Stock market and the Baltic Dry Index: Volatilities and correlations in China's business cycle

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Abstract

The paper uses volatility (GARCH-MIDAS-X) and dynamic correlation (DCC-MIDAS-X) models to investigate the effect of China's business cycle on volatilities and correlations associated with the Baltic Dry Index (BDI) and China's stock market. A mixed data sampling (MIDAS) technique is utilized to overcome the differential frequencies associated with data for macroeconomic and financial variables. Our results suggest that macroeconomic variables are significant determinants of the long-term component of BDI. Further, we posit that the volatilities of the international bulk commodity market and China's stock market are negatively correlated when China's economy is in recession; while the two markets exhibit a weak negative correlation when the economy is in boom periods. During the financial crisis, China's economy fluctuated dramatically, the correlation between stock market and BDI strengthened and turned negative. After 2012, China's growth rate decreased and the correlation of two markets slowly became negative again because of the supply-side reform.

Keywords: Business cycle, Baltic dry index, CSI300 index, Volatility, Correlation,

1 Introduction

Along with the continuous advancement of financial liberalization and economic globalization, volatility correlations and spillovers between the financial market and other markets are becoming increasingly common. Investors, also, are attaching growing importance to the linkage effect between financial markets and other markets, expecting to better optimize with respect to investment objectives, and hedging against asset portfolio risks. With its growing prominence on the world stage, China's economy is exerting an increasingly heightened influence on international financial markets, especially commodity markets. Focusing on the relationship between China's stock and commodity markets, this paper establishes that the correlation between international commodity markets and China's stock market largely depends on macro-economic conditions in China. We firstly employed mixed-frequency data technology to build volatility models (GARCH-MIDAS-X) respectively for international commodity markets and China's stock market in order to examine the effect of China's macroeconomy on volatilities of the

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two markets. Using the results of the volatility models, we then constructed a dynamic conditional correlation model (DCC-MIDAS-X model) to study the effect of China's macroeconomy on the correlation of volatilities between the two markets. The study found that China's macroeconomy has a pro-cyclicality property with respect to these correlation dynamics; that is, the two markets exhibit a weakened correlation when the economy is booming, and a strengthened, negative, correlation when the economy is in recession. In addition, China's macroeconomy serves as a leading indicator for the correlation of the two markets, able to forecast, to some extent, variations in market correlations. This is of potential significance for inter-market hedging against financial risks.

With continuous development and innovation of the financial industry, commodities, given their superior natural properties and hedging functions, have become a financial instrument for many traders and financial institutions; and their derivative markets even have an investment function similar to that of financial assets, such as stocks and bonds, etc. making them an important investment target for participants in capital markets. On the other hand, the universalization of trading in commodity futures and other derivatives has prompted the commodity market to become an integral part of the overall financial market, attracting substantial short-term speculative funds using leverages to participate in the trading of commodity markets. Between 2003 and 2011, as investors' demand for financial instruments related to commodities had ballooned, the value of commodity-related assets grew to USD 450 billion from USD 13 billion, far exceeding actual consumption needs (Nishimura 2011).

The connection between commodity and stock markets exhibits two important properties: an economic property and an investment property. Firstly, the commodity market is associated with the development of a variety of macro-economic sectors like trading and manufacturing, etc. thereby affecting the performance of stocks issued by relevant firms. Moreover, the investment property of commodities turns the commodity market into an integral part of the financial market, while macro-economic variations drive the circulation of funds across various markets. Therefore, the commodity market, the stock market and the correlation between markets are all connected to macroeconomic conditions. In addition, it is an indisputable fact that the growth of China's economy has resulted in robust demand for commodities; therefore, it is of both theoretical and practical significance for this paper to carry out modeling on the macro foundations for these volatilities.

The contributions of this paper can largely be specified in three respects. First, a mixed-frequency model is applied to explore the correlation between commodity market volatility and stock market volatility in China, as well as the macroeconomic foundations and time-varying nature of this correlation. Relevant literature both from China and abroad is sparse and currently insufficient for the purposes of reliably informing decision-making. Second, this paper establishes that the correlation of the volatilities of the two markets exhibits distinct procyclicality, making the macroeconomic variable a leading variable for the correlation of the two markets. It is also found that both the global financial crisis in 2008 and supply-side reforms since 2013 have resulted in slowdowns of China's economic growth and a heightened negative inter-market correlation between volatilities; but there are certain differences in terms of the influences of these two phenomena. Third, this paper employs a model confidence set (MCS) approach to select the optimal model combination from models comprised of a variety of macroeconomic variables.

