Commodity Volatility Index using TVP-FAVAR

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TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

CVI	Commodity volatility index
MSCI	Morgan Stanley Capital International (MSCI)
VAR	Vector autoregressive
TVP-VAR	Time varying parameter vector autoregressive
TVP-FAVAR	Time varing parameter Factor augmented vector autoregressive
GARCH	Generalized autoregressive conditional heteroscedasticity
MCMC	Markov chain Monte Carlo
ADF	Dickey-Fuller
OLS	Ordinary lesat square
EWMA	Exponentially weighted moving average

ABSTRACT

A factor augmented vector auto regressive model with time-varying parameters is used to constructing commodity volatility index (CVI) to explore the volatility transmission between commodity markets and the stock markets from Europe, Asia and US. The daily commodity volatility range in the sectors of energy and precious metals and for three MSCI stock market indexes spanning from the period of January 1, 2007 to May 21, 2017 are considered to construct the CVI. Time variation in the model parameters allows for the weights attached to each commodity range in the index to evolve over time. The volatility from commodity to stock markets is time changing. The volatility transmission from US market and Asian market is more related to commodity volatility than from European stock market to commodity. To carry out the forecasting performance of the three market indexes, the method of dynamic model averaging is used, based on the mean squared forecast error (MSFE).

Key words: commodity volatility index, TVP-FAVAR, commodity market, financial market, time-varying volatility

Chapter 1

INTRODUCTION

Commodity prices exhibit a high volatility since the recent changes in market conditions. As a global market, commodity is sensitive to the variables of other markets. A good number of works has emerged to examine the nature of information transmission across markets. After the onset of 2007-2008 financial crisis, the correlation between commodity price and stock price appears to be enhanced and commodity is increasingly included in portfolios (Lombardi and Ravazzolo, 2016).

Understanding the moves in commodity price becomes a fundamental task in the world economy. Diverse international organizations take volatility of commodity price as central issue. That was the case during the 2009 G20 summit in Pittsburgh, which addressed the issue of excessive commodity price volatility. Examining be carefully the inter-market dependency in volatility of commodity and financial market is as well a priority for international investors since it has figured out as a possible investment area. Policy makers at macroeconomics level give a particular interest to commodity price, since it influences on monetary and fiscal policy decisions.

Empirical works devoted on the relationship between commodity and stock markets to analyze in depth the price′s volatility transmission. Using a DCC-GARCH approach, Creti et al. (2013) investigated the correlation between raw materials (energy, metals, agricultural, food) and stock market, by concluding that the link is time-varying and highly volatile from the recent impact of 2008 financial crisis. Similar transmission between international food, energy and financial market was carried out by Jebabli et al. (2014) to assess the volatility linkage during the financial shocks period. It was found, by utilizing the TVP-VAR model with stochastic volatility presenting a parsimonious specification, the presence of volatility spillover from crude oil and international stock markets to food markets.

Nevertheless, there is still more to explore about the transmission between commodity and stock market's volatility in order to clear in details the mechanism, to help investors in their investment strategies and policy markers in the decision taking regarding fiscal and inflation issues. In order words, they is still need of extending the existing literature discussing the link between commodity market and stock markets or MSCI stock markets indexes.

In this work, we focus the attention on the volatility structure of the commodity market. In particular, we investigate the transmission across MSCI stock market indexes and commodity market by exploring the volatility linkage between both markets. The dynamic of the volatility range in commodity and stock markets are illustrated in the figures 1.1 and 1.2.

The motivation behind this empirical work relies on providing a comprehensive and coherent picture of the commodity price's volatility. The study contributes to the pass literature in seeking at capturing the movement in commodity market cleaning for financial market. To do this, we combine the standard structural VAR analysis with recent developments in factor analysis for large data sets. To be accurate, we deal with the factor augmented vector autoregressive models FAVARs with time-varying coefficients (TVP-FAVARs) and stochastic volatility.

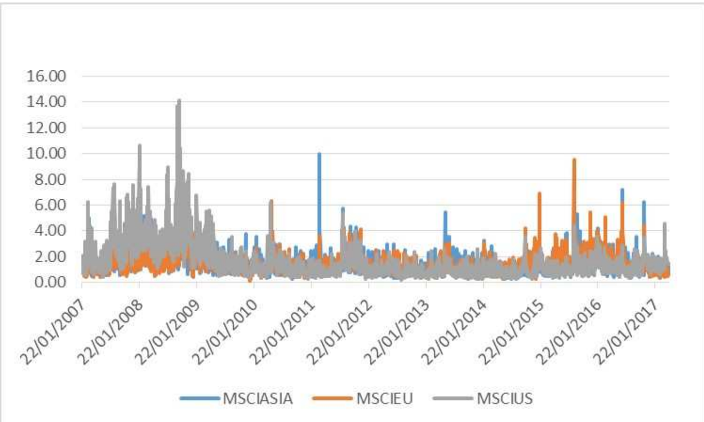

Figure 1.1: Volatility range of MSCI indexes from 01/22/2007 to 04/21/2017

Regarding the sample of study, we considered the daily volatility range of 3 geographical areas, i.e. Asia, EU and US (see 1.1) and of 8 commodities as raw materials in the different sectors of energy and precious metals (see 1.2), ranging from the period of January 1, 2007 to May 21, 2017.

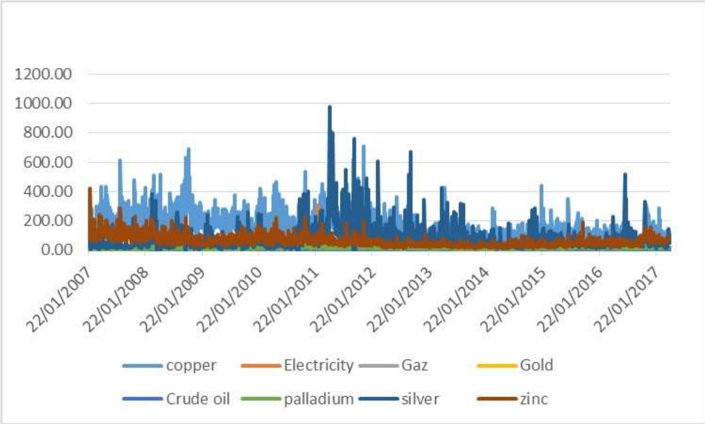

Figure 1.2: Volatility range of 8 Commodity markets from 01/22/2007 to 04/21/2017

In the following chapter, we present the modeling framework related to the TVP-FAVAR and detail the features of the used estimation algorithm. In chapter 3, we carry out the preliminary analysis based on the data and the choice of priors distribution. Chapter 4 discusses the empirical results, where we give the estimates of parameters and provide an extensive discussion about the factor. The last chapter offers the conclusion on the study.

