Optimal Dynamic Hedging in Selected Markets®

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ABSTRACT

This study examined the most optimal hedging portfolio for some selected emerging and developed markets by employing dynamic conditional variances and dynamic conditional covariances. Throughout the study, the daily index values of some selected investment instruments were used. The data contained the period from 02/01/2006 to 01/11/2018. In this essay, to obtain the most efficient hedging portfolio for each emerging country, first, dynamic conditional correlation-fractionally integrated generalized autoregressive conditional heteroskedasticity model specifications were used to measure volatility. In this regard, AIC and log-likelihood were performed to measure how well a particular model fits the data. Also, for univariate and multivariate models, Box-Pierce and Li-McLeod test statistics were used to determine the existence of the autocorrelation problem and the ARCH effects on standardized residuals and squared standardized residuals. Second, the robustness of the model was checked by observing its out-of-sample forecast performance. Then, the mean absolute deviation was calculated to detect the most fitted model. Third, two methods were mentioned: optimal hedge ratio and optimal portfolio weight. The optimal hedge ratio provided specific determination of which part of the GOLD in the long-term position should be invested in the Stock Market Indices in the short-term position. With the direction of the above-mentioned model, the most optimal investment portfolio was analyzed by using optimal portfolio weight. Finally, the economic rationale behind the results was proposed, implying that, first, investors are risk-averse. Especially in a financial crisis, each market player has a tendency to keep their profits at a certain level because the aggregate demand for commodity is most likely expected to lessen, and they are prone to making risk diversification of their asset by selling some part of it in the short term. GOLD is the most valuable asset in the long run, as it is a safe haven asset, reflecting that it is lowly correlated with other investment instruments. For a short-term position, the reason why BOVESPA and FTSE_100 are most convenient investment instruments to be invested in the short term were explained.

Key words: *DCC-FIGARCH, Out-of-Sample Forecast, Mean Absolute Deviation, Optimal Hedge Ratio, Optimal Portfolio Weight*

JEL Codes: G11, G17

1. INTRODUCTION

Over the past decade, emerging countries have had significant growth in their stock markets, both in value and volume. This has also enabled great investment opportunities for market agents, as they are more likely to obtain high returns from emerging markets rather than earning by investing in developed markets. As a result, on a big scale, capital inflows from developed markets to emerging markets occur. However, negative views and events happening in other markets crucially impact the emerging markets, certainly producing

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institutional investment flowing in to or out of the market. Eventually, high fluctuations in stock prices and uncertainty take place in these emerging markets. Moreover, many crises and turbulences have hit global stock markets. Financial analysts and policymakers have been concerned that stock markets in emerging markets have demonstrated excessive volatility and a drastic drop in their values through these periods. Hence, the reason why major market agents must be prudent while making investments and seeking an appropriate hedging instrument is that portfolio managers and investors have considerably suffered from uncertainty and excess fluctuations, which are caused by crises and unforeseen events.

To consider precious metals as a hedging instrument, gold is financially sound and universally accepted as a permanent asset between those commodities (Kumar 2014). Gold can be regarded as the most optimal hedging strategy for investors due to some specific reasons. One of which is that gold has always been considered as a precious asset by human beings. The reason for this is that people have constantly evaluated gold as a medium of exchange or a tool for saving. The USD is counted as the most valid reserve currency worldwide. Thus, when the value of the dollar is expected to decrease by financial market agents, they have a strong tendency to purchase the security of gold, which raises gold prices, which happened between 1998 and 2008. Hence, the weakness of the USD is another reason why investors should consider gold as the most optimal investment diversification strategy. Another factor is that gold has a finite supply, mostly having two material factors. One of which is that global central banks have been trading gold in the financial markets since the 1990s. Another is that there has been gradually diminished production of gold since the 2000s. This situation also determines its value. Silver also can be regarded as a close substitute for gold (Lucey and Trully, 2006). In this direction, silver can also pursue arbitrage and low risk spreading of trading properties. The majority of the demand for platinum constitutes the automobile industry, in which part of it is used as a catalytic converter. Only 10% of the total demand for platinum is preferred for use in investments. Here, there are two remarkable facts. One of which is that investors need to improve the hedging strategies for their assets with other investment instruments, such as gold and other precious metals, in order to make risk diversification of the portfolio in the stock markets. Thus, researchers and practitioners in the financial area have recently drawn great attention to precious metals, as argued by Arouri et.al. (2014). Second, due to different fluctuations and weak correlations with stock returns, a trend has occurred, in which investors have started to regard precious metals as an alternative hedging instrument. Therefore, adding precious metals to the hedging strategy is necessary.

The goal herein was to form a portfolio that minimizes the hedging risk and includes developed stock market indices, domestic market indices, precious metals, and oils. These portfolios were created to observe the measurement of hedging in emerging markets. Because the literature has not paid attention to developed market indices, some emerging market indices, precious metals, and oils together, it was aimed herein to make a comprehensive analysis. Abdullah and Mensi (2015) as well as Nagayev et.al. (2016) gave specific instances that should be carefully be paid attention to in this asset mixture. Moreover, they concentrated on some sets of countries, such as Singapore, Malaysia, Philippines, and Saudi Arabia, which comprise in a limited region. Hence, a decision was made to do more comprehensive research, which should observe the connection between precious metals, such as gold, silver, platinum, and palladium; exchange rates of some emerging markets such as Brazil, Turkey, India, and Malaysia, in terms of the USD; domestic stock market indices of those countries, such as BOVESPA, BIST_100, BSE_SENSEX_30, and FTSE_BURSA_KLCI, respectively.

The main aim of this study is three-fold. This was initially attempted to examine the dynamic percentage return by employing the dynamic conditional correlation-fractionally integrated generalized autoregressive conditional heteroskedasticity (ARCH) model (DCC-FIGARCH). The forecast performance of these models was also checked. Subsequently, the results of the model were employed to calculate and observe the optimal weights and hedge ratios for the portfolio holdings. Eventually detected were the portfolio diversification of some selected (developed and developing) stock market indices, precious metals, as well as oil, which was attributed to the different competing multivariate FIGARCH-specifications. Finally, after the most optimal hedging portfolio was obtained, the economic rationale was proposed in the conclusion section by questioning the investor's behavior as well as the economic conditions of the emerging countries.

This paper has two main contributions to the existing literature. Initially, presenting the DCC-FIGARCH estimation, some combinations of the investment instruments in financial markets were constructed. In this direction, in order to acquire the most fitted models, a sample forecast and mean absolute deviation (MAD) were used. Models that had the lowest MAD represented the most fitted model in this regard. At the second stage, using some hedging portfolio implications, it was aimed to find the most optimal hedging portfolio in the selected markets.

This study is organized as follows: Section 2 gives information about the literature. Section 3 presents the methodology. In section 4, data description and descriptive statistics of the percentage return series are introduced. Section 5 proposes the empirical results of the DCC-FIGARCH specifications. It also shows the outcomes of the MAD for the DCC-FIGARCH model to find the most fitted combination in each selected market. Moreover, this section includes implications for the hedging portfolio. Finally, Section 6 introduces the Conclusion. In this section, the findings are shown, and the economic rationale of the results are justified.

2. LITERATURE REVIEW

As a model enabling the determination of which part of the combination gives the most appropriate portfolio hedging was chosen, in this context, some previous articles were chosen as examples of the optimal hedge ratio and hedging diversification. First, emphasis was placed on the development of ARCH. Hedging is preferred as an investment instrument because the volatility of financial asset returns differentiates over time. Correspondingly, this endows investors with many significant implications for risk diversification. Because ARCH is commonly employed to define as well as forecast the fluctuations of some financial indicators, many researchers and academicians have considered volatility and portfolio hedging as fundamental issues in financial economics since Engle (1982) introduced ARCH, Bollerslev (1986) included logged conditional variances in the ARCH specifications, which was regarded as an extended ARCH type of the model. According to him, generalized ARCH (GARCH) class models take into account conditional variance to be autoregressive moving average (ARMA) process in ARCH models, which means that the conditional variance is attributed to past conditional variances and some shocks that can emerge in markets, such as financial crises and earthquakes. Note that the GARCH model has parameters that are limited to being strictly non-negative for the positive variance condition. Therefore, GARCH models give information about the strength of the shock without specifying its sign. Thus obtained would be the integrated GARCH (IGARCH) specification process if the sum of the estimated ARCH and GARCH effect coefficients, which are represented as α and β, respectively, are close or equal to one (Dijk and Franses, 2003). Thus, IGARCH models are commonly referred to as unit-root GARCH models. Although the IGARCH model is not covariance-stationary, as shown by Nelson (1990), it may still be strictly stationary (Dijk and Franses, 2003). The reason why the impact of shocks on conditional variances lessens very little is that, with $\alpha 1$ small and $\beta 1$ large, financial data that has high-frequency eyes on a model that give a total of the parameters of $\alpha 1$ and $\beta 1$, which is close to 1. Moreover, Ding, Granger, and Engle (1993) introduced the asymmetric power ARCH (APARCH). This model can nicely specify the fat tails, excess kurtosis, and leverage effects.