Our analyses are based on two types of literature. The first type concerns the modeling of long-term volatility trends and correlations. The idea of modeling the long and short-term trends of volatilities can be traced back to Ding and Granger (1996) and Engle and Lee (1999). As the concept of multi-trend models became progressively, and widely, recognized over time, Engle and Rangel (2008) and Engle, Ghysels, and Sohn (2013) suggested that volatility trend decomposition offered a new line of investigation for the association between stock market and macroeconomic volatilities. Through the GARCH-MIDAS model, this paper employs macroeconomic variables to explain long-term volatility. In normal circumstances, both the commodity market and stock market yield data at an intra-day frequency, while macroeconomic data are collected monthly or quarterly. As such, to incorporate macroeconomic variables into the model using intra-day data, a mixed-frequency data model (MIDAS) must be applied. Via MIDAS polynomial, the GARCH-MIDAS model allocates different weights to macro-economic data in the expectation of depicting the long-term volatility trend. Zheng and Shang (2014) found that the GARCH-MIDAS model based on macroeconomic data can precisely predict volatility in China's stock market.

Moving on, the other type of literature relevant herein, explores the linkages between different markets and their relationships with the macroeconomy. To the financial market, factors influencing linkages between markets can be summed up as industrial structure, monetary policy, bilateral trade and spatial distance, etc. Pretorius (2002) pointed out one certain economic variable could not fully explain the connection mechanisms of financial markets between nations. In the meantime, since these economic variables are low-frequency variables, there still exists an inconsistency between the availability of economic data and the requirements of volatility modeling. Colacito, Engle, and Ghysels (2011) proposed to extend Engle (2002)'s DCC model into a DCC-MIDAS-RC model of long- and short-term trends. Subsequently, in considering the effect of industrial production, unemployment rate, national economic vitality and a prosperity index on the correlation between oil prices and the stock market, Conrad, Loch, and Rittler (2014) incorporated the macroeconomic variable into the DCC-MIDAS-RC model, extending the model into a DCC-MIDAS-X model via a Fisher transformation, in which X denotes a certain type of macroeconomic variable. Given its ability to incorporate data of different frequencies into one analytical system, the DCC-MIDAS-X is widely used to study the macro-driving mechanisms of the linkages between different markets. Therefore, the linkage mechanisms between different markets has gradually become a research hotspot. Using principal component analysis, Hossein, Charlotte, and Hou (2015) examined long-term stock market and debt securities from four perspectives: inflation and interest rates, liquidity, economic conditions, and uncertainty. By incorporating economic indices like GDP growth and inflation, etc., and cultural indices like religious background, etc., Asma et al. (2016) examined the linkage mechanisms between stock markets of different countries.

Through reviewing the literature, we found that existing studies place emphasis on the linkage properties and mutual effects between the commodity market and the stock market. Even studies that focus on the effect of China's economy on commodity markets can only carry out modeling on low-frequency data owing to limited analytical techniques. The innovation of this paper rests on its employment of a mixed-frequency data model to maximize the utilization of currently available data and integrate high-frequency intra-day financial data with low-frequency monthly macro-data, so as to analyze the effect of China's economy on the volatility of commodity markets. Moreover, the paper also employs a DCC-MIDAS-X model to analyze the dynamic effects of the linkage mechanisms between the macroeconomy, commodity and stock markets.

The Baltic Dry Index (BDI) is employed as the measure of the commodity market. The China stock market index (CSI300 index) is similarly employed to capture China's stock market; this index focuses on the effect mechanism of China's macroeconomy on the correlation between the BDI and CSI300. The second section introduces the GARCH-MIDAS-X and DCC-MIDAS-X models; the third, fourth and fifth sections relate to data specification, empirical results and model comparison respectively. The final section concludes the paper.

2 Method

We consider the bivariate vector of asset returns $r_t = [r_{1t}, r_{2t}]'$, where r_{1t} refers to the stock return and r_{2t} refers to the bulk commodity return. To proceed let us assume that the vector of returns r_t follows the process:

$$r_t \sim i.i.d(u_t, H_t)$$

$$H_t = D_t R_t D_t$$

where u_t is the vector of unconditional means, H_t is the unconditional covariance matrix, $D_t = \begin{pmatrix} h_{11,t}^{1/2} & 0 \\ 0 & h_{22,t}^{1/2} \end{pmatrix}$ is the diagonal volatility matrix and $R_t = \begin{pmatrix} 1 & \rho_{12,t} \\ \rho_{21,t} & 1 \end{pmatrix}$, is the correlation matrix.