Chapter 2

MODELING FRAMEWORK

More often, in the economic literature, the GARCH models are used to examine the volatility of commodity prices. They provide information about the conditional correlation of different price series changes in their multivariate versions. However, the GARCH models do not provide a clear methodology and unified to discover the dynamics of volatility operating between the variables involved and to recognize structural changes.

To overcome that limit contained in the GARCH models, others models are developed to help capturing volatility structure such as the structural vector autoregressions (VARs). Similarly to that, in this work, the basic FAVAR model is set out to analyze the volatility structure of the commodity market and it is explained how it can be extended to a time varying parameter (TVP) model. The TVP-FAVAR model with stochastic volatility enables us to understand how changes in stock markets influence commodity market over time.

2.1 Factor Augmented Vector Auto Regression (FAVAR) models

The classical approach to assess the structure of volatility of commodity market to is to estimate a structural VAR on some key variables. Such models are of the following form :

$$z_t = b_1 z_{t-1} + \ldots + b_p z_{t-p} + v_t \tag{2.1}$$

with $z' = [x'_t, y_t]$, x_t is a $(n \times 1)$ vector of (volatility range commodity) variables gathering the daily prices of 8 commodities from two sectors (energy, metals), and y_t a $(s \times 1)$ vector of (volatility range financial indexes) variables of interest, representing the daily MSCI stock market index of EU, US and ASIA; $(b_1, \ldots, b_p)$ are the dimensional $(n \times n)$ VAR coefficients and v_t the zero-mean Gaussian error terms with ϵ_t a $(n \times n)$ covariance matrix.

To the standard VARs , k unobserved factors that summarizes n-dimensional vector of observable variables x_t, was augmented. By considering the Factor-augmented VAR (FAVAR), it helps capturing most of the structure of commodity volatility using as many as series necessary through the k factors (k smaller than n). The p-lag TVP-FAVAR is given by the following equation:

$$z_t = b_{1,t} z_{t-1} + \ldots + b_{p,t} z_{t-p} + v_t \tag{2.2}$$

with $z' = [f_t', y_t]$, f_t a $(k \times 1)$ vector of latent factors standing for the commodity market condition as volatility, $b_{i,t}$ (for $t = 1, \ldots, T$ and $i = 1, \ldots, p$) are $(k \times k)$ coefficients matrices and $v_t \sim N(0, \varepsilon_t)$ where ε_t is a $(k \times k)$ full covariance matrix for each time t.

Following Bernanke et al. (2005)), the informational time series x_t are linked to the latent factors f_t and the observed variable y_t by the following given equation:

$$x_t = \Lambda_t^y y_t + \Lambda_t^f f_t + u_t \tag{2.3}$$

with Λ_t^f a $(n \times k)$ factor loading, Λ_t^y a $(n \times s)$ regression coefficients and u_t a $(n \times 1)$ vector of zero-mean Gaussian disturbances with time varying covariance U_t .The errors terms U_t is diagonal and assumed to guarantee that u_t is a vector of idiosyncratic shocks and f_t assembles information common to commodity markets, i.e. $E(u_{i,t}, f_t) = 0$ and $E(u_{i,t}, u_{j,t}) = 0$ for all $i, j = 1, \ldots, n$ and $t, s = 1, \ldots, T$ with $i \neq j$ and $t \neq s$.

For the flexibility of the model, it is interesting to follow Pricemeri (2005) through the reduced triangular form:

$$A_t \varepsilon_t A_t' = \Sigma_t \Sigma_t' \tag{2.4}$$

with

$$A_t = \begin{pmatrix} 1 & 0 & \dots & 0 \\ c_{21,t} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ c_{(k+1)1,t} & \dots & c_{(k+1)k,t} & 1 \end{pmatrix} \tag{2.5}$$

and

$$\Sigma_t = \begin{pmatrix} \alpha_{1,t} & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \alpha_{(k+1),t} \end{pmatrix} \tag{2.6}$$

Here, we specify by letting $c_t = \left(c_{j1,t}, \dots, c_{j(j-1),t}\right)^{'}$ be a stacked vector of the lower triangular elements in A_t, $B_t = (b_{1,t}, \dots, b_{p,t})^{'}$, the loading vector $\Lambda_t = \left(\Lambda_t^f, \Lambda_t^y\right)^{'}$ and $h_t = \left(h_{1,t}, \dots, h_{(k+1),t}\right)^{'}$ with $h_{j,t} = log\alpha_{j,t}^2$, for $j = 1, \dots, k+1$. The time varying parameter (TVP) is evolved and the parameters need to follow a random walk process such as:

$$\begin{aligned} \Lambda_t &= \Lambda_{t-1} + u_t \\ B_t &= B_{t-1} + \alpha_t \end{aligned} \tag{2.7}$$

where $u_t \sim N(0, W_t)$, and $\alpha_t \sim N(0, M_t)$. We present a simple form of the model detailed in the Eqs (2) and (3) as follows:

$$\begin{gathered} x_t = \Lambda_t^y y_t + \Lambda_t^f f_t + u_t \\ \begin{bmatrix} y_t \\ f_t \end{bmatrix} = a_t + b_{1,t} \begin{bmatrix} y_{t-1} \\ f_{t-1} \end{bmatrix} + \dots + b_{p,t} \begin{bmatrix} y_{t-p} \\ f_{t-p} \end{bmatrix} + v_t \end{gathered} \tag{2.8}$$

with a_t a vector of intercepts and the other components as earlier defined . The TVP-FAVAR is represented by the full model described in Eqs (5) and (6) and all the errors terms discussed in the above equations are uncorrelated each other and and over time. Note that, we let ε_t and U_t to be time-varying and consider homoscedasticity when $\varepsilon_t = \varepsilon$ and $U_t = U$.

2.2 Parameter estimations

The most common estimation method employed to carry out inference about the TVP-FAVARs is the Bayesian approach using Markov Chain Monte Carlo (MCMC) algorithm. Applications as Primiceri (2005) or Del Negro and Otrok (2008), stipulated that the method through a computational framework enables to derive complex multivariate joint posterior estimates of the latent factors and the rest of the model parameters. Unfortunately, when it comes of multiple TVP-FAVARs with recursive forecasting, dealing with such an estimation algorithm is avoided because of the difficulty and the time consuming to correctly capturing the factors. The TVP-FAVAR is preferred for its specificity to characterize accurately the behavior of the volatility in commodity market and the most efficient estimation approach would contain all the restriction contained in the model's structure.