Baillie et al. (1996) gave a suggestion for the class of fractionally IGARCH (FIGARCH) specifications. Moreover, Tse (1998) proposed a fractionally integrated APARCH specification that allows for persistence, which means long memory and asymmetry impacts in the conditional volatility. While making the estimation, herein, the FIGARCH and fractionally integrated asymmetric power (FIAPARCH) models were used; thus, these models will be extensively mentioned in the methodology section. Bollerslev, Chou, and Kroner (1992) quickly developed ARCH-family models and also implemented financial markets extensively. For establishing multivariate GARCH models, Bauwens et al. (2003) considered it in three sections. First, they emphasized direct generalizations of the univariate GARCH model, which was proposed by Bollerslev (1986), such as the vector error correction (VEC), Baba, Engle, Kraft, and Kroner (BEKK), and factor models, flexible MIGARCH, RiskMetrics, Cholesky, and full factor GARCH models. Second, they mentioned linear combinations of univariate GARCH models, such as (generalized) orthogonal models and latent factor models. Third, they presented nonlinear combinations of univariate GARCH models, such as constant and dynamic conditional correlation models, the general dynamic covariance model, and copula-GARCH models. Bollerslev, Engle, and Wooldridge (1988) proposed the diagonal vectorization conditional heteroskedasticity multivariate GARCH (DVECH MGARCH) models. Bollerslev (1990) came up with a constant conditional correlation (CCC) multivariate GARCH model, giving the time-varying conditional variances and covariances, as well as CCCs, which made a great contribution on a substantial reduction for computational complexity.

Moreover, it endows conditions that provides positive definites for the time-varying covariance matrices. The BEKK formulation was offered by different scientists at different times, such as Engle and Kroner (1995). This model constituted a general quadratic form for the conditional covariance equation, which has a target to eliminate the issue of supplying the positive accurateness of the conditional covariance estimate of the original VECH model. Engle (2001) proposed the DCC multivariate GARCH specification, which allows for the correlations to change over time. Hafner and Herwartz (2006) brought about volatility impulse response functions (VIRFs) for a multivariate time series, which showed conditional heteroskedasticity. According to their consideration, to make a comparison of the VIRFs with traditional conditional volatility profiles, the latter one faces some difficulties from a lot of disabilities which compel market respondents to the arbitrary choice of baseline and shock. They suggested instruments to compute the VIRFs for the VEC representation of a multivariate GARCH model, which was correctly embedded into most popular multivariate GARCH specifications and to assist in understanding the complex dynamic behavior of financial time series.

Second, Diebold and Mariano (1995) primarily proposed test statistics, such as the MAE and root mean squared error (RMSE), which allow for one to categorize the models based on out-of-sample accuracy. In several empirical studies, researchers examined the forecast performance for various GARCH models. As an illustration, Poon and Granger (2003) presented a survey providing an interesting and extensive outline of them. Poon et al. (2006) made a comparison for the out-of-sample forecasting performance of various short and long memory volatility models. They found that the FIGARCH specification was mostly a fitted model for a 10-day forecast horizon. Mohammadi and Su (2010) offered these test statistics to classify the models: GARCH, exponential GARCH, APARCH, and FIGARCH.

Third, the background of the optimal hedge ratio and portfolio weight are considered. For the optimal hedge ratio, Kroner and Sultan (1993) first constituted a ratio that included the covariance of the two instruments in terms of one variance from one of them, offering an inexpensive hedging portfolio. In addition to this, Kroner and Ng (1998) proposed a portfolio that minimized risk without lowering the expected returns. In this mechanism, there were two instruments, one of which may be assets, stock indices, or precious metals. For example, Hammoudeh et al. (2010) considered those aforementioned models to measure the risk between precious metals and exchange rates. Moreover, Mensi et al. (2013) proposed those models to make a diversification of the risks between precious metals, energies, and foods. Juhl et al. (2012) made a comparison between a simple regression on price changes and an error correction model (ECM) in order to size a hedge position and measure hedging effectiveness. This study indicated that both of the specifications acquired similar results, which are based on the hedge horizon when the prices of the hedged item and hedging instrument are cointegrated. If price changes are measured in the short term, the estimated hedge ratio and regression will be small. However, in the long term, both the estimated ratio and regression converge toward one. Generally, if prices are cointegrated, an optimal hedge ratio will be closer to one, provided by a longer hedge horizon, while simultaneously increasing the ability to qualify for hedge accounting. Moreover, Raza et al. (2018) researched the hedging performance of commodities futures for US real estate portfolios in a multi-scale setting. The authors attempted to estimate dynamic asymmetric conditional correlations and thereafter optimal hedge ratios of real estate stock returns with the commodities index, gold, oil, and bond returns, so as to examine hedging effectiveness under heterogeneous market expectations. This framework showed that gold ensures the best hedge to US real estate stocks for short-term investments. Moreover, Zghal et al. (2018) presented time-varying correlations estimation using asymmetric DCC (ADDC) and DCC, whose purpose was that a credit default swap (CDS) can be served to investors to efficiently hedge their risky investment and act as a safe haven in the European stock markets. Accordingly, financial practitioners measured the portfolio implications on daily and weekly databases, containing almost a 10-year-period. The empirical results demonstrated that safe haven roles, which are related to the CDS, as well as the portfolio design, proposed evidence of differing crucially across the time horizons and one model to another. In addition to this, Huang et al. (2018) mentioned about return smoothing and performance resistance, which is defined as a source of autocorrelation in hedge fund returns. According to their paper, before conducting the analysis, the practice of pre-processing of the data was performed in order to remove the smoothing impacts on the predictability of hedge funds. They created a simulation, showing evidence that smoothing produces vigorous biases in standard estimates of abnormal performance, factor loadings, and idiosyncratic volatility. Jying-Nan Wang et al. (2018) investigated the difference between fully hedged and unhedged portfolios including 10 different risky assets. The primary reason for this was that the Chinese renminbi (RMB) internalization process was importantly accelerated. This circumstance triggered Chinese institutions and investors to produce an alternative investment strategy, and accordingly, they searched for low risk and profitable investments in other stock markets. Thus, Chinese investors have acquired a lot of occasions to invest in foreign assets with respect to the USD, as well as the capability to pursue a risk-minimizing currency in their portfolios. This framework empirically found that the fully hedged portfolios have crucially higher expected return and lower standard deviation of the measured risky asset, resulting in higher Sharpe ratios.

Concerning profit maximization, risk-averse investors have a great tendency to annually make further payment toward the establishment of the fully hedged portfolio, as they want to diversify currency risk in terms of the Chinese Yuan Renminbi (CNY) and Chinese offshore currency (CNH), caused by RMB convertibility. To exemplify this statement, investors who have an equal-weighted portfolio strategy pay more than 7.2% and 3.3% per year, for CNY and CNH, respectively. The authors argued that the significance of currency hedging in portfolio management for investors will dramatically enhance RMB convertibility. In the next section, the methodology offered herein will be presented.

3. METHODOLOGY

The methodology proposed herein distinguished four approaches: 1) make an estimation for DCC-FIAPARCH and DCC-FIGARCH (DCC-MFIGARCH). 2) check forecast performance by calculating the MAD. 3) calculate the optimal hedge ratio by Kroner and Sultan (1993). 4) find the portfolio weight of two investment instrument holdings in order to make diversification the risk.
In order to clearly express the period, it was aimed to present the methods of how to use econometric methods in a more widespread manner. First, some combinations were constructed, which included developed stock market percentage returns, emerging stock market percentage returns, exchange rates, and as precious metals or oils. Then, the multivariate DCC-MFIAPARCH specification was used. For some of the percentage return series, optimization problems were encountered, which meant that there was no convergence for the numerical derivatives, such as S&P 500, Nasdaq, and Nikkei_225. However, for the multivariate DCC-FIGARCH specification, no optimization problems were encountered. Thus, a decision was made to use both types of estimation methods. Therefore, the two approaches were seperated. Some combinations were constituted, excluding developed stock market percentage returns for DCC-MFIAPARCH specification. On the other hand, some combinations were presented, including developed stock market percentage returns. Then, numerous estimations were acquired for those abovementioned combinations. Next, there was difficulty with the serial correlation problem. To solve this, the ARMA order was increased. As a result of this, some of them worked well, but others remained the same. Hence, it was necessary to eliminate the remaining ones. Next, the robustness of the model was checked by observing its forecast performance. An ex-ante evaluation of the DCC-FIGARCH specification was conducted as a compliment to the evaluation of the in-sample model accuracy. In this direction, actual samples, covering the forecast period were systematically extracted from the observations. Then, an estimation of the parameters was employed through the medium of sample information, which was assumed to be convenient for a forecaster. It was the opinion herein that out-of-sample forecasting was more appropriate to be used because it allows the empirical evidence to be more sensitive to outliers and data mining. Moreover, it better reflects the information available to the forecaster in real-time. Then, the MAD was used, which can be defined as the absolute value of the dynamic difference between the actual value (return) and the mean forecast. This is the main usage for this mechanism. However, because conditional variances were used for the hedging (how to use it will be proposed below), the MAD was calculated as an absolute value of the dynamic difference between the square of the actual values and the forecast variances. After the results were obtained, they were ranked. The smallest MAD value provided a combination that had

the best forecast performance. Thus, the most optimal combination for hedging was obtained, which contained four investment instruments for portfolio mechanism.

As a next step, two methods were used, comprising the optimal hedge ratio and optimal portfolio weight. The first presents a risk-minimizing ratio between two asset holdings in order to inexpensive hedge. The second offers a portfolio that provides the optimal holding of one asset.
FIGARCH has been especially proposed to model the long memory existence of financial volatility. Engle (2002) was the first to present the DCC model, which extended the CCC model by allowing the conditional correlations to be time varying.