The decomposition of the conditional covariance matrix $H_t = D_t R_t D_t$ suggests a two-step model specification (and estimation) strategy. Consequently, it allows us to separately model the conditional volatilities and the conditional correlations. Having introduced the MIDAS specification (Engle, Ghysels, and Sohn 2013; Colacito, Engle, and Ghysels 2011) that allows us to extract two components of volatility and correlation, one pertaining to short-term fluctuations, the other pertaining to a secular component, we are ready to revisit the relationship between financial markets and macroeconomic activity.

2.1 Conditional volatility: GARCH-MIDAS model

Consider a return series $r_{i,t}$ on day t during month i that follows the process:

$$r_{i,t} - E[r_{i,t}|F_{it-1}] = \sqrt{g_{i,t}\tau_i}\varepsilon_{i,t}$$

where $F_{i,t-1} = \sigma(r_{i,t-1}, r_{i,t-2}, \ldots)$ is the σ-field generated by the information available through day $t-1$ of month i, $g_{i,t}$ is the short-run trend of volatility at day t which changes every day and τ_i is the secular trend of volatility in month i which is relatively stable. Daily expected returns are assumed to be constant, i.e. we set $E(r_{i,t}|F_{i,t-1}) = \mu$ for all i and t. The long-run trend is driven by macroeconomic variables and varies monthly.

Assume that the short-run volatility component follows a mean-reverting unit GARCH(1, 1) process

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i,t-1}-u)^2}{\tau_i} + \beta g_{i,t-1}$$

with $0 < \alpha < 1$, $0 < \beta < 1$ and $\alpha + \beta < 1$. Then, the long-run volatility component τ_i is modeled as a a slowly varying function of a covariate which is either the realized volatility (RV) or a macroeconomic variable using the MIDAS specification

$$\log(\tau_i) = m + \theta_v \sum_{k=1}^{K} \varphi_k(w_1, w_2) X_{i-k}$$

with the beta weighting scheme:

$$\varphi_k(w_1, w_2) = \frac{(k/(K+1))^{w_1-1} \cdot (1-k/(K+1))^{w_2-1}}{\sum_{k=1}^{K}(k/(K+1))^{w_1-1} \cdot (1-k/(K+1))^{w_2-1}}$$

K indicates the number of lags used in the MIDAS[1]. The beta lag, based on the beta function, can easily accommodate various lag structures.

2.2 Conditional correlation: DCC-MIDAS model

The DCC-MIDAS specification proposed by Colacito, Engle, and Ghysels (2011) decomposes the correlation between two returns into short-term and long-term components. The long-term correlation is modeled as the weighted average of the lagged values of the realized correlation (Colacito, Engle, and Ghysels 2011) and the explanatory variables; and the short-term correlation fluctuates around the long-term trend.

Instead of modeling the correlation matrices R_t directly, we follow Engle (2002) and first specify the so-called 'quasi-correlations' $Q_t = [q_{ij,t}]_{i,j=1,2}$ as

$$Q_t = (1-a-b)\bar{R}_t + a\eta_{t-1}\eta_{t-1}^{'} + bQ_{t-1}$$

or

$$q_t = \bar{\rho}_t + a(\eta_{1,t-1}\eta_{2,t-1} - \bar{\rho}_t) + b(q_{t-1} - \bar{\rho}_t)$$

with $a + b < 1$, $a > 0$, $b > 0$ and $\bar{R}_t = \begin{pmatrix} 1 & \bar{\rho}_t \\ \bar{\rho}_t & 1 \end{pmatrix}$, and where $\eta_t = (\eta_{1,t}, \eta_{2,t})$, is the standardized residual vector from the above GARCH-MIDAS model.

Colacito, Engle, and Ghysels (2011) assumes that $\bar{\rho}_t$ is a function of a weighted average of K prior realized correlations (RC).

