12th December 2011 to 30th August 2016, comprising of 1232 periods and a total number of 7392 observations. The coefficients obtained for the independent variables chosen to explain the variance of the VIX are illustrated in table 4.

Table 4

Variable	*Coefficient*	*Std. Error*	*Prob.*	*Occurrence*
C	25.58722	0.54269	0	
WR	–0.004447	0.005592	0.4266	57.34%
SMI	–0.006729	0.007026	0.3383	66.17%
SIGNAL	0.004518	0.005104	0.3761	62.39%
LT	–0.000592	0.00	0	100.00%
GOLD	0.000231	0.00	0	100.00%

Table 4.1

R-squared	0.76747	Mean dependent var	23.80421
Adj R-squared	0.720549	S.D. dependent var	10.04661
S.E. of regression	5.310958	Sum squared resid	173468.6
Durbin-Watson St	0.102352	J-statistic	6150
Instrument rank	1243	Prob(J-statistic)	0

Random Effects model (Estimated Generalized Least Squares or EGLS) signifies no correlation allowed between variables at all, so obviously the accuracy (by Adjusted R squared) fell to 39%. Random Effect Panel Data Regression has clearly showed that Gold and LT or Line of Trade Price is the two defining parameters with a precision of about 39% accuracy (by Adjusted R squared). So, interestingly both Random Effects Model and Fixed Effects Model are indicating to the same variable, that in turn ensures that fear do percolate to all the possible layers of investors in the market. So, when the Line of Trade Price is indicating overbought and oversold zones, market participants with reasonable understanding are shifting their allocations to Gold. If fear or uncertainty is not percolated, then this kind of behaviour would have been quite unexpected. Again we can also observe the behavioural traces too, as William%R, the measure of overbought and oversold condition is only occurring for approximately 57% occasions both the tests. This in turn hints towards a reverse behavioural bias that is "Reverse Anchoring". Kahneman & Tversky has defined Anchoring as a mental attachment to a particular level or price or zone (could be overbought or oversold). If that holds good, then here the moment William%R reaches close to the mark of being oversold, investors would have started buying, however here it is happening for about 57% occasions, hinting that there could be a concept called Reverse Anchoring too. However we cannot compare Fixed Effect, Random Effect and Generalized Method of Moments by estimation of R Squared. As the calculation rationale and ingredients have to follow a similar methodology for that. So, we cannot conclude by R squared, which is the better Model among the three. Thus we needed Hausman Test to choose the apt final model among the three probable models.

Comparing RE against FE by Hausman Test

Correlated Random Effects - Hausman Test		
Test Summary	*Chi-Sq. Statistic*	*Prob.*
Cross-section random	4.990463	0.417

Hausman Test (between RE and FE)

Ho: Random Effects is preferred

Ha: Fixed effects (FE) is consistent and thus preferred.

Here in this case P value is almost 42%, signifying the fact that Random Effects is preferred, when compared with the Fixed Effect Model.

Comparing RE against GMM by Hausman Test

Correlated Random Effects - Hausman Test		
Test Summary	Chi-Sq. Statistic	Prob.
Cross-section random	2374.72316	0.00

Hausman Test (between RE and GMM)

Ho: Random Effects is preferred

Ha: Generalized Method of Moments (GMM) is preferred.

Here in this case P value is 0%, signifying the fact that GMM is preferred, when compared with the Random Effect Model.

All the three models are shown below

Fixed Effect Model

$$\begin{aligned} \text{VIX} = {} & 25.5872183724 - 0.00444659123501 \times \text{WR} - 0.00672912712506 \times \text{SMI} \\ & + 0.0045179094525 \times \text{SIGNAL} - 0.00059218828904 \times \text{LT} \\ & + 0.000230772955146 \times \text{GOLD} \end{aligned} \tag{1.4}$$

Random Effect Model

$$\begin{aligned} \text{VIX} = {} & 25.5627437568 - 0.00443307037501 \times \text{WR} - 0.00672060609292 \times \text{SMI} \\ & + 0.0044992582602 \times \text{SIGNAL} - 0.000589503403042 \times \text{LT} \\ & + 0.000230332013807 \times \text{GOLD} \end{aligned} \tag{1.5}$$