4. DATA DESCRIPTION

In this framework, the daily index values of stock market indices of selected emerging and developed countries, and also some precious metals, such as GOLD, SILVER, PLATINUM, and PALLADIUM, as well as some oils, such as BRENT OIL and West Texas Intermediate (WTI), were employed as an investment instrument. These data comprise the period from 02/01/2006 to 01/11/2018. Throughout the study, to represent developed stock markets, S&P 500 (USA), NASDAQ (USA), FTSE_100 (UK), NIKKEI_225 (JAPAN), and DAX_30 (GERMANY) were used, and the emerging stock markets were represented by BIST_100 (Turkey), BOVESPA (Brazil), BSE_SENSEX_30 (India), and FTSE_BURSA_KLCI (Malaysia). GOLD and SILVER were obtained from the New York Mercantile Exchange (NYMEX) and Platınum and PALLADIUM were obtained from (COMEX). BRENT Oil futures were obtained from the Intercontinental Exchange (ICE) and WTI was acquired from NYMEX. Moreover, the exchange rates of some emerging markets were used, such as Brazil, Turkey, India, and Malaysia, in terms of the USD. Daily percentage returns were calculated as log differences in the price levels, as follows:

$$R_t = 100 \times [lnP_{i,t} - lnP_{i,t-1}] \tag{4.1}$$

Descriptive statistics for the percentage return series are presented in Tables 4.1–4.5, where it can be seen that the stock percentage returns of the developed and emerging markets, exchange rate percentage returns of the emerging markets presented above, and precious metals and oils had excess kurtosis (fat tails) and negative skewness. Furthermore, the ARCH effects significantly showed the presence of the ARCH effects. This justified the use of ARCH-type modeling techniques. Descriptive statistics contain summary statistics of the percentage return series, such as the mean, median, maximum, standard deviation, skewness, and excess kurtosis. Moreover, the normality test was used. The Jarque-Bera test can be defined as a measure of applicability to make a decision about whether the sample data have skewness and kurtosis that matches normal distribution. The test statistic is always nonnegative. In order to check whether the data had normal distribution or not, the test statistic value was observed, which should be far from zero.

Note that the asymptotic critical values for the augmented Dickey-Fuller (ADF) test were –2.5672, –1.9403, and –1.61663 at 1%, 5%, and 10%, respectively. Critical values of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) were 0.739, 0.463, and 0.347 at 1%, 5%, and 10%, respectively. Critical values of the Schmidt-Phillips test were –25, 2; –18, 1; and –15 at 1%, 5%, and 10%, respectively.

Table 4.1 shows the descriptive statistics of the stock percentage return series for the emerging markets. For BIST_100, FTSE_BURSA, and BSE_SENSEX, the skewness value was between –0.5 and 0.5. Hence, their data were fairly symmetrical. Moreover, BIST_100 and FTSE_BURSA had positive skewness values, which meant that the left-hand tail was typically longer than the right-hand tail. However, BSE_SENSEX had a skewness value that was lower than zero, which was why the right-hand tail was longer than the left-hand tail. FTSE_BURSA had a negative skewness value, and also this value was lower than –1, so the data were highly skewed, and the left-hand tail will typically be longer than the right-hand tail. The excess kurtosis values for FTSE_BURSA and BSE_SENSEX were positive and very high. The distributions for these percentage return series were more peaked, which meant that observations that were close to the mean were more frequent. The distribution had a fatter tail than the normal distribution, which was why extreme values were more frequent. This kind of distribution is called leptokurtic or leptokurtotic. However, the excess kurtosis values for BIST_100 and BOVESPA were around four. The distribution of this series was also more peaked and had a fatter tail than the normal distribution. For the Jarque-Bera test, a value of zero means errors are normally distributed, but the Jarque-Bera test statistics for the percentage returns of these series were very large, so the errors were not normally distributed for all of the return series in Table 4.1. The ARCH effect test results for the percentage returns of all of these series were highly significant, which meant that the percentage returns of these series that exhibited conditional heteroskedasticity had an ARCH effect. All of the return series were stationary because the ADF and Schmidt-Phillips test statistics were highly significant. Contrary to this, the KPSS test had a different method. The null hypothesis was so if there was a stationary in the series. Thus, although the KPSS test statistics for the percentage return series was insignificant, the series were stationary.

	BIST_100	BOVESPA	FTSE_BURSA	BSE_SENSEX
Mean	0.02516	0.02879	0.01912	0.03881
Median	0.008855116	0.0000000	0.009079966	0.002512937
Maximum	12.127	9.5192	4.2587	15.99
Minimum	-11.064	-10.526	-9.9785	-11.604
Standard Deviation	1.6249	1.6943	0.71179	1.3917
Skewness	-0.28700	-0.14031	-1.16872	0.10065
Excess Kurtosis	4.1534	4.0060	15.739	13.36338
Jarque-Bera	2452.5	2249.7	35320.	14988.
ARCH 1-5	51.813 [0.00]	119.28 [0.00]	213.93 [0.00]	63.935 [0.00]
ARCH 1-10	30.530 [0.00]	84.524 [0.00]	132.11 [0.00]	46.998 [0.00]
ADF	-32.4625	-35.3625	-31.0778	-33.9066
KPSS	0.0405334	0.0731018	0.217032	0.0459583
SCHMIDT-PHILLIPS	-3337.31	-3186.95	-2801.41	-2951.67
Observations	3327	3327	3327	3327

Table 4.1 Descriptive statistics of percentage stock return series for emerging markets results.

Table 4.2 indicates the descriptive statistics of the stock percentage return series for the developed markets. For all of the percentage returns series of the developed stock market, the skewness value was between –0.5 and 0.5. Hence, their data were fairly symmetrical. Moreover, all of the percentage return series of the developed stock market had negative skewness values, which meant that the right-hand tail was typically longer than the left-hand tail. The excess kurtosis values for all of the series were positive and very high. The distributions for these percentage return series were more peaked, which meant that observations that were close to the mean were more frequent. The distribution had a fatter tail than normal distribution, which was why extreme values were more frequent. The Jarque-Bera test statistics for the percentage returns of these series were very large, so the errors were not normally distributed for all of the percentage return series, as seen in Table 4.2. The ARCH effect test results for the percentage returns of these series were highly significant, which meant that the percentage returns of these series that exhibited conditional heteroskedasticity had an ARCH effect. All of the percentage return series were stationary.

	S&P_500	NASDAQ	FTSE_100	DAX_30	NIKKEI_225
Mean	0.023486	0.043545	0.0070504	0.022222	0.0088774
Median	0.035000905	0.066696558	0.00528686	0.57877674	0.0000000
Maximum	10.957	11.849	9.3843	10.797	13.235
Minimum	-9.4695	-11.115	-9.2656	-7.4335	-12.111
Standard Deviation	1.1878	1.301	1.1506	1.3448	1.4942
Skewness	-0.38383	-0.22620	-0.14372	-0.026245	-0.52342
Excess Kurtosis	11.997	8.5383	8.4001	6.4294	8.6049
Jarque-Bera	20160.	10198.	9855.0	5766.9	10482.
ARCH 1-5	213.93 [0.00]**	128.07 [0.00]**	194.30 [0.00]**	107.22 [0.00]**	237.03 [0.00]**
ARCH 1-10	132.11 [0.00]**	99.046 [0.00]**	108.94 [0.00]**	67.393 [0.00]**	131.03 [0.00]**
ADF	-35.2771	-34.9013	-36.7605	-34.6858	-35.3218
KPSS	0.147996	0.126373	0.0362804	0.0448833	0.238046
SCHMIDT-PHILLIPS	-3523.84	-3458.18	-3201.56	-3267.46	-3351.75
Observations	3327	3327	3327	3327	3327

Table 4.2 Descriptive statistics of percentage stock return series for developed markets results.

Table 4.3 demonstrates the descriptive statistics of the market percentage return series for the precious metals. For all of the percentage returns series of the precious metals, the skewness values were greater than one. Hence, their data were highly skewed. Moreover, all of the percentage return series of the precious metals had a positive skewness value, which meant that the left-hand tail was typically longer than the right-hand tail. The excess kurtosis values for all of the series were positive and greater than four. The distributions for these percentage return series were more peaked, which meant that observations that were close to the mean were more frequent. Additionally, the excess kurtosis value for PLATINUM was very high. The distribution of the PLATINUM series was dramatically peaked. The distribution also had a fatter tail than the distribution of the other percentage returns, which was why extreme values were very frequent. The Jarque-Bera test statistics for the percentage returns of the precious metals series were very large, so the errors were not normally distributed for these percentage return series, as seen in Table 4.3. The ARCH effect test results for the percentage returns of these series were highly significant, which meant that the percentage returns of these series that exhibited conditional heteroskedasticity had an ARCH effect. All of the percentage return series were stationary.

	GOLD	SILVER	PLATINUM	PALLADIUM
Mean	0.02597	0.01495	-0.00375	0.04365
Median	0.0000	0.0000	0.0000	0.0000
Maximum	6.8555	13.665	20.313	10.92
Minimum	-9.5962	-12.997	-16.491	-17.859
Standard Deviation	1.1794	2.0344	1.4393	1.9931
Skewness	-0.36339	-0.51448	0.77948	-0.55014
Excess Kurtosis	5.6089	5.0635	27.035	5.4811
Jarque-Bera	4462.3	3724.4	1.0230e+005	4359.8
ARCH 1-5	39.072 [0.00]	37.909 [0.00]	2.6585 [0.0210]	26.267 [0.00]
ARCH 1-10	31.879 [0.00]	23.537 [0.00]	2.8274 [0.00]	19.906 [0.00]
ADF	-33.4147	-33.7057	-32.1804	-34.2051
KPSS	0.377974	0.235082	0.208751	0.0557029
SCHMIDT-PHILLIPS	-3256.49	-3255.11	-2858.05	-2568.41
Observations	3327	3327	3327	3327

Table 4.3 Descriptive statistics of percentage stock return series for precious metals results.