[1] In this paper we set K = 16.

$$\bar{\rho}_t = \sum_{k=1}^{K_\tau} \varphi_k(w_{12}) RC_{t-k}$$

with

$$RC_t = \frac{\sum_{k=t-N_c}^{t} \eta_{1,k}\eta_{2,k}}{\sqrt{\sum_{k=t-N_c}^{t} \eta_{1,k}^2 \sum_{k=t-N_c}^{t} \eta_{2,k}^2}}$$

In this paper, the long-term component of the correlation $\bar{\rho}_t$ is given by

$$\bar{Z}_t = m + \theta_c \sum_{k=1}^{K} \varphi_k(w_{c,1}, w_{c,2}) X_{t-k}$$

with Fisher's transformation:

$$\bar{\rho}_t = \frac{\exp(2\bar{Z}_t) - 1}{\exp(2\bar{Z}_t) + 1}$$

Finally, to arrive at the correlation matrix R_t the quasi-correlation matrix Q_t needs to be transformed:

$$R_t = (Q_t^*)^{-1/2} Q_t (Q_t^*)^{-1/2}$$

with

$$Q_t^* = \text{diag}(Q_t)$$

Fisher's transformation only can only be used in the bivariate model; it ensures that the off-diagonal elements of R_t are less than one in absolute term; since the diagonal elements are all one, it fulfills the necessary conditions for the matrix to be positive semi-definite. When the number of return series is larger than two, DCC-MIDAS becomes extremely complex and positive positive semi-definition conditions cannot be satisfied.

2.3 Estimation

The log likelihood function for this model can be expressed as

$$\begin{aligned} \text{LLF} = -1/2 \sum_{t=1}^{T} (2\log(2\pi) + 2\log(|D_t|) + \varepsilon_t^{'} D_t^{-2} \varepsilon_t) \\ -1/2 \sum_{t=1}^{T} (\log(|R_t|) + \eta_t^{'} R_t^{-1} \eta_t - \eta_t^{'} \eta_t) \end{aligned}$$

which can simply be maximized over the parameters of the model. However, the number of model parameters will become very large when we incorporate the MIDAS technique into the GARCH-DCC specification. Therefore, we follow Engle (2002) and Colacito, Engle, and Ghysels (2011) and invoke the two-step approach in order to more easily estimate our model even when the covariance matrix is very large.

Let the parameters in GARCH-MIDAS model be denoted $\Theta = (\mu, \alpha, \beta, \gamma, m, \theta_v, \omega_1, \omega_2)$ and the parameters in DCC-MIDAS model be denoted $\Phi = (m, a, b, \theta_c, \omega_{c1}, \omega_{c2})$. The log-likelihood LLF can be written as the sum of a volatility part LLF_v and a correlation part LLF_c:

$$\mathrm{LLF_v}(\Theta) = -1/2 \sum_{t=1}^{T} (2 \log(2\pi) + 2 \log(|D_t|) + \varepsilon_t^{'} D_t^{-2} \varepsilon_t)$$

$$\mathrm{LLF_c}(\Theta, \Phi) = -1/2 \sum_{t=1}^{T} (\log(|R_t|) + \eta_t^{'} R_t^{-1} \eta_t - \eta_t^{'} \eta_t)$$

The two-step approach firstly maximizing the likelihood function LLF(Θ) to find

$$\hat{\Theta} = \mathrm{argmax}\{\mathrm{LLF}(\Theta)\}$$

and then take this value as given in the second stage.

$$\max_{\Phi}\{\mathrm{LLF_c}(\hat{\Theta}, \Phi)\}$$

3 Data

3.1 Baltic Dry index (BDI) and Hushen 300 index (CSI300)

This paper studies the determinants of volatilities and correlations in China's stock market and the international bulk commodity market. For the bulk commodity series, we employ the daily return on BDI, which measures the transport costs of the major industrial raw materials. Because dry bulk primarily consists of materials that function as raw material inputs to the production of intermediate or finished goods, such as concrete, electricity, steel, and food. The index is also seen as an efficient economic indicator of future economic growth and production. For the stock series, we employ the daily return on Hushen 300 Index (CSI300), which is based on stocks in the Shanghai and Shenzhen Stock Exchanges. Our data covers the period from January 2004 to December 2015.

3.2 Macroeconomic data

We employ the following macroeconomic variables: China's macroeconomic climate index (CLI), exports (EX), imports (IM) and money supply (MS3). These variables are supposed to reflect the role of market participants' expectations concerning China's economic development. In addition, we take the OECD's composite leading index (GLI) as an indicator of the global economy. All variables are monthly data from OECD, Wind, iFind and CEIC databases. For exports (EX), imports (IM) and money supply (MS3) varaibles, we compute month-to-month growth rates according to $log(X_i) - log(X_{i-1})$. We use the equation $(LI - 100) \cdot 0.01$ to deal with the initial CLI and GLI series. Monthly RV is calculated as $RV_i = \sum_{t=1}^{N^{(i)}} r_{i,t}^2$. Summary statistics for all variables can be found in Table 1.