Similarly to the estimation procedure of Koop and Korobilis (2014), we use the fast two-step algorithm which less burdensome and time saving. The process results from a combination of variance discounting methods with the Kalman filter. The idea behind this is to reach a fast analytic posteriors mean for both the latent factors f_t as state variable and the time- varying parameters Λ_t and B_t. Recalling that f_t and Λ_t are both unexpected in the model$'$s structure, a dual Kalman filters or smoother was developed to reach to an estimation of the unobserved state f_t as well as the other parameters which was not realizable with the classical Kalman filter (see Doz et al. (2011), Nelson and Stear (1976)).

Based on the strong theoretical and empirical results from the work of Stock and Watson (2009) and Bates et al. (2013), the algorithm presents a best approach using, $\widetilde{f}_t$ the principal components estimate of f_t based on x_t, in the estimation of the time-varying parameters Λ_t and B_t.

Following Quintana and West (1988) and Koop and Korobilis (2014), we estimate the error covariance matrices ε_t, U_t, M_t and W_t using the simulation-free variance matrix discounting methods in a recursive way. Here for ε_t and U_t, we consider the exponentially weighted moving average (EWMA) estimators which relies on decay factors k_1 and k_2. As with Koop and Korobilis (2012, 2013, 2014), we employ the forgetting factor methods to estimate the covariance matrices M_t and W_t based on k_3 and k_4 . The choice of such decay-forgetting factors is done through the expected amount of time variation in the model parameters.

The full algorithm for estimating the TVP-FAVAR involves the following steps:

1.) Obtain the principal component estimates of the factors $\widetilde{f}_t$ after initializing all the parameters $(\Lambda_0, B_0, f_0, \varepsilon_0, \mathrm{U}_0)$.

2.) Estimate the TVP (Λ_t, B_t) given $\widetilde{f}_t$.

- Estimate Λ_t, U_t, M_t and W_t using Variance discounting methods.
- Estimate (Λ_t, B_t), given $(\varepsilon_t, U_t, M_t, W_t)$ using the Kalman filters and smoother.

3.) Estimate the factors f_t given (Λ_t, B_t), using the Kalman filters and smoother.

The algorithm described above is quite simple and avoid iterating over these steps thousands of times as in MCMC algorithm. The recursive estimators for the covariances are computationally efficient and estimates are obtained within second times. Most importantly, the algorithm guarantees the fact that, the factors f_t capture movements common to x_t standing for volatility rang in commodity price after cleaning for financial markets volatility through the presence of the $\Lambda_t^y y_t$ term.

2.3 Dynamic model averaging and selection of many TVP-FAVARs

This work presents a set M, of L possible regression models, $M = \{m_1, \ldots, m_L\}$, where the model m_l can be written as:

$$
\begin{gathered}
x_t^{(l)} = \Lambda_t^{y(l)} y_t + \Lambda_t^{f(l)} f_t + u_t^{(l)} \\
\begin{bmatrix} y_t \\ f_t^{(l)} \end{bmatrix} = a_t^{(l)} + b_{1,t} \begin{bmatrix} y_{t-1} \\ f_{t-1}^{(l)} \end{bmatrix} + \ldots + b_{p,t} \begin{bmatrix} y_{t-p} \\ f_{t-p}^{(l)} \end{bmatrix} + v_t^{(l)}
\end{gathered}
\tag{2.9}
$$

with the potential explanatory variables x_t regrouping different subsets $x^{(l)}$, together with $f^{(l)}$ making up the constructing of the CVI as volatility range. Following the restriction in Koop and Korobilis (2014), m_l assumes for a specific combination of x_t to have no loading on the factor at time. The n explanatory variables contained in x_t, implies a maximum $L = 2^n$ of combinations of commodity variables that can be involved into the generating of the CVI.

Dealing with the time-varying parameters with a large set of regressors, needs to employ alternative dynamic models to better eliminate any possible over-fitting sample issues. As it was developed by Raftery et al. (2010) and employed by different works (eg. Koop and Korobilis (2014), Aye, G., et al. (2015)), we use dynamic model averaging (DMA), that enables to generate both the regression model and the regression parameters by letting them to switch over time. The DMS stands for model selecting over time. DMA averages across models using a recursive updating scheme More precisely, the DMA involves computing at time t given information through $t-1$, the probabilities $\Psi_{t|t-1,l}$ for the models $l = 1, \ldots, L$, and averaging forecasts across those L models using $\Psi_{t|t-1,l}$ as weights. DMS involves, using in each point in time the model with the highest values for $\Psi_{t|t-1,l}$ to forecast. We emphasis that, the DMA is dynamic since $\Psi_{t|t-1,l}$ can vary over time.

In the the recursive updating algorithm of Raftery et al. (2010), the following equation for DMA was derived:

$$\Psi_{t|t,l} = \frac{\Psi_{t|t-1,l} T_l(y_t \mid y_{1:t-1})}{\Sigma_{\zeta=1}^{l} \Psi_{t|t-1,\zeta} T_\zeta(y_t \mid y_{1:t-1})} \tag{2.10}$$

where $T_l(y_t \mid y_{1:t-1})$ represents the predictive density of y_t for model l (predictive likelihood) as a measure of fit of the model l. Using a forgetting factor α, the algorithm derives the weights to be used in the next following,

$$\Psi_{t+1|t,l} = \frac{\Psi_{t|t,l}^{\alpha}}{\Sigma_{\zeta=1}^{l} \Psi_{t|t,\zeta}^{\alpha}} \tag{2.11}$$

Following Raftery et al. (2010) which set the parameter α to numbers slightly below one, we use $\alpha = 0.99$. Taking from $\Psi_{0|0,l}$, for $l = 1, \ldots, L$, we are able to recursively compute the potential weights $\Psi_{t|t,l}$ and $\Psi_{t|t-1,l}$ for DMA. The next section lays out the data and the necessary analysis that is carried out before to proceed to the empirical results.

Chapter 3

DATA DESCRIPTION

To elaborate an index of commodity volatility, we rely on spot prices series, rather than futures prices according to Vivian and Wohar (2012) suggestions. Thus, the data set consists of 8 daily commodity prices listed in US dollars and ranging from 1/22/2007 to 4/21/2017. Based on the availability in commodity volatility range, we use commodities from the sectors of energy and precious metals. As regarded to energy sector we consider oil, electricity and gaz (see Fig 3.1). Precious metal regroups silver, copper, gold, palladium and zinc (see Fig 3.2).

Regarding the financial market, we consider for the same period, the Morgan Stanley Capital International (MSCI) stock market index of Asia, Europe and America (see Fig 3.3). These series are downloaded from the Bloom-berg database and we first test the stationarity properties of our series using the augmented Dickey-Fuller (ADF) test where the alternative hypothesis is stationary. ADF test shows stationarity of the series where the null hypothesis of the existence of a unit root is rejected for all series.