Tables 4.4 and 4.5 demonstrate the descriptive statistics of the exchange rate market percentage return series and the percentage return series of the oil future. For the BRL, INR, MYR, and WTI percentage return series, the skewness values were between –0.5 and 0.5. Hence, their data were fairly symmetrical. However, the TRY percentage return series had a skewness value that was greater than one. Therefore, its data were highly skewed. Additionally, the BRENT percentage return series had a skewness value that was close to zero, which meant that the distribution of the BRENT percentage return series was almost normally distributed. Moreover, the exchange rates of the percentage returns for all of these series, as well as the WTI, had positive skewness values, which meant that the left-hand tail was typically longer than the right-hand tail. However, the MYR and BRENT had negative skewness values, which was why the right-hand tail was typically longer than the left-hand tail. The excess kurtosis value for the TRY percentage return series was positive and very high. The distribution of this percentage return series was very peaked, which meant that observations that were close to the mean were more frequent. Additionally, the excess kurtosis values for other percentage returns of these series were greater than four, excluding BRENT. The excess kurtosis value for the BRENT percentage return series was 3.58, which was why it can be safely argued that BRENT percentage return series had nearly normal distribution. Specifically, the TRY had very high Jarque-Bera test statistics; hence, the errors were not normally distributed for the TRY percentage return series, as seen in Table 4.4. All of the exchange rate percentage returns and percentage returns of the oil futures had series that had significant ARCH effect test results. Hence, the percentage returns of these series that exhibited conditional heteroskedasticity had an ARCH effect. All of the percentage return series were stationary.

	TRY	INR	MYR	BRL
Mean	0.04200	0.01466	0.00300	0.01375
Median	-0,020086902	0.00000	0.00000	-0.003650045
Maximum	14.761	3.2513	2.026	8.1242
Minimum	-7.9672	-3.0639	-3.5957	-7.3866
Standard Deviation	0.96981	0.43932	0.42254	0.98963
Skewness	1.47480	0.24789	-0.35333	0.42972
Excess Kurtosis	22.653	5.2054	4.7677	7.8481
Jarque-Bera	72801.	3814.2	3240.6	8695.3
ARCH 1-5	114.37 [0.00]**	90.240 [0.0000]**	60.005 [0.00]**	141.74 [0.00]**
ARCH 1-10	58.657 [0.00]**	53.009 [0.0000]**	41.215 [0.00]**	86.294 [0.00]**
ADF	-35.9631	-33.3532	-32.9298	-34.1863
KPSS	0.358715	0.152136	0.415562	0.303027
SCHMIDT-PHILLIPS	-3087.66	-2988.09	-3268.9	-3293.78
Observations	3327	3327	3327	3327

Table 4.4 Descriptive statistics of exchange rate market percentage return series.

	BRENT	WTI
Mean	0.04200	0.01466
Median	-0,020086902	0.00000
Maximum	14.761	3.2513
Minimum	-7.9672	-3.0639
Standard Deviation	0.96981	0.43932
Skewness	1.47480	0.24789
Excess Kurtosis	22.653	5.2054
Jarque-Bera	72801.	3814.2
ARCH 1-5	114.37 [0.00]**	90.240 [0.0000]**
ARCH 1-10	58.657 [0.00]**	53.009 [0.0000]**
ADF	-35.9631	-33.3532
KPSS	0.358715	0.152136
SCHMIDT-PHILLIPS	-3087.66	-2988.09
Observations	3327	3327

Table 4.5 Descriptive Statistics of Brent and West Texas Intermediate stock market percentage return series.

5. EMPIRICAL RESULTS

5.1. Univariate Results for the DCC-FIGARCH Estimation

Table 5.1 reports the estimation results of the DCC-FIGARCH model for the percentage returns of the developing stock markets, computed under student-t distribution. As seen, the Ar(1) parameters for all of the investment instruments were positive and significant, at a significance level of 1%, implying that past stock percentage returns were positively correlated with the current percentage returns for Ftse_Bursa, and were instantaneously and rapidly embodied in the current stock percentage return. The fractional integration coefficients, d's, were positive and significant for all of the indices, demonstrating that volatility processes were persistent over time. Also, the coefficients of the Q and Q^2 represents Box-Pierce test statistics on standardized residuals and squared standardized residuals at 20 and 50 lags. The null hypothesis is that the model does not exhibit lack of fit.For each univariate model of domestic stock market percentage return series, the Box-Pierce test statistics on standardized residuals and square standardized residuals was insignificant. This significance is measured by checking the probability value. If $P < 0.05$, the null hypothesis should be rejected. Thus, one can presume that the values indicate a dependence on each other. If $P > 0.05$, there is no sufficient statistical evidence to reject the null hypothesis. Thus, it should not be assumed that the values are dependent. In the Table 5.1, it is shown that all probability values is higher than 0.05. So, the null hypothesis should be failed to reject,which means that there is no autocorrelation for standardized residuals and squared standardized residuals.

	BIST_100	BOVESPA	FTSE_BURSA	BSE_SENSEX
Cst(M)	0.089991***	0.054927	0.036898***	0.072660***
AR(1)	0.816773***	0.611834***	0.212900***	0.190594***
MA(1)	-0.819610	-0.646877	-0.091202	-0.132056
Cst(V)	0.190465	0.391715	0.023614***	0.027901
d-Figarch	0.331284***	0.249668***	0.385749***	0.5493584***
ARCH(Phil)	0.097511	-0.140012	0.049028	0.117448
GARCH(Beta1)	0.342318	0.079097	0.298773	0.633846
No.Parameters	7	7	7	7
Log.Likelihood	-6046.170	-6162.315	-2974.702	-5051.851
Q(20)	10.8359 [0.54236]	11.8098 [0.52391]	12.2354 [0.5124]	15.7565 [0.45329]
Q(50)	38.9125 [0.86.1152]	40.8514 [0.84236]	41.0288 [0.8131]	48.3950 [0.5379772]
$Q(20)^2$	12.5857 [0.8944455]	13.2853 [0.86480]	15.4539 [0.7498]	17.2222 [0.6384990]
$Q(50)^2$	42.3308 [0.7710890]	35.3612 [0.94168]	34.3383 [0.9553]	36.6345 [0.92235]
Observations	3327	3327	3327	3327

Table 5.1 Stock Market percentage return indices for domestic markets.

Table 5.2 reports the estimation results of the DCC-FIGARCH model for the developed stock market percentage returns, computed under student-t distribution. It can be seen that the AR(1) parameters for FTSE_100, NASDAQ, S&P_500, and DAX_30 were positive and significant at a significance level of 1%, implying that past stock percentage returns were positively correlated with current percentage returns for those investment instruments, and past information about the stock percentage returns was instantaneously and rapidly embodied in the current stock percentage returns. However, the AR(1) parameters for NIKKEI_225 and DAX_30 were insignificant, implying that past information about the percentage returns of the indices in the developed market was uncorrelated with the percentage returns of the current indices of the developed market. The fractional integration coefficients, d's, were positive and significant for all of the developed market indices, implying that volatility processes were persistent over time. Moreover, the coefficients of the Q and Q^2 represents Box-Pierce test statistics on standardized residuals and squared standardized residuals at 20 and 50 lags. The null hypothesis is that the model does not exhibit lack of fit.For each univariate model of developed stock market indices percentage return series, the Box-Pierce test statistics on standardized residuals and square standardized residuals was insignificant. The significance of Box-Pierce test statistics is measured by checking probability. In the Table 5.2, it is presented that all probability values is higher than 0.05.So,the null hypothesis should be failed to reject. Values are not dependent. The model does not show lack of fit. There is no autocorrelation problem for standardized residual and squared standardized residuals.

	DAX_30	NIKKEI_225	S&P_500	NASDAQ	FTSE_100
Cst(M)	0.072707	0.061239	0.066397	0.084364	0.039705
AR(1)	0.948105***	0.080965	0.630977***	0.738769***	0.682460 ***
MA(1)	-0.963221	-0.049952	-0.693513	-0.775097	-0.718451
Cst(V)	0.046360	0.056568	0.033038	0.043583	0.028885
d-Figarch	0.481725***	0.550556***	0.512468***	0.472934***	0.470311***
ARCH(Phil)	0.096770	0.168022	0.054632	0.199777	0.129738
GARCH(Beta1)	0.516031	0.609694	0.476745	0.580666	0.497219
No.Parameters	7	7	7	7	7
Log.Likelihood	-5173.333	-5517.491	-4279.283	-4929.248	-4483.493
Q(20)	17.8597 [0.65209]	16.6117 [0.6780269]	17.810 [0.65823]	14.1002 [0.59823]	14.3478 [0.60537]
Q(50)	35.2823 [0.92364]	42.1404 [0.7774901]	34.0200 [0.9591266]	32.6523 [0.973257]	33.0753 [0.963659]
Q(20)2	18.8671 [0.82349]	15.5264 [0.88523]	15.8820 [0.87103]	17.8632 [0.85377]	16.9236 [0.86236]
Q(50)2	42.2341 [0.7743512]	44.6104 [0.6887466]	44.8713 [0.68237]	41.3621 [0.789634]	40.5684 [0.813551]
Observations	3327	3327	3327	3327	3327

Table 5.2 Stock Market percentage return indices for developed markets.