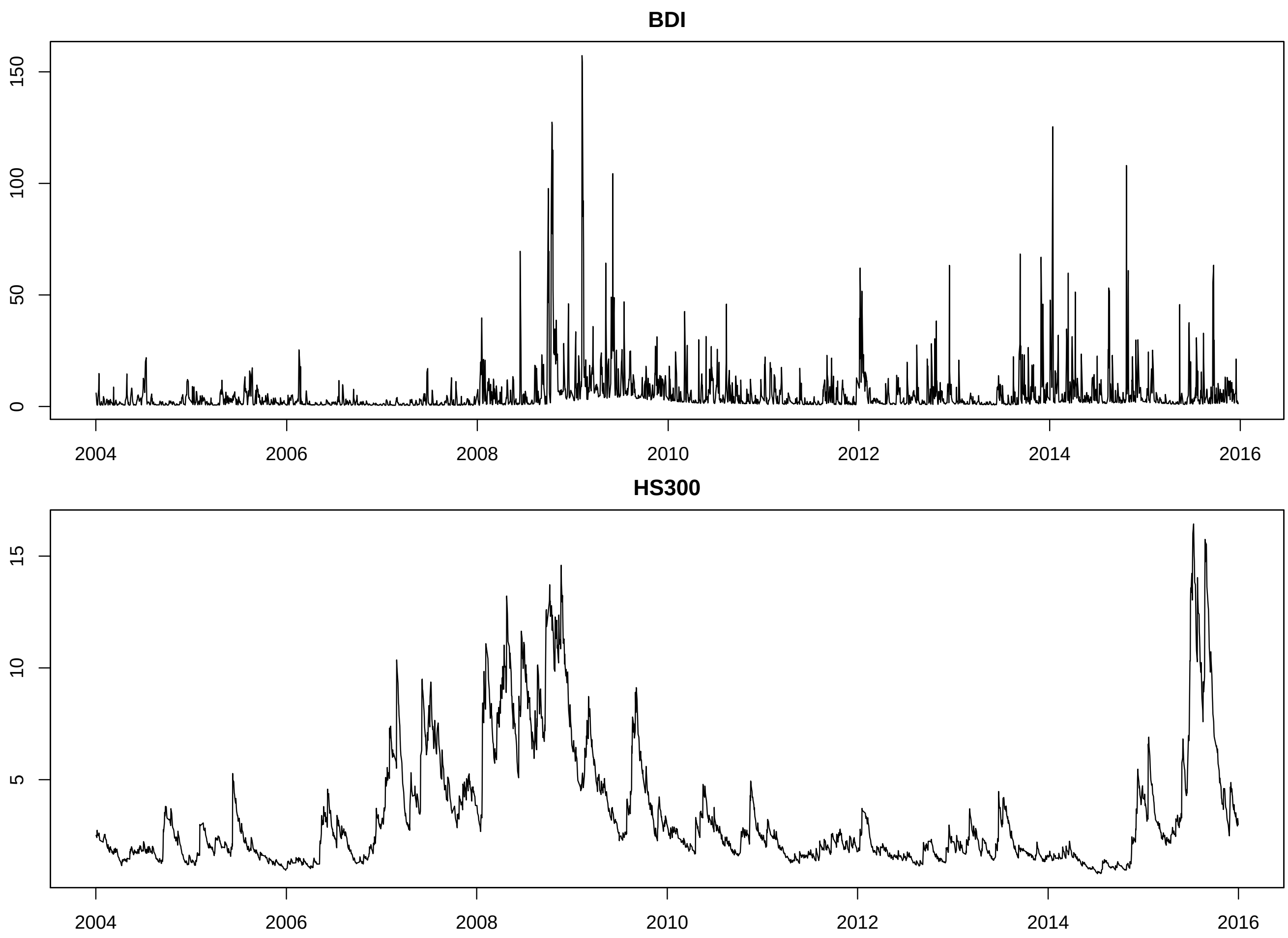


Figure 1: BDI and CSI300

Table 1: Descriptive statistics for stock market and macro data

	Obs.	Min.	Max.	Mean	SD	Skew.	Kurt.
CSI300	2915	-9. 695	8. 931	0. 039	1. 845	-0. 430	6. 148
BDI	2998	-12. 072	13. 658	-0. 077	2. 219	0. 087	6.824
RV_{CSI300}	160	8. 397	340. 920	64. 264	64. 717	2. 109	7. 3313
RV_{BDI}	160	1. 253	1013. 300	94. 991	126. 700	3. 979	24.274
CLI	160	-0. 070	0. 058	0. 012	0. 018	-0. 384	4. 737
EX	160	-0. 026	0. 059	0. 013	0. 018	0. 146	2. 761
GLI	160	-0. 040	0. 014	0. 000	0. 011	-1. 827	6. 853
IM	160	-0. 236	0. 307	0. 011	0. 072	0. 574	7. 379
MS3	160	-0. 004	0. 049	0. 013	0. 006	1. 530	9. 759

Notes:The returns are collected from January 2004 to December 2015, and the macroeconomic data is collected from January 2004.

4 Empirical Results

In this section, we firstly present the results for the GARCH-MIDAS models and then analyze the impact of China's economy on the volatility of the stock and BDI markets. We also discuss the DCC-MIDAS specifications that focus on long-run correlations between the two markets. Estimation results for BDI and CSI300 from GARCH-MIDAS-X models are summarized in Table 2 and Table 3, respectively. In particular, we also present the estimation of GARCH(1, 1) model as a benchmark.

4.1 Volatility analysis: BDI

For BDI, the estimated θ_v are highly significant and have expected signs for all the macroeconomic variables. Moreover, the estimated θ_v in Table 2 are negative for macroeconomic variables, which consistently indicates that long-run volatilities of BDI increase when economic growth slows down. During the global financial crisis, the volatility of BDI rapidly increased, peaking in mid 2009. Then, China's government introduced a raft of economic policies and instigated many large-scale infrastructure construction projects. The demand for raw materials from China drives the decrease in BDI volatility, and it remains relatively low level.