In our implementing, x_t and y_t stand for the volatility range for commodity price and stock market index respectively, with the volatility range defined as $R_t = Hp_t - Lp_t$, where Hp_t denotes the higher price and Lp_t the lower price, the both estimated at the same time t.

Table 3.1 provides some descriptive statistics regarding the commodity and stock markets series. Electricity and the group of precious metals commodities seem to differ from other variables in terms of volatility: the variance of electricity, is higher than that obtained for gaz and crude oil. The electricity series is extremely volatile, as its high kurtosis value shows. This is not surprising given that electricity is not storable and prices reflect the real-time equilibrium between demand and supply, with contingencies that vary greatly from one day to another. Statistics also reveal that all the 11 variables are skewed (positively) and exhibit an excess kurtosis.

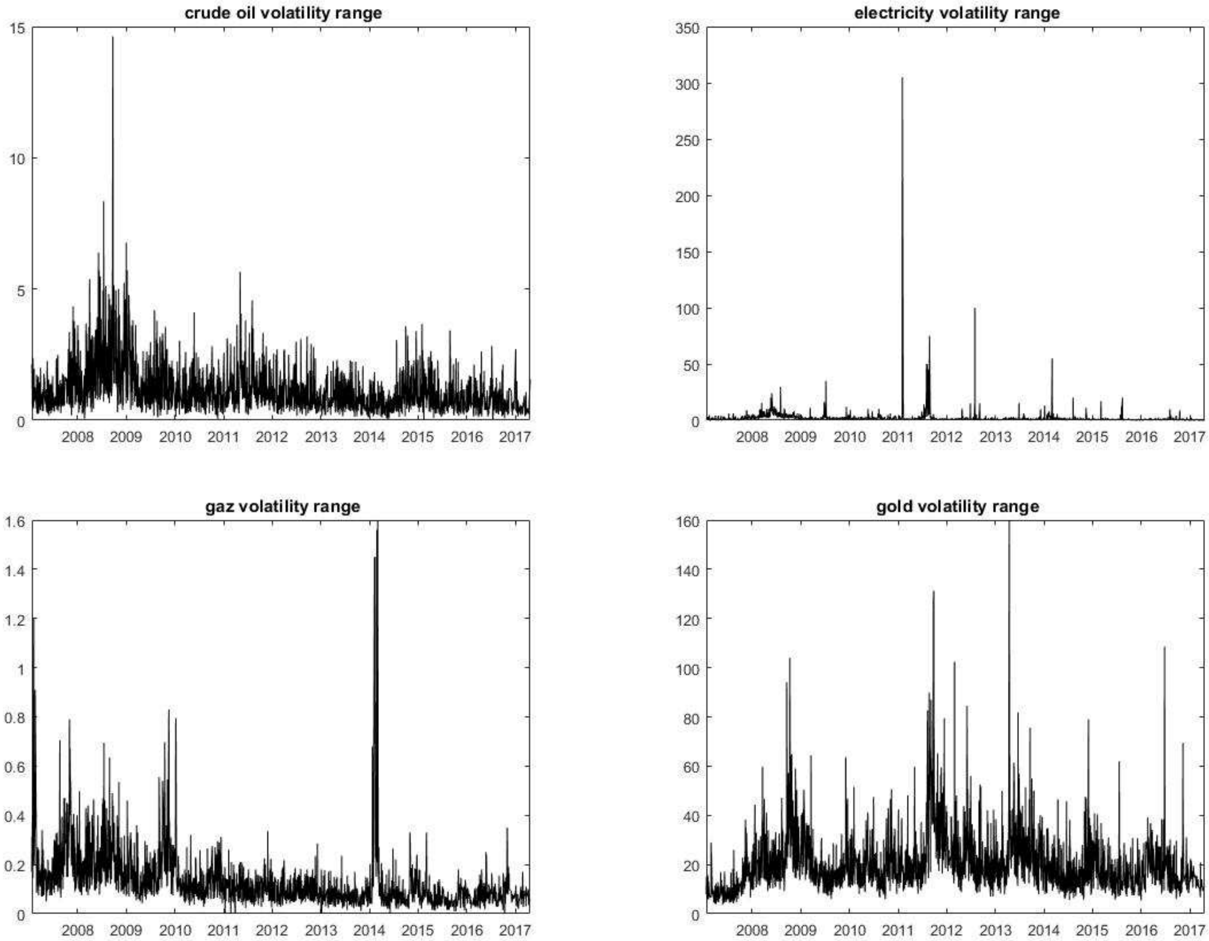

Figure 3.1: Evolution of gold and energy's volatility ranges

In this study, we adopt the non-informative choice of the priors distributions for all parameters of the models. Following the suggestions of Primiceri (2005), we use a training sample, spanning the first 10 days observations to estimate a FAVAR with constant parameters using OLS estimation. The priors hyper-parameters depending on the remaining sample of the data are obtained using the OLS estimates. Starting from an initial state, the priors distributions of the models parameters are described as follows :

$$
\begin{aligned}
f_0 &\sim N(0,4), \\
\Lambda_0 &\sim N(0, 4 \times I_{n(n+1)}), \\
B_0 &\sim N(0, V_{min}), \\
U_0 &\equiv 1 \times I_n, \\
\varepsilon_0 &\equiv 1 \times I_{s+1}, \\
\Psi_{0|0,l} &= \tfrac{1}{L}
\end{aligned}
\tag{3.1}
$$