Table 5.3 reports the estimation results of the DCC-FIGARCH model for the precious metals percentage returns, computed under student-t distribution. It can se seen that the Ar(1) parameters for all of the developed market indices were positive and significant for all of the investment instruments, at a significance level of 1%, reflecting that the past stock percentage returns were positively correlated with the current stock percentage returns, and past information about the percentage returns of those investment instruments was instantaneously and rapidly embodied in their current returns. The fractional integration coefficients, d's, were positive and significant for all of the precious metals, at a significance level of 1%, indicating that volatility processes were persistent over time. Also, the coefficients of the Q and Q^2 represents Box-Pierce test statistics on standardized residuals and squared standardized residuals at 20 and 50 lags. The null hypothesis is that the model does not exhibit lack of fit. For each univariate model of precious metals percentage return series, the Box-Pierce test statistics on standardized residuals and square standardized residuals was insignificant. The significance of Box-Pierce test statistics is measured by checking probability. In the Table 5.3, it is shown that all probability values is higher than 0.05.So,the null hypothesis should be failed to reject. Values are not dependent. The model does not exhibit lack of fit. There is no autocorrelation problem for standardized residual and squared standardized residuals.

	GOLD	SILVER	PLATINUM	PALLADIUM
Cst(M)	0.014246	0.010176	0.000970	0.047328
AR(1)	0.025094***	0.107785***	0.809907***	0.057743***
MA(1)	-0.025221	-0.117509	0.793656	0.087625
Cst(V)	0.020251	0.086543	0.135322	0.059860
d-Figarch	0.472145***	0.344213***	0.210030***	0.520305***
ARCH(Phil)	0.320879	0.553747	0.669394	0.267460
GARCH(Beta1)	0.737824	0.773253	0.794640	0.723424
No.Parameters	7	7	7	7
Log.Likelihood	-4906.849	-6780.910	-5795.284	-6663.588
Q(20)	18.7522 [0.541428]	15.8745 [0.604573]	16.2315 [0.7038942]	15.2517 [0.7618304]
Q(50)	46.9399 [0.5969295]	47.6512 [0.573265]	48.3265 [0.56214]	49.2516 [0.542136]
Q(20)2	6.39857 [0.9982409]	10.2356 [0.90567]	12.1463 [0.86215]	14.6589 [0.78956]
Q(50)2	12.856 [0.95521]	20.856 [0.89457]	22.564 [0.84265]	23.981 [0.82453]
Observations	3327	3327	3327	3327

Table 5.3 Precious Metals.

Table 5.4 shows the estimation results of the DCC-FIGARCH model for the exchange rates percentage returns, computed under student-t distribution. As can be seen, the Ar(1) parameters were positive and significant for all of the exchange rates in terms of USD, at a significance level of 1%, demonstrating that that past exchange percentage returns for all of the emerging countries were positively correlated with the current percentage returns, excluding the TRY, and the past information about all of the exchange rate percentage returns were instantaneously and rapidly embodied in their current percentage returns. The fractional integration coefficients, d's, were positive and significant for all of the exchange rates, implying that volatility processes were persistent over time. Also, the coefficients of the Q and Q^2 represents Box-Pierce test statistics on standardized residuals and squared standardized residuals at 20 and 50 lags. The null hypothesis is that the model does not exhibit lack of fit. For each univariate model of exchange rates in terms of USD percentage return series, the Box-Pierce test statistics on standardized residuals and square standardized residuals was insignificant. The significance of Box-Pierce test statistics is measured by checking probability. In the Table 5.4, it is shown that all probability values is higher than 0.05. So, the null hypothesis should be failed to reject. Values are not dependent. The model does not exhibit lack of fit. There is no autocorrelation problem for standardized residual and squared standardized residuals.

	TRY	INR	MYR	BRL
Cst(M)	0.021836	-0.012572	0.005845	-0.013706
AR(1)	0.559880***	0.590695***	0.885189***	0.709632***
MA(1)	-0.559593	-0.533891	-0.868155	-0.738250
Cst(V)	0.581231	0.050331	0.125575	0.867002
d-Figarch	0.414821***	0.541277***	0.365583***	0.482450***
ARCH(Phil)	0.276234	0.120759	0.237587	0.125933
GARCH(Beta1)	0.528645	0.605479	0.487969	0.507020
No.Parameters	7	7	7	7
Log.Likelihood	-3933.791	-1358.936	-1509.131	-4124.572
Q(20)	17.896 [0.40924]	17.365 [0.41826]	18.694 [0.40345]	16.365 [0.45341]
Q(50)	43.1163 [0.763621]	42.2876 [0.7725479]	48.9605 [0.5150889]	41.3942 [0.793584]
Q(20)2	17.2423 [0.6371917]	18.3215 [0.602145]	16.2546 [0.663987]	13.3654 [0.736915]
Q(50)2	36.1642 [0.9290059]	38.6547 [0.882475]	34.2653 [0.942635]	31.3251 [0.981245]
Observations	3327	3327	3327	3327

Table 5.4 Exchange Rates

5.2. Multivariate Results for the FIGARCH Estimation

5.2.1 Dcc-Figarch Estimation Results in Brazilian Market

The Table 5.5 presents the multivariate results of a combination that includes Brazilian Real, GOLD, BOVESPA, and FTSE_100. For Brazilian market, in order to determine how well a model bestly fits the data, Akaike Information Criterion (AIC) is used to compare different possible models. Correspondingly, since AIC value of this model is smaller than other possible models , it is considered better fitting model. Also, log-likelihood provides to make a comparison for different possible models. This model has higher log likelihood value (closer to zero) than others, indicating better fit model.

Note that α represents the ARCH effect coefficient. β shows the GARCH effect coefficient, v is the degrees of freedom for the t distribution, Li-McLeod is the multivariate Portmanteau statistics on standardized residuals, and Li-McLeod squared is the multivariate Portmanteau statistics on squared standardized residuals. The null hypothesis of the Li-McLeod test is that there is no autoregressive conditional heteroskedasdicity among the lags considered, which means that there are no arch effects. Given a confidence level of 95%, p-values are above the 0.05. Therefore, Mcleod multivariate portmanteau test statistics on standardized residuals and squared standardized residuals is insignificant at 20 and 50 lags. In this regard, the null hypothesis should be failed to reject, and there are no arch effects.

Coefficient	Value	Probability
α	0.009180	0.0012
β	0.985389	0.0000
v	7.209017	0.0000
Number of Observations	3327	-
Number of Parameters	41	-
AIC	11.027371	-
Log Likelihood	-18303.03	-
Li-McLeod (20)	198.123	[0.1437111]
Li-McLeod Square (20)	334.873	[0.2470165]

Table 5.5 Ftse_100-Brl-Bovespa-Gold.

5.2.2 DCC-FIGARCH Estimation Results in Malaysian Market

Table 5.6 demonstrates the multivariate results of a combination that includes Malaysian Ringgit, GOLD, FTSE_BURSA, and FTSE_100. For Malaysian market, in order to determine how well a model bestly fits the data, Akaike Information Criterion (AIC) is used to compare different possible models. Correspondingly, since AIC value of this model is smaller than other possible models, it is considered better fitting model. Also, log-likelihood provides to make a comparison for different possible models. This model has higher log likelihood value (closer to zero) than others, indicating better fit model. Given a confidence level of 95%, p-values are above the 0.05. Therefore, Mcleod multivariate portmanteau test statistics on standardized residuals and squared standardized residuals is insignificant at 20 and 50 lags. In this regard, the null hypothesis should be failed to reject, and there are no arch effects.

Coefficient	Value	Probability
α	0.013529	0.0089
β	0.967406	0.0000
v	6.583234	0.0000
Number of Observations	3327	-
Number of Parameters	41	-
AIC	7.684791	-
Log Likelihood	-12742.650	-
Li-McLeod (20)	190.344	[0.2498841]
Li-McLeod Square (20)	139.861	[0.9842609]

Table 5.6 Ftse_100-Myr-Ftse_Bursa-Gold.

5.2.3 DCC-FIGARCH Specification Results for Turkish Markets

Table 5.7 reports the multivariate results of a combination that includes the TRY, GOLD, BIST_100, and FTSE_100. For Turkish market, in order to determine how well a model bestly fits the data, Akaike Information Criterion (AIC) is used to compare different possible models. Correspondingly, since AIC value of this model is smaller than other possible models, it is considered better fitting model. Also, log-likelihood provides to make a comparison for different possible models. This model has higher log likelihood value (closer to zero) than others, indicating better fit model. Given a confidence level of 95%, p-values are above the 0.05. Therefore, Mcleod multivariate portmanteau test statistics on standardized residuals and squared standardized residuals is insignificant at 20 and 50 lags. In this regard, the null hypothesis should be failed to reject, and there are no arch effects.