GMM Model

$$VIX = 25.5627437568 - 0.00443307037501 \times WR - 0.00672060609292 \times SMI$$

$$\begin{aligned} VIX = 25.5872183725 &- 0.00444659123511 \times WR - 0.00672912712516 \times SMI \\ &+ 0.00451790945255 \times SIGNAL - 0.000592188289041 \times LT \\ &+ 0.000230772955145 \times GOLD \end{aligned} \tag{1.6}$$

Residual Fitting Model as per GMM

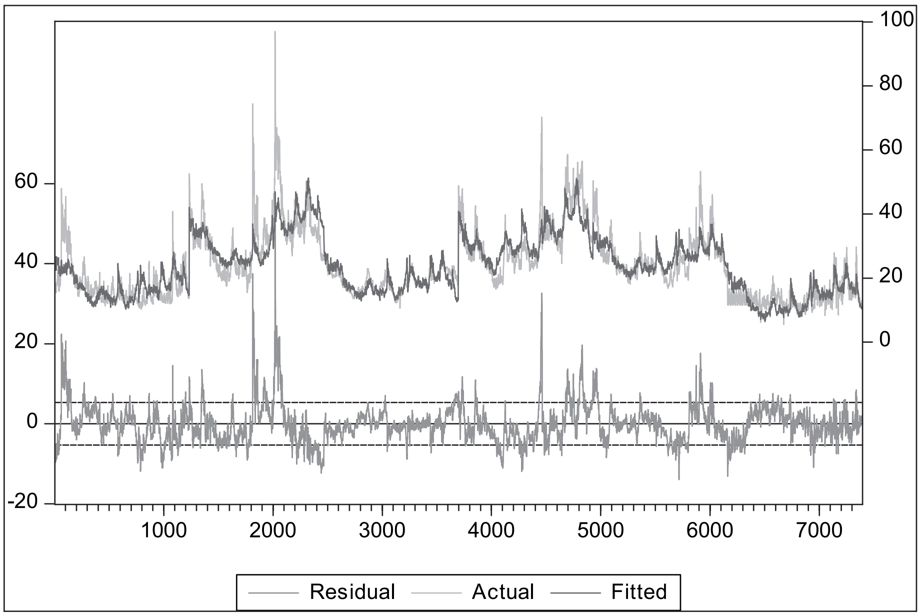


Figure 16.2

5. FINAL REMARKS AND CONCLUSIONS (FINAL COMPOSITE FEAR INDEX MODEL)

The final shape of the model is presented in equation 1.7

$$\begin{aligned} VIX = 25.5872183725 &- 0.00444659123511 \times WR - 0.00672912712516 \times SMI \\ &+ 0.00451790945255 \times SIGNAL - 0.000592188289041 \times LT \\ &+ 0.000230772955145 \times GOLD \end{aligned} \tag{1.7}$$

So, out of the three models, the GMM model emerges out as the most efficient one to capture the link between Fear Index and behaviour of market participants; also it links the transfer of assets to a safer asset class during the phases of high volatility thus Fear. Another interesting fact to be noted here is, in the final selected model (i.e. GMM model) LT has a negative signed coefficient signifies, trade goes down with increasing VIX i.e. volatility, whereas GOLD has a positive signed coefficient, signifying asset transfer to GOLD is directly proportional to the implied volatility factor, for BRICS and UK, in these phase of financial consolidation (post the 2008 crash). So, this model doesn't try to outright ignore the current fear gauge i.e. VIX, on the contrary this model makes it robust, adding the trend (with LT or Trade Line) and the commodity aspect (Gold) as well. This study being focussed on BRICS and UK; so a clear heterogeneity is evident. Though the geopolitical levels, financial literacy levels, income distributions levels (Gini index of China is 45, India is 33 and South Africa is 64), financial regulations and economic activity measurements are quite diverse in this universe, yet a strong generalized trend and equation came out as a common thread. Presence of "Reverse Anchoring" proves that the presence of behavioural bias during "Fear Zones" cannot be confirmed every time.

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