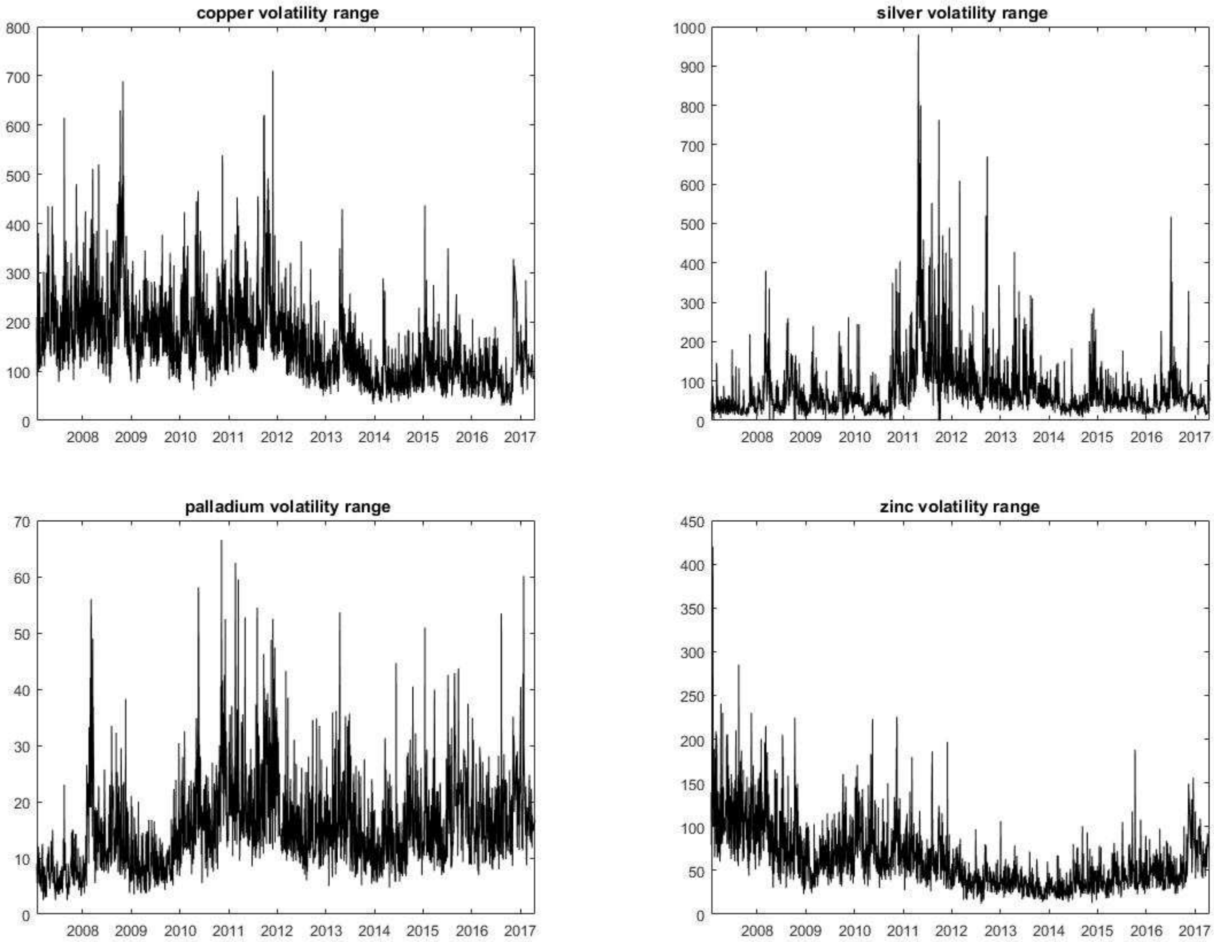

Figure 3.2: Evolution of precious metal's volatility range

where, I is the identity matrix and V_{min} denotes the diagonal covariance matrix following the Minnesota priors with $V_{min} = 4$ for intercepts and $0.1 \times r^{-2}$ for coefficients on the p-lag r.

Table 3.1: Summary statistics results (whole sample)

	Mean	Min	Max	Var	St.Dev	Kurtosis	Skewness
Energy							
Oil	1.169	0.030	14.62	0.882	0.939	26.518	3.097
Gaz	0.132	0	1.600	0.016	0.126	41.110	4.807
Eltricity	2.118	0	305	58.909	7.675	1.08e+03	29.064
Precious metals							
Gold	20.579	3.640	160	161.04	12.690	19.659	2.950
Silver	80.421	0	98	6.4e+03	79.929	26.411	3.795
Copper	161.18	30	710.25	7.7e+03	87.872	6.928	1.549
Palladium	15.503	2.500	66.500	69.269	8.323	7.146	1.607
Zinc	62.046	12	420	1.3e+03	36.44	9.718	1.86
Indexes							
MSCI AS	1.4989	0.2700	9.9600	1.0082	1.0041	14.4949	2.6873
MSCI EU	1.4570	0.1400	9.570	0.7602	0.8719	14.8017	2.5755
MSCI US	1.6028	0.220	14.150	1.9414	1.3836	14.9439	2.8122