Of note, the estimated θ_v for the policy uncertainty index is significant with the expected positive sign, which indicates that policy uncertainty in China can affect the volatility of BDI. Since the money supply of China mainly affects domestic assets and housing markets, MS3 has an insignificant effect on the international bulk commodity market.

Now, we compare the performance of the various GARCH-MIDAS-X models in terms of Akaike (AIC) and Bayesian (BIC) information criteria. According to AIC, all GARCH-MIDAS-X models are parsimoniouos relative to their GARCH(1,1) counterparts. But with respect to BIC, GARCH(1,1) is perfered in terms of money supply (MS3).

To measure the explanatory power of macroeconomic variables, variance ratios (Engle, Ghysels, and Sohn 2013; Conrad and Loch 2015) are presented in the last column of Table 2.

$$VR = \frac{\widehat{var}(log(\tau_i^X))}{\widehat{var}(log(\tau_i^{RV} g_i^{RV}))}$$

As we can see, the model based on exports (EX) achieves the highest VR. Roughly 48% of the variation in expected monthly volatility of BDI is explained by China's exports (EX). RV also has a highly significant impact on the BDI volatility. Indeed, all the variables related to international trading exhibit relatively large VR values, which implies international trading between China and other countries could be main largely explain the influence on the international bulk commodity.

In Figure 2, monthly aggregated long-term components ($\sqrt{N^{(i)}\tau_i^X}$) and monthly conditional voatilities ($\sqrt{\tau_i^X g_i^X}$ with $g_i^X = \sum_{t=1}^{N^{(i)}} g_{i,t}^X$) are respectively shown the long-term and short-term volatilities of BDI in models with different macroeconomic variables. Clearly, monthly aggregated long-term components peaked during the global financial crisis. The results are reasonably similar to those of Engle, Ghysels, and Sohn (2013), Conrad and Loch (2015) and Asgharian, Christiansen, and Hou (2015), which discussed financial volatilities during the Great Depression and the global financial crisis.