Coefficient	Value	Probability
α	0.007787	0.0000
β	0.988873	0.0000
v	6.714517	0.0000
Number of Observations	3327	-
Number of Parameters	41	-
AIC	10.834270	-
Log Likelihood	-17981.80	-
Li-McLeod (20)	175.351	[0.5420888]
Li-McLeod Square (20)	169.209	[0.6694226]

Table 5.7 Ftse_100-Trl-Bist_100-Gold.

5.2.4 Dcc-Figarch Estimations Results for Indian Markets

Table 5.8 presents the multivariate results of a combination that includes INDIAN RUPEE, GOLD, BSE_SENSEX_30, and FTSE_100. For Indian market, in order to determine how well a model bestly fits the data, Akaike Information Criterion (AIC) is used to compare different possible models.Correspondingly, since AIC value of this model is smaller than other possible models , it is considered better fitting model. Also, log-likelihood provides to make a comparison for different possible models. This model has higher log likelihood value (closer to zero) than others, indicating better fit model. Given a confidence level of 95%, p-values are above the 0.05. Therefore, Mcleod multivariate portmanteau test statistics on standardized residuals and squared standardized residuals is insignificant at 20 and 50 lags. In this regard, the null hypothesis should be failed to reject, and there are no arch effects.

Coefficient	Value	Probability
α	0.014866	0.0000
β	0.967225	0.0000
v	6.818865	0.0000
Number of Observations	3327	-
Number of Parameters	41	-
AIC	8.873910	-
Log Likelihood	-14720.749	-
Li-McLeod (20)	182.526	[0.413193]
Li-McLeod Square (20)	170.916	[0.6349950]

Table 5.8 Ftse_100-Inr-Bse_Sensex-Gold.

Table 5.9 shows the dynamic conditional correlation targeting for selected markets, which meant that the mean of the DCC, which contained twelve years, was calculated using the DCC-FIGARCH specification. The primary reason why only GOLD was used as a commodity was that mostly all of the fitted DCC-FIGARCH models for the combination of each of the emerging markets included GOLD and FTSE_100 as developed stock market indices. GOLD and all of the stock market indices had low correlations, demonstrating that there were hedging opportunities between them. However, as GOLD and the exchange rates in terms of USD had high correlations with respect to the stock market indices, it was not advisable to invest in domestic currencies in the short term.

Coefficient	Value
ρGold-Bovespa	0.095366
ρGold-Ftse_Bursa	0.068788
ρGold-Bse_Sensex	0.080772
ρGold-Bist_100	0.117909
ρGold-Trl	-0.152562
ρGold-Myr	-0.233175
ρGold-Brl	-0.231997
ρGold-Inr	-0.220726
ρGold-Ftse100	0.095366

Table 5.9 Dynamic Conditional Correlation Marketing for the selected markets.

5.3 Robustness Check

In this section, the forecast performance of the econometric models presented above were analyze. The MAD was used for this. Formally,

$$MAD = \frac{\sum_{i=1}^{n} |y_i - \bar{y}_i|}{t} \tag{5.3.1}$$

y_i and $\overline{y_i}$ are represented as the actual value and forecasting value. MAD can be defined as the sum of the absolute value and the difference of the actual and forecasting value, denominated by t, which is described as the number of time intervals observed. In order to check the robustness of those models, first, an ex-ante evaluation was conducted of the DCC-FIGARCH specification as a complement to the evaluation of the in-sample model accuracy. For this purpose, certain available observations, such as the forecast period, were systematically removed from the sample. Then, the estimation of the parameters was performed through sample information, which was assumed to be available to a forecaster. In was the opinion herein that the out-of-sample forecasting was more suitable for use in this manner. The primary reason for this was that the out-of-sample forecast performance will provide empirical evidence that will be more sensitive to outliers and data mining. Moreover, it better reflects the information available to the forecaster in real-time. Then, the MAD values of these models in the ranking were analyzed. For each developing country, which included Brazil, Turkey, India, and Malaysia, separately, the smallest one was chosen. Then, accordingly, investment portfolio decisions were constructed. Before an analysis of the MAD for the DCC-FIGARCH specifications in those countries was conducted, for each developing country, the MAD was calculated by imposing the actual value and forecasting value as the square of one investment instrument, as well as the forecast value for the conditional variance of this investment instrument, because the conditional variance of the percentage return of the investment instrument was considered to get most optimal hedging. The method proposed herein was to separately calculate each instrument, and take the arithmetic mean of the MADs for each investment portfolio, and then accordingly, choose the smallest value for each country. Just how this process was undertaken will be presented below.

Note that, in this paper, the value of the MAD was not proposed in each emerging country because some DCC-FIAPARCH models were not fitted ones, which means that there was an optimization problem when some combination of DCC-FIAPARCH specification was runned.

COEFFICIENT	VALUE
Brl-Bovespa-Ftse_100-Gold	1.78*
Myr-Ftse_Bursa-Ftse_100-Gold	0.51*
Trl-Bist_100-Ftse_100-Gold	1.46*
Inr-Bse_Sensex-Ftse_100-Gold	2.78*

Table 5.10 Robustness assesment for the selected models.

Table 5.10 reports the smallest MAD values for the DCC-FIGARCH specification for the emerging markets. In fact, numerous values for the MAD were found for each specific combination. Correspondingly, it was decided to present them in the Appendix. These values, which were the smallest MADs, represent the most appropriate investment instrument to make a hedging portfolio implication. In the next section, some analyses of this investment portfolio will be conducted.

Moreover, none of the multivariate results obtained from DCC-FIAPARCH specification were better fitted as a forecasting performance than the multivariate results acquired from the DCC-FIGARCH estimation.

5.4 Implications for the Hedging Portfolio

The purpose, in this case, was to build up the most efficient portfolio. In this direction, some decisions were made to obtain risk diversification and allocate the portfolio. Thus, two examples using the DCC-FIGARCH specification for hedging portfolio are given below.

5.4.1 Optimal Hedge ratio

As a first example, we utilized the method of Kroner and Sultan (1993) concerning risk-minimizing hedge ratios and proposed a portfolio including two assets (commodities, indices, or exchange rates). To minimize the risk of a portfolio, if we have $1 of an asset in a long-term position (commodity), financial practitioners should sell $β of the asset in a short-term position (stock market indices or exchange rates). This mechanism implies that holding the asset in the investors' pocket in the long term has a risk in the short run. In order to make diversification, those financial practitioners must calculate the optimal hedge ratio to determine which part of the commodity in long-term position should be invested in the asset in the short-term position. The risk-minimizing ratio is presented below:

$$\beta^{COM,(Stock\ Market\ Indices)} = \frac{h_t^{COM,Stock\ Market\ Indices}}{h_t^{Stock\ Market\ Indices}} \tag{5.4.1}$$

Here, $h_t^{COM,Stock\ Market\ Indices}$ are the conditional covariances of the commodity and stock, and $h_t^{Stock\ Market\ Indices}$ are the conditional variances for the stock market indices at time t.

5.4.2 Portfolio Designs

As a second example for the optimal portfolio, the approach proposed by Kroner and Ng (1998) was employed, which assesses a portfolio that provides risk-minimization without expected returns. The portfolio weight of the holdings of commodity indices/stock market indices is given by:

$$W_t^{COM,Stock\ Market\ Indices} = \frac{(h_t^{Stock\ Market\ Indices} - h_t^{COM,Stock\ Market\ Indices})}{(h_t^{Stock\ Market\ Indices} + h_t^{COM} - h_t^{COM,Stock\ Market\ Indices}}$$

$$W_t^{COM,Stock\ Market\ Indices} = \begin{cases} 0, if\ W_t^{COM,Stock\ Market\ Indices} < 0 \\ W_t^{COM,Stock\ Market\ Indices}, if\ 0 \leq W_t^{COM,Stock\ Market\ Indices} \leq 1 \\ 1, if\ W_t^{COM,Stock\ Market\ Indices} > 1 \end{cases} \tag{5.4.2}$$

Here, $W_t^{COM,Stock\ Market\ Indices}$ is the weight of commodities in $1 of two assets (commodities, stock market indices) at time t and the term $h_t^{COM,Stock\ Market\ Indices}$ shows the conditional covariance of the commodities and stock market indices at time t. The stock market index in the considered portfolio has a weight, named as 1- $W_t^{COM,Stock\ Market\ Indices}$.

More precisely, suppose that we have a $1 investment portfolio, then according to the value of the portfolio weight, we should invest money in the investment instrument situated in a long-term position. The remaining proportion should be invested in the asset-based in a short-term position.

	$W_t^{COM,Stock\ Market\ Indices}$	$\beta_t^{COM,Stock\ Market\ Indices}$
Gold/Bovespa	0,65	0,07
Gold/Ftse_Bursa	0,23	0,13
Gold/Bse_Sensex	0,50	0,07
Gold/Ftse_100	0,43	0,06
Gold/Try	0,40	-0,23
Gold/Brl	0,45	-0,32
Gold/Myr	0,18	-0,82
Gold/Inr	0,19	-0,62
Gold/Bist_100	0,63	0,08

Table 5.11 Portfolio Weight and Hedge Ratios.