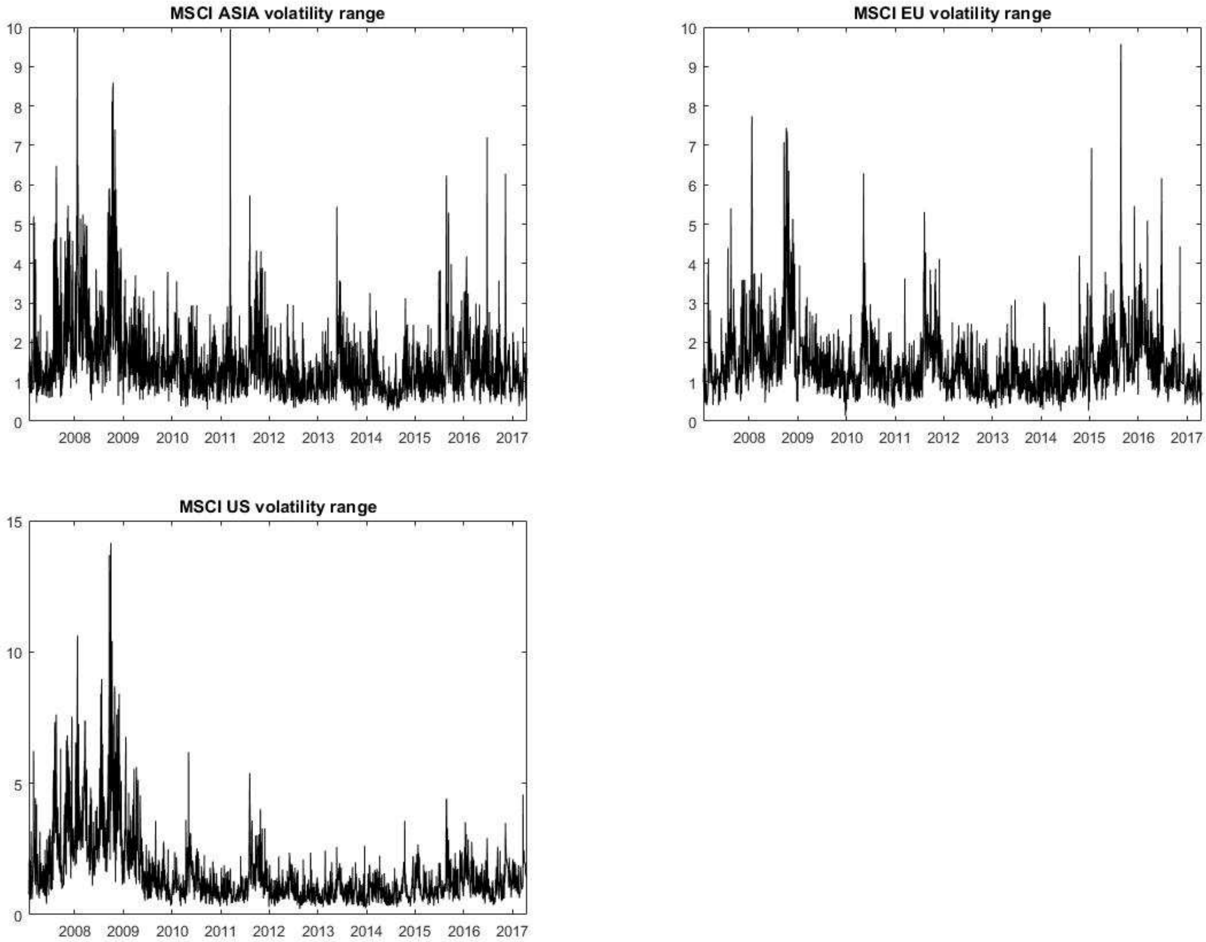

Figure 3.3: Evolution of MSCI Index's volatility range

Chapter 4

EMPIRICAL RESULTS

This section gives our main results on the factors of commodity volatility range extracted using Time varying parameters FAVAR. We present the empirical results in two subsections. The first section reports results on factor and the volatility spill-over from commodity market to stock market. The second subsection is based on the approach of forecasting performance using DMA.

4.1 Estimates of commodity volatility index

The figure 4.1 represents the factor constructed for the commodity volatility index using all the 8 commodity variables from the single TVP-FAVAR following Koop and Korobis (2014). The TVP-FAVAR produces a noticeable volatility of the CVI for most of the period considered.

We also determine the volatility's sensitivity from/to MSCI Asia, MSCI EU and MSCI US stock market to/from commodity market (see Fig 4.2-4.4). We based on the graphical representation of the estimated parameter β to produce a good interpretation of the volatility transmission across commodity and the three stock markets. In fact, β_t stands for the measure of the volatility's sensitivity across each financial and commodity market at time t. When its direction goes down (negative), or stable(constant) , the volatility correlation across market is negative or stable. In other word, when β_t is negative, the commodity market volatility increase and stock market volatility decrease. This correlation should met the one that the figure 4.5 interprets between stock and oil market.

The figure 4.2 plots the volatility spill-over effect of Asian stock market. The volatility's sensitivity goes quite stable from 2008 to 2009 , and starts increasing from 2009 up to a point in 2013 where it is observed two downward peaks exactly around mid 2013 and mid 2014. The senses of the direction of the volatility's sensitivity of Asian stock market translate a positive correlation of the volatility across both markets from 2008-2009 and 2009-2013 and

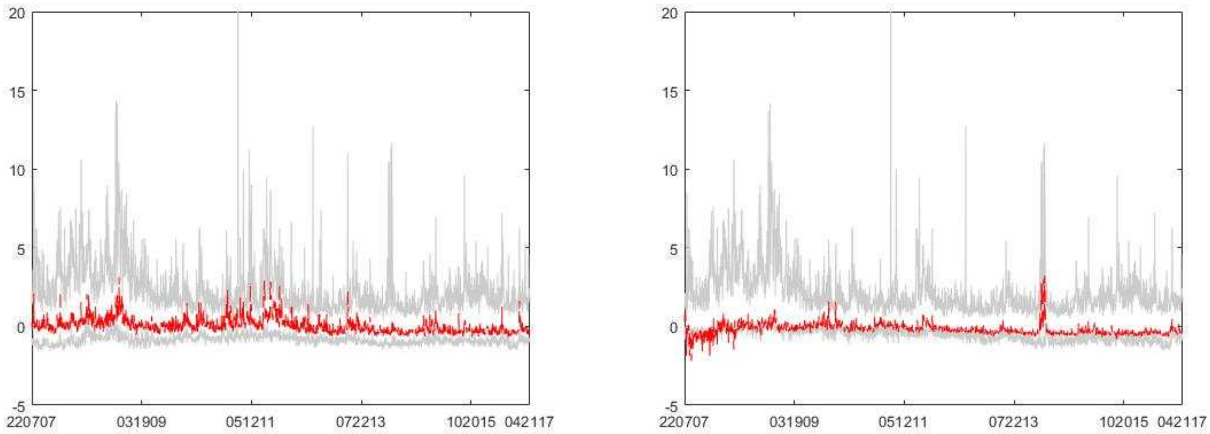

Figure 4.1: CVI constructed from the TVP-FAVAR (left) and TVP-FAVAR-DMA (right) models using all 8 commodities

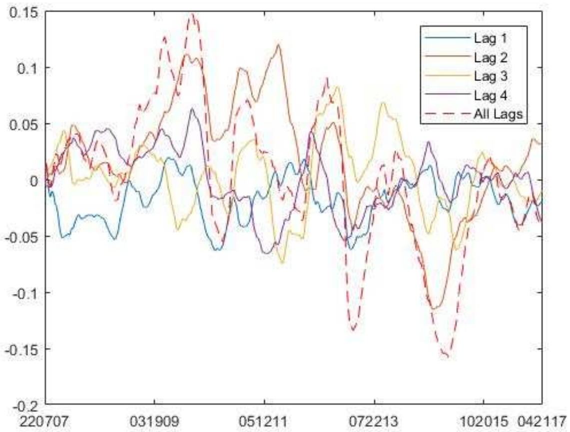

Figure 4.2: MSCI ASIA lagged spill-over effects

a negative correlation from the second downward peak in 2014. As we can also notice in the figure 4.5, the correlation between volatility is the same between oil price and MSCI Asia index.

By analyzing the direction of the volatility's sensitivity on figure 4.4, it is worth noting that a similar link in volatility transmission between US stock markets and commodity markets with the relationship between stock and oil markets. In fact there is a slight decrease (negative correlation between oil market and stock markets from 2007-2008 in figure 4.5) of the volatility's sensitivity from the 2007 to 2008. From 2009 to mid 2012 , the volatility in commodity market and US market goes the same direction, sharing a positive correlation in volatility on that period (same correlation between oil market and stock markets from 2008-2009 and 2009-2014 in figure 4.5). It is interesting to notice a change of direction of the volatility's sensitivity from