Table 2: GARCH-MIDAS-X models: BDI

	μ	α	β	m	θ_v	ω_1	ω_2	$-LLF$	AIC	BIC	VR
RV	0.023	0.826***	0.09	1.544***	0.008***	0.503	1.391**	5836.7	11687	11729	44.2
	(0.064)	(0.05)	(0.056)	(0.475)	(0.001)	(0.353)	(0.678)				
CLI	0.017	0.841***	0.101	2.947***	-17.599***	499.28***	271.88***	5879.5	11773	11815	13.1
	(0.067)	(0.057)	(0.078)	(0.679)	(5.364)	(154.33)	(90.106)				
EX	0.045	0.815***	0.077	2.747***	-49.987***	1.43***	1.517***	5835.1	**11684**	**11726**	47.3
	(0.068)	(0.047)	(0.058)	(0.412)	(6.663)	(0.364)	(0.402)				
GLI	0.019	0.818***	0.11***	2.519***	-39.2***	15.605	399.71	5865.9	11746	11788	25.7
	(0.067)	(0.034)	(0.024)	(0.645)	(5.233)	(46.964)	(504.390)				
IM	-0.006	0.83***	0.085	2.658***	-26.901***	1.301**	0.912*	5872.8	11760	11802	18.4
	(0.07)	(0.052)	(0.074)	(0.518)	(6.818)	(0.518)	(0.529)				
MS3	0.013	0.809***	0.154	3.301***	-23.4	444.8***	500***	5892.3	11799	11841	3.4
	(0.066)	(0.091)	(0.108)	(0.673)	(14.524)	(95.665)	(108.51)				
GARCH(1,1)	0.017	0.844***	0.156	0.722***				5893.1	11794	11818	
	(0.069)	(0.083)	(0.116)	(0.0257)							

Notes:The numbers in brackets are Bollersev-Wooldridge robust standard errors. ***, ** and *indicate the significances at 1%, 5% and 10% level respectively.