The values for the portfolio weight computed from the DCC-MFIGARCH models are reported in Table 5.11. During the whole sample period, the average values of optimal gold weight range between 0.18 for Malaysian exchange rate in terms of USD and 0.65 for Brazilian stock index. This result suggest that, for a $1 Gold/Bovespa portfolio, the optimal weight of gold investing should be around 65 cents with the remaining 35 cents should be invested in the Bovespa index. For a $1 Gold/Bist_100 portfolio, the optimal weight of Gold investing should be around 63 cents with the remaining 27 cents should be invested in the Turkish stock market index (Bist_100). For a $1 Gold/Ftse_Bursa portfolio, the optimal weight of Gold investing should be around 23 cents with the remaining 77 cents should be invested in the Malaysian stock market index (Ftse_Bursa). For a $1 Gold/Bse_Sensex portfolio, the optimal weight of Gold investing should be around 50 cents with the remaining 50 cents should be invested in the Indian stock market index (Bse_Sensex). For a $1 Gold/Ftse_100 portfolio, the optimal weight of Gold investing should be around 43 cents with the remaining 57 cents should be invested in London stock exchange index (Ftse_100). For a $1 Gold/Try portfolio, the optimal weight of Gold investing should be around 40 cents with the remaining 60 cents should be invested in Turkish currency (Try). For a $1 Gold/Brl portfolio, the optimal weight of Gold investing should be around 45 cents with the remaining 55 cents should be invested in Brazilian currency (Brl). For a $1 Gold/Myr portfolio, the optimal weight of Gold investing should be around 18 cents with the remaining 72 cents should be invested in Malaysian currency (Myr). For a $1 Gold/Inr portfolio, the optimal weight of Gold investing should be around 19 cents with the remaining 71 cents should be invested in Indian currency (Inr). This result showed how DCC-MFIGARCH models could be used by participants in the financial market for making optimal portfolio allocation decisions. Moreover, the values of the optimal hedge ratio between the Gold and stock market indices as well as exchange rates of some emerging markets in terms of USD was presented in Table 5.11. For hedging strategies with short term positions in stock market indices, the average hedge ratios range from $0.06 to $0.13, whereas it ranges from $-0,82 to $-0.23 in exchange rate indices in terms of USD. These results were crucial in establishing that a $1 long-term position in GOLD can be hedged for 0.07,0.13,0.06 and 0.08 cents with a short-term position in BOVESPA, FTSE_BURSA, BSE_SENSEX, FTSE_100 and BIST_100, respectively. As seen, for a $1 long-term position in GOLD, investing in stock market indices in short-term position provides cheaper way than investing exchange rates in terms of USD. The another reason of this is that, Brooks (2002) specified the optimal hedge ratio, negative ones implies the purchase of futures contracts. Therefore, for any $1 long position in the GOLD index, investors can make purchases of about 82 cents, 62 cents, 32 cents, and 23 cents for the MYR, INR, BRL, and TRL, respectively. Hence, no suggestions were given herein regarding the construction of an investment portfolio with exchange rates because the results were contradictory to the nature of hedging. Additionally, in the literature, researchers have assumed commodities in a long-term position. Contrary to this, they put the stock market indices in a short-term position, as presented in the portfolio above. The emerging market currencies were also considered in terms of USD as an investment instrument that has to be placed in a short-term position. Generally, all of the endeavors attempted in this paper were to minimize risk, and in this direction, for each emerging market, to make up an optimal hedging portfolio. The main reason why effort was made to minimize risk stemmed from the behavior of the investors. While investing, all investors are risk-averse. Risk aversion can be defined as a preference made by an investor who faces two investment instruments, which have the same expected return but different risks, as well as who select lower-risk one. Therefore, in each emerging country, risk-minimizing hedging portfolios were searched for. What was found was that, for each emerging country, there were four combinations, including exchange rates in terms of USD, domestic stock markets, precious metals, and developed stock markets. For Turkey, Brazil, India, and Malaysia, respectively, there were Try-BIST_100-FTSE_100-GOLD,BRL-BOVESPA-FTSE_100-GOLD, INR-BSE_SENSEX-FTSE_100-GOLD, as well as MYR-FTSE_BURSA-FTSE_100-GOLD, as the most fitted model, which were obtained via DCC-MFIGARCH specification. In these combinations, for each emerging market, GOLD came into prominence instead of the other precious metals, BRENT, and WTI. The main reason why GOLD came forward was that it is a safe haven asset. This was why the GOLD was used in the long-term position. If this asset is uncorrelated with another investment instrument, it can be considered as a weak safe haven. If it is negatively correlated with another asset, it can be regarded as a strong safe haven. A safe haven asset, such as gold, maintains the investment of the money holders, especially during financial crises. Thus, in times of market turbulence, it is expected that a safe haven asset, such as gold, can retain or increase its value when the prices of most other assets decrease.

6. CONCLUSION

This study conducted an empirical investigation concerning the most efficient hedging portfolio for four emerging countries, which included Turkey, India, Brazil, and Malaysia. This was conducted using the daily data from January 02, 2006, to November 11, 2018, for some developed and developing stock market percentage returns, precious metal percentage returns, and oil returns. The developed stock markets comprised NASDAQ, NIKKEI_225, S&P_500, DAX_30, and FTSE_100. The emerging stock markets consisted of BOVESPA, BIST_100, FTSE_BURSA, and BSE_SENSEX. GOLD, SILVER, PLATINUM, and PALLADIUM were used as the precious metals. Finally, BRENT Oil and WTI were used as the petroleum futures.

This study was divided into four approaches. First, the DCC-MFIGARCH specification was used to measure volatility. As there are many different possible models in selected markets, Akaike Information Criterion (AIC) and log likelihood function were used to measure of how well a particular model fits the data. To check whether the univariate and multivariate models are fit, the Box-Pierce test was used to determine the existence autocorrelation problem of standardized residuals and squared standardized residuals and Li-McLeod's multivariate portmanteau test was performed to find the ARCH effect in the model. Second, the forecast performances of those models were checked using out-of-sample forecasting and the MAD values were obtained. For each emerging country, only one multivariate result was selected, which had the smallest MAD value. Hence, there were four multivariate results. Moreover, conditional correlations of these investment instruments were analyzed, including the acquired multivariate results mentioned above. By obtaining those results, an optimal portfolio weight and hedging ratio were constructed for minimizing the portfolio risk. As a result of checking the optimal portfolio weight and hedging ratio, the most efficient portfolio was GOLD in long-term position and BOVESPA and FTSE_100 in the short-term position, because the value of the portfolio weight for GOLD/BOVESPA was 0.65 and the hedging ratio was 0.07. The hedging ratio of 0.07 showed that investment into the BOVESPA in the short-run would be very cheap for the investors. Moreover, the remaining 65% of the whole portfolio in the long-run position was a fair enough amount of asset to evaluate in additional investment projects. In addition, the value of the hedging ratio for GOLD/FTSE_100 was 0.06 and quite low. The index of FTSE_100 was really credible, which was why the value of the portfolio weight for GOLD/FTSE_100, which was 0.43, enabled the investors to keep their asset in safe. When for each 1$, if there is a 0.57-cent investment in FTSE_100, they can easily produce an alternative plan to manage the remaining assets. The reason for this is that the index of FTSE_100 is a sufficiently financial scale to preserve assets at a particular level. The economic rationale behind these outcomes, is that, first, investors are risk-averse. In the globalized world, the countries have interconnected economies. Trading an investment instrument with other assets in stock markets can be so rapid. In this direction, through financial crises, each market player may suddenly perform some transactions to make a trade, leading the demand for this asset to change, and correspondingly, the volatility of the price of the assets may sharply take place. Moreover, GOLD is a safe haven asset, providing some advantages for financial practitioners. One of which is that it can protect against inflation risks. With the growing economy, the demand for money increases, depreciating the value of money. If investors prefer to make an investment into GOLD in the long run, it is most probably to make a more profitable return than investing in cash. In addition to this, GOLD does not deteriorate over time. It does not lose its value due to its age. Another reason why investors should invest in GOLD in the long run is that it can be passed on easily to next generations. It may be used for a gift or estate. Actually, this happens traditionally in many countries. For BOVESPA, after the financial crisis, the Brazilian government declared the needed for a program for economic reform. Policymakers produced a solution to recover from the dependency on the capital flows. In this context, capital controls are an efficient way to destabilize financial inflows. They proposed an effective mechanism "Imposto Sobre Operações Finaceiras" (IOF), to regulate capital flows. This reform contributed to stabilizing the Brazilian economy by preventing structural breaks and irregularities in the time series of stock market prices. Hence, for investors, the Brazilian economy presents investment opportunities with low risk. Moreover, in the short term, FTSE_100 can be easily counted as an effective motivation to invest for financial practitioners. The reason for this is that the Ftse_100 has remarkably increased since early last February. Stocks in certain sectors pushed the market up, including mining, energy firms, and industrials. It can be strongly claimed that the expansionary fiscal policy is reflationary and has increased productivity due to IT technology, which in turn, enhances the GDP and FTSE_100's company profits. Moreover, interest rates in the UK are historically low, giving investors an incentive to keep their money in stock markets. Finally, it can safely be contended that investors should invest in BOVESPA and FTSE_100 in a short-term position.