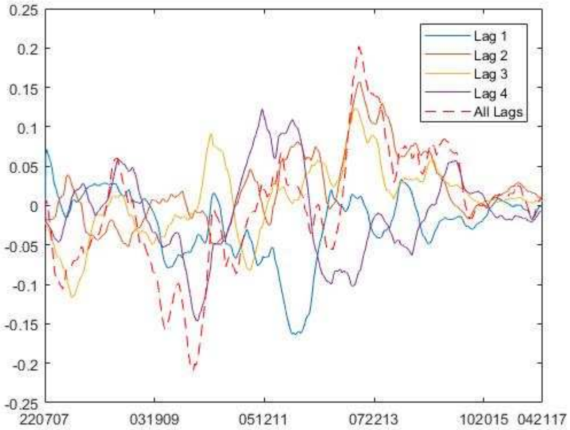

Figure 4.3: MSCI EU lagged spill-over effects

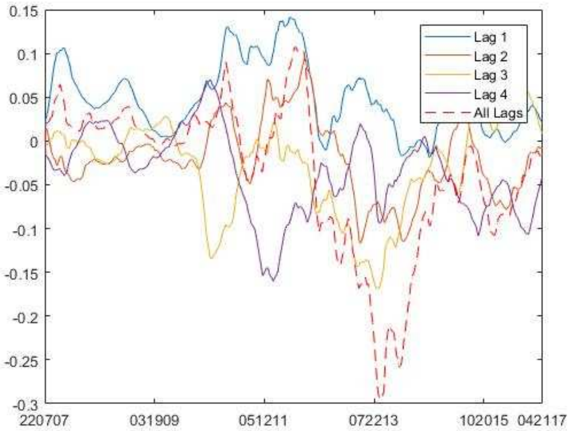

Figure 4.4: MSCI US lagged spill-over effects

mid 2012, interpreting a negative correlation between both markets, precisely focused around 2013-2014 as highlighted by the downward peak (negative correlation between oil market and stock markets from 2014 in figure 4.5).

From 2007 to 2009, the volatility's sensitivity of MSCI EU stock market in figure 4.3 goes in the opposite sens to the similarity observed in volatility transmission between both Asian and US stock markets to commodity market. However, we remark an increase of the volatility's sensitivity on the commodity market from 2009 to the end 2013 (same correlation between oil market and stock markets from 2009-2014 in figure 4.5). From the end 2013, a decrease of the volatility's sensitivity of EU stock market to commodity market is observed, meaning a

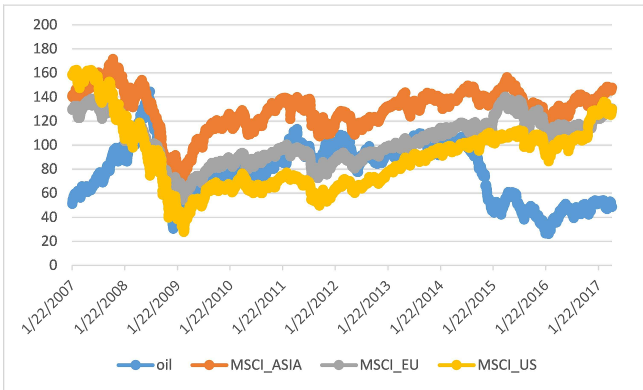

Figure 4.5: Interpreting relationship between oil price and MSCI Indexes

negative volatility transmission between both markets (negative correlation between oil market and stock markets from 2014 in figure 4.5).

According to the results obtained above, we summarize that the volatility transmission between commodity market and the three stock markets is time varying. We also find that the times changes of the volatility's sensitivity of the three stock markets to commodity market over all the period of study occurred around the years 2008-2009, 2013 and 2014 (negative correlation explained on the figures 4.5 as well). We are able to connect each of these periods to Oil's events since past studies found that oil price shocks contain information for forecasting stock return. The period 2008 matches with the moment where oil prices peak at 145.85 dollars then bottom at 32 dollars caused by easing of tensions between the US and Iran. The period 2009 might be the period during which oil prices rose temporarily because of tensions in the Gaza Strip. The period 2013 is relatively marked by the trouble in Libya and the sanctions against Iran. The period 2014 is in line with the great oil bust of 2014, where the oil price collapses mainly reflecting too much supply chasing too little demand, and China and Europe's demand for oil decreased following the economist Larry Goldstein arguing that the real surprise, was lower-than-expected global demand.

4.2 Forecasting

In this section, we investigate the performance of the single TVP-FAVAR compared to the TVP-FAVAR-DMA. Using the DMA, presents crucial advantages, in the sens where it allows the forecasting model to switch over time, meaning the parameters and the predictors may vary over time. We turn to compare for each stock market the final mean square forecast error from the TVP-FAVAR to that of the TVP-FAVAR-DMA on $h = 1$ and $h = 2$. The figures 4.6-4.11 represent the mean square forecast error (MSFE) for each model evaluated over the whole period (from $t = 10$) for $h = 1$ and $h = 2$.

Apart from the first horizon where the TVP-FAVAR model presents a slight performance over the TVP-FAVAR with DMA by forecasting the MSCI EU and MSCI US, it is interesting to observe that the model with DMA is always doing better over the single TVP-FAVAR when forecasting the MSCI Asia stock market and on the second horizon when forecasting both MSCI Asia and MSCI EU.

This result makes a sense and is in perfect line with the DMA performance, since the dynamic model averaging is known to lead to substantial forecasting improvements over simple benchmark regressions and more sophisticated approaches such as those using time varying over coefficient models. The MSCI Asia seems to be a good predictor for constructing commodity volatility index over MSCI EU followed by MSCI US.

4.3 Discussion

This work seeks to investigate the link between volatility range of commodity market and stock markets, by focusing on energy raw materials, especially the oil. Relying on the TVP-FAVAR estimates, we are able to study the trend of the volatility between them. Our main results can be summarized as follows:

First, Over the period January 1, 2007 to May 21, 2017, the volatility correlation between commodity and stock markets evolves through time. This finding completes the work of Creti et al. (2013) who found that the link between stock market and raw materials (energy, metals, agricultural, food) is time-varying and highly volatile from the recent impact of 2008 financial crisis.

The link is negative on a short run particularly from the period of financial crisis 2008 to 2009, putting forward that investment in equities constitutes an alternative to commodity, as a mechanism for substitution between asset classes. From the period 2009, the highest positive correlation is observed after the post crisis period, up to 2012. Both markets move upward during episodes of growing world demand for industrial commodities, giving an important role to commercial traders who use commodity futures to hedge their business activities. The divergence of the correlations between stock markets and commodity market specially oil market from 2012 onward on US market and the period 2013 on Asian market can be explained by the Syrian civil war, as well as, the continued conflicts in the Middle East crisis. These events trigger positive oil-market specific shocks (i.e. price hikes) and stock markets respond negatively to such news. The disrupt link of the volatility around the period 2013-2014 matches with the great oil bust of 2014, where the oil price collapses mainly reflecting too much supply chasing too little demand, and China and Europe's demand for oil decreased.

Second, we find that the volatility in US market and Asian market are more related to commodity volatility than the volatility in European stock market to commodity market.