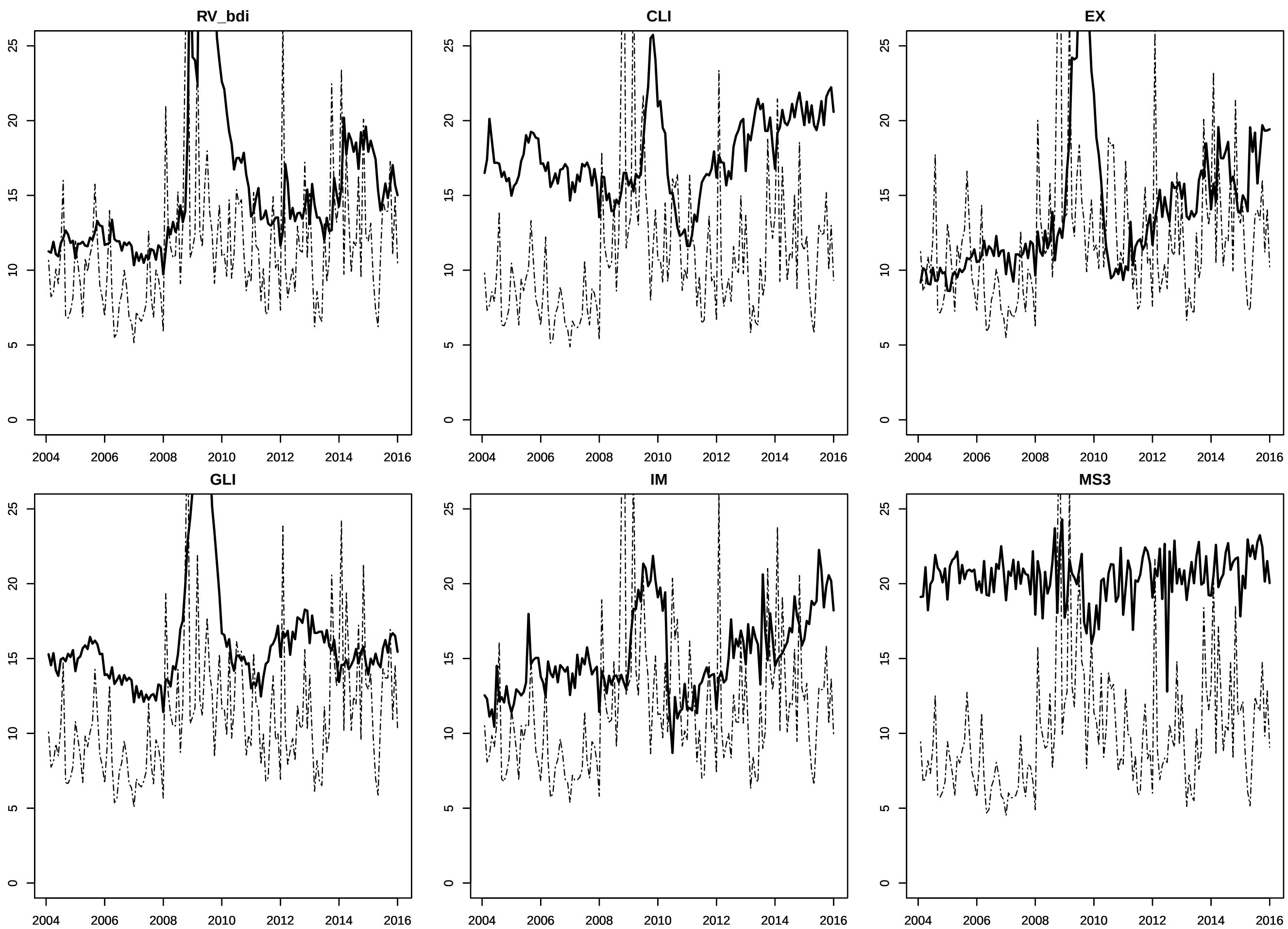


Figure 2: Monthly aggregated conditional volatility $\sqrt{\tau_i^X g_i^X}$(grey line) and long-run volatility components $\sqrt{N^{(i)}\tau_i^X}$(black line) for all GARCH-MIDAS-X models.

4.2 Volatility analysis: Hushen 300 index

Different from stock markets in other countries (Engle, Ghysels, and Sohn 2013; Conrad and Loch 2015; Hossein, Charlotte, and Hou 2015), the volatilities of China's stock market are not negatively related to most macroeconomic variables. The estimated θ_v suggest that only RV and exports(EX) have significant impacts on stock market volatilites. It is interesting that the volatilities of China's stock market are positively related to China's economic growth; this is consistent with the results of Zheng and Shang (2014). China's stock market is not well connected to world financial markets, so it is difficult for investors to diversify when China's economy slows down.

Figure 3 shows that some macroeconomic variables fail to explain the long-run component of stock volatilities. The highest VR values in the stock models are RV, which are much less than the contribution of macroeconomic variables to BDI. According to the AIC and BIC, GARCH-MIDAS-X models are not discernably optimal relative to the benchmark model.

Table 3: GARCH-MIDAS-X models: CSI300

	μ	α	β	m	θ_v	ω_1	ω_2	$-LLF$	AIC	BIC	VR
RV	0.037	0.055***	0.932***	0.777***	0.006***	10.876	12.89	5590.4	11195	11237	17.4
	(0.03)	(0.009)	(0.011)	(0.234)	(0.002)	(7.997)	(8.103)				
CLI	0.038	0.054***	0.937***	1.04***	7.635	494.44**	126.48	5592.7	11199	11241	3.5
	(0.03)	(0.009)	(0.011)	(0.23)	(6.972)	(233.93)	(77.645)				
EX	0.036	0.054***	0.937***	1.123***	2.25**	309.62***	497.89***	5590.3	11195	11237	1.7
	(0.03)	(0.009)	(0.01)	(0.205)	(1.114)	(2.891)	(7.552)				
GLI	0.036	0.053***	0.939***	1.196***	12.705	498.34	208.43*	5593.2	11200	11242	4.3
	(0.03)	(0.009)	(0.011)	(0.244)	(27.037)	(366.66)	(123.43)				
IM	0.033	0.053***	0.938***	1.172***	-1.189	499.25*	63.722**	5589.2	11192	11234	1.7
	(0.03)	(0.008)	(0.01)	(0.207)	(0.725)	(296.28)	(27.02)				
MS3	0.035	0.055***	0.937***	1.328***	-12.018	446.06***	499.86***	5591.1	11196	11238	1.3
	(0.03)	(0.009)	(0.01)	(0.245)	(7.591)	(69.019)	(80.625)				
GARCH(1,1)	0.039	0.055***	0.928***	0.027***				5594.5	11197	**11221**	
	(0.030)	(0.011)	(0.009)	(0.010)							

Notes:The numbers in brackets are Bollersev-Wooldridge robust standard errors. ***, ** and *indicate the significances at 1%, 5% and 10% level respectively.

4.3 Correlation: BDI and CSI300

In this section, we focus on the determinants of long-run BDI-CSI300 correlation. We take the GARCH-DCC(Engle 2002) model and DCC-MIDAS-RC(Colacito, Engle, and Ghysels 2011) as our benchmark model. According to the results of GARCH-MIDAS models, we respectively use the RV and exports(EX) as first-step MIDAS filtering