APPENDICES

APPENDIX A: Tables for DCCs

COEFFICIENT	VALUE	COEFFICIENT	VALUE
$\rho S\&P\_500-Brl$	-0.278050	$\rho Gold-Bovespa$	0.095366
$\rho S\&P\_500-Bovespa$	0.556542	$\rho Silver-Brl$	-0.295247
$\rho Nasdaq-Brl$	-0.227083	$\rho Silver-Bovespa$	0.193723
$\rho Nasdaq-Bovespa$	0.495724	$\rho Platinum-Brl$	-0.247167
$\rho Nikkei\_225-Brl$	-0.170566	$\rho Platinum-Bovespa$	0.171027
$\rho Nikkei\_225-Bovespa$	0.132038	$\rho Palladium-Brl$	-0.222532
$\rho Ftse\_100-Brl$	-0.396018	$\rho Palladium-Bovespa$	0.160691
$\rho Ftse\_100-Bovespa$	0.448918	$\rho Brent-Brl$	-0.254139
ρDax_30-Brl	-0.349198	$\rho Brent-Bovespa$	0.300396
$\rho Dax\_30-Bovespa$	0.412214	$\rho W t\imath-Brl$	-0.251381
$\rho Gold-Brl$	-0.231997	$\rho W t\imath-Bovespa$	0.302063

Table A.1 Dynamic Conditional Correlation Targeting for Brazil.

COEFFICIENT	VALUE	COEFFICIENT	VALUE
$\rho S\&P\_500-Myr$	-0.146863	$\rho Gold-Ftse\_Bursa$	-0.233175
$\rho S\&P\_500-Ftse\_Bursa$	-0.333563	$\rho Silver-Myr$	0.068788
$\rho Nasdaq-Myr$	-0.132359	$\rho Silver-Ftse\_Bursa$	-0.233776
$\rho Nasdaq-Ftse\_Bursa$	0.120580	$\rho Platinum-Myr$	0.129119
$\rho Nikkei\_225-Myr$	-0.234737	$\rho Platinum-Ftse\_Bursa$	-0.194723
$\rho Nikkei\_225-Ftse\_Bursa$	0.391982	$\rho Palladium-Myr$	0.105574
$\rho Ftse\_100-Myr$	-0.236029	$\rho Palladium-Ftse\_Bursa$	-0.278760
$\rho Ftse\_100-Ftse\_Bursa$	0.262585	$\rho Brent-Myr$	0.201478
ρDax_30-Myr	-0.216770	$\rho Brent-Ftse\_Bursa$	-0.173668
$\rho Dax\_30-Ftse\_Bursa$	0.237228	$\rho W t\imath-Myr$	0.103985
$\rho Gold-Myr$	-0.233175	$\rho W t\imath-Ftse\_Bursa$	-0.171290

Table A.2 Dynamic Conditional Correlation Targeting for Malaysia.

COEFFICIENT	VALUE	COEFFICIENT	VALUE
ρS&P_500−Trl	-0.419879	*ρGold− Bist_100*	0.117909
ρS&P_500−Bist_100	0.314715	*ρSilver− Trl*	-0.221642
ρNasdaq− Trl	-0.359005	*ρSilver− Bist_100*	0.174565
ρNasdaq−Bist_100	0.272232	*ρPlatinum− Trl*	-0.194542
ρNikkei_225− Trl	-0.061453	*ρPlatinum− Bist_100*	0.136875
ρNikkei_225− Bist_100	0.215002	*ρPalladium− Trl*	-0.137581
ρFtse_100− Trl	-0.341034	*ρPalladium− Bist_100*	0.177797
ρFtse_100− Bist_100	0.441513	*ρBrent− Trl*	-0.218116
ρDax_30− Trl	-0.349000	*ρBrent− Bist_100*	0.157872
ρDax_30− Bist_100	0.430224	*ρWtı− Trl*	-0.222871
ρGold− Trl	-0.152562	*ρWtı− Bist_100*	0.144586

Table A.3 Dynamic Conditional Correlation Targeting for Turkey.

COEFFICIENT	VALUE	COEFFICIENT	VALUE
ρS&P_500−Bse-Sensex	0.259601	*ρGold− Bse_Sensex*	0.080772
ρNasdaq−Inr	-0.155470	*ρSilver− Inr*	-0.264092
ρNasdaq− Bse-Sensex	0.221757	*ρSilver− Bse_Sensex*	0.150771
ρNikkei_225−Inr	-0.204017	*ρPlatinum− Inr*	-0.202060
ρNikkei_225− Bse-Sensex	0.322600	*ρPlatinum− Bse_Sensex*	0.134735
ρFtse_100− Inr	-0.272224	*ρPalladium− Bse_Sensex*	0.201502
ρFtse_100− Bse-Sensex	0.384679	*ρPalladium− Inr*	-0.157982
ρDax_30− Inr	-0.263694	*ρBrent− Bse_Sensex*	0.169844
ρDax_30− Bse-Sensex	0.390197	*ρBrent− Inr*	-0.144445
ρGold− Inr	-0.220726	*ρWtı− Bse_Sensex*	0.152991
ρS&P_500− Bse-Sensex	0.259601	*ρWtı− Bse_Sensex*	0.080772

Table A.4 Dynamic Conditional Correlation Targeting for India.

APPENDIX B: Tables for MADs

BRL-BOV- D_30-BR 2.52	BRL-BOV Na-BR 3.40	BRL-BOV F_100-BR 9.85	BRL-BOV S&P500-BR 2.78	BRL-BOV D_30-G 1.83	BRL-BOV F_100-G 1.78*	BRL-BOV Na-G 2.72
BRL-BOV S&P500-G 2.10	BRL-BOV D_30-PAL 2.36	BRL-BOV F_100-PAL 2.31	BRL-BOV Na-PAL 2.26	BRL-BOV D_30-P 2.05	BRL-BOV F_100-P 1.99	BRL-BOV Na-P 2.93
BRL-BOV D_30-S 2.07	BRL-BOV F_100-S 2.015	BRL-BOV Na-S 2.95	BRL-BOV S&P500-S 2.33	BRL-BOV D_30-WTI 2.50	BRL-BOV F_100-W 2.08	BRL-BOV N_225-WTI 3.4
BRL-BOV N_225-G 2.20	BRL-BOV N_225-S 2.43	BRL-BOV N_225-P 2.41	BRL-BOV N_225-PAL 2.73	BRL-BOV N_225-BR 2.88	BRL-BOV N_225-WTI 2.87	

Table B.1 Robustness Assessment for Brazil.

MYR-FBUR-G-BR	1.09	MYR-FBUR-Na-G	1.46	MYR-FBUR-Na-BR	1.65	MYR-FBUR-D_30-P	0.63
MYR-FBUR-P-BR	1,29	MYR-FBUR-D_30-PAL	0.67	MYR-FBUR-N_225-BR	1.12	MYR-FBUR-Na-p	1.53
MYR-FBUR-S-BR	1,30	MYR-FBUR-Na-PAL	1.56	MYR-FBUR-S&P_500-BR	1.02	MYR-FBUR-S&P_500-P	0.90
MYR-FBUR-G-WTI	1.08	MYR-FBUR-F_100-G	0.51*	MYR-FBUR-D_30-WTI	0.76	MYR-FBUR-F_100-S	0.57
MYR-FBUR-PAL-WTI	1.60	MYR-FBUR-N_225-G	0.93	MYR-FBUR-F_100-WTI	0.70	MYR-FBUR-N_225-S	0.99
MYR-FBUR-P-WTI	1,27	MYR-FBUR-S&P_500-G	0.84	MYR-FBUR-Na-WTI	1.65	MYR-FBUR-F_100-P	0.58
MYR-FBUR-S-WTI	1,28	MYR-FBUR-F_100-PAL	0.62	MYR-FBUR-N_225-WTI	1.12	MYR-FBUR-N_225-P	1.000
MYR-FBUR-D_30-BR	0.76	MYR-FBUR-S&P_500-PAL	0.94	MYR-FBUR-S&P_500-WTI	1.02	MYR-FBUR-D_30-S	0.63
MYR-FBUR-F_100-BR	0.70	MYR-FBUR-S&P_500-S	0.90	MYR-FBUR-D_30-G	0.57	MYR-FBUR-Na-S	1.52

Table B.2 Robustness Assessment for Malaysia.

Trl-Bst-G-Br	1.98	Trl-Bst-Na-Br	2.59
Trl-Bst-G-Wtı	1.96	Trl-Bst-N_225-Br	2.07
Trl-Bst-S-Br	2.18	Trl-Bst-S&P_500-Br	1.97
Trl-Bst-S-Wtı	2.18	Trl-Bst-D_30-G	1.51
Trl-Bst-P-Br	2.17	Trl-Bst-F_100-G	1.46*
Trl-Bst-Pal-Br	2.50	Trl-Bst-Na-G	2.40
Trl-Bst-Pal-Wtı	2.49	Trl-Bst-N_225-G	1.88
Trl-Bst-D_30-Br	1.70	Trl-Bst-S&P_500-G	1.78
Trl-Bst-F_100-Br	1.65	Trl-Bst-D_30-Pal	1.62
Trl-Bst-F_100-Pal	1.57	Trl-Bst-Na-Pal	2.51
Trl-Bst-N_225-Pal	1.99	Trl-Bst-S&P_500-Pal	1.89
Trl-Bst-D_30-P	1.58	Trl-Bst-F_100-P	1.53
Trl-Bst-Na-P	2.48	Trl-Bst-N_225-P	1.95
Trl-Bst-S&P_500-P	1.85	Trl-Bst-D_30-S	1.57
Trl-Bst-F_100-S	1.52	Trl-Bst-Na-S	2.46
Trl-Bst-N_225-S	1.94	Trl-Bst-D_30-Wtı	1.70
Trl-Bst-S&P_500-S	1.84	Trl-Bst-F_100-Wtı	1.65
Trl-Bst-S&P_500-Wtı	1.97	Trl-Bst-N_225-Wtı	2.07

Table B.3 Robustness Assessment for Turkey.

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