Importantly, the second finding completes the existing literature which has already established that the stock market response to oil price shocks is different (see Degiannakis et al. (2014)). The study reveals that the relationship in volatility between oil market and MSCI EU stock market seems to differ on the period 2008-2009.

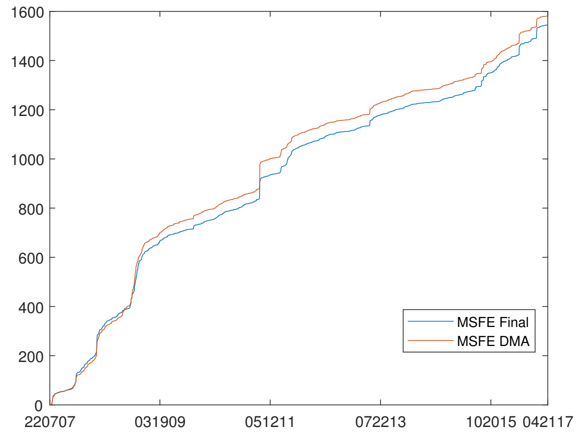

Figure 4.6: Forecasting MSCI ASIA Index one day ahead ($h = 1$)

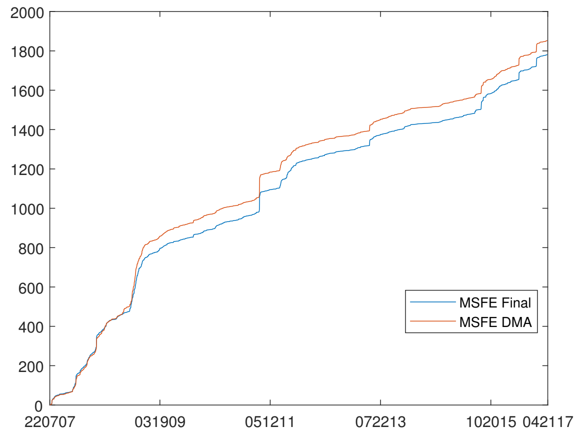

Figure 4.7: Forecasting MSCI ASIA Index Index two days ahead ($h = 2$)

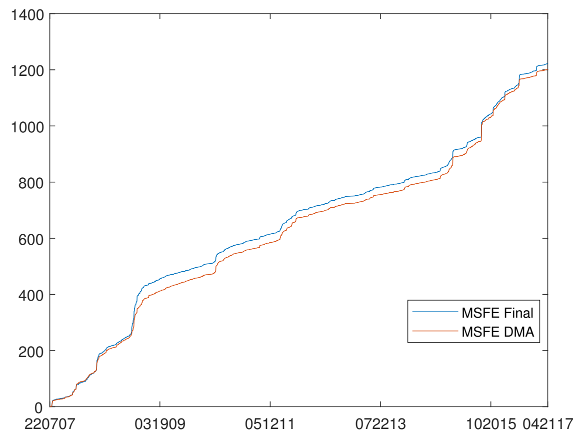

Figure 4.8: Forecasting MSCI EU Index Index one day ahead ($h = 1$)

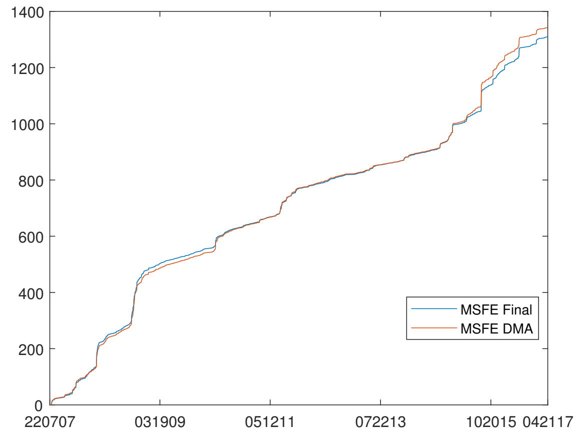

Figure 4.9: Forecasting MSCI EU Index Index two days ahead ($h = 2$)

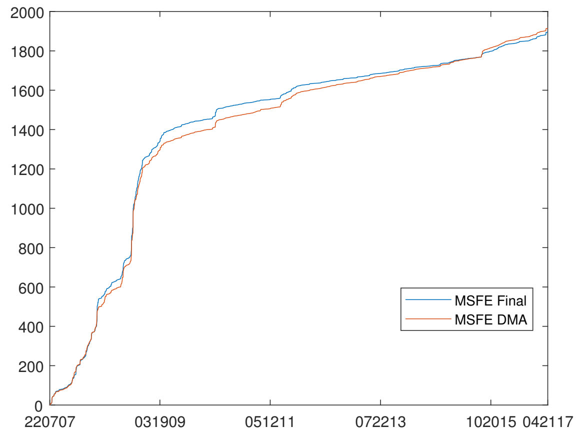

Figure 4.10: Forecasting MSCI US Index Index one day ahead ($h = 1$)

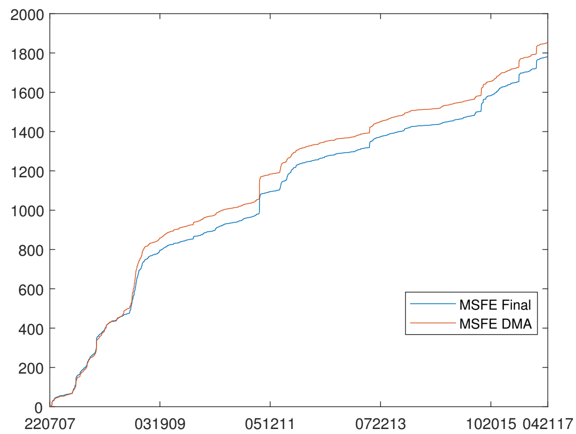

Figure 4.11: Forecasting MSCI US Index Index two days ahead ($h = 2$)

Chapter 5

CONCLUSION

In this work, we desire at constructing a dynamic commodity volatility conditions index (CVI) which takes into account changes in volatility range in commodity with the financial markets and data availability. In particular, we use a single TVP-FAVAR model to extract the factor for commodity volatility range and presents the sensitivity of volatility of each stock market. We follow Koop and Korobis (2014) and build the CVI using the conventional method of estimation with choice in prior distributions. We find that the volatility transmission from commodity to stock markets are time changing. The finding shows that the volatility's sensitivity presents the same direction in MSCI Asian and MSCI US over the whole period considered. This guides us to conclude that the volatility in US market and Asian market is more related to commodity volatility than the volatility in European stock market to commodity volatility. When performing forecasting error for the three stock market predictors, using MSFE, the model with DMA forecasts well over the TVP-FAVAR and indicates the MSCI Asia as good predictor of commodity volatility index.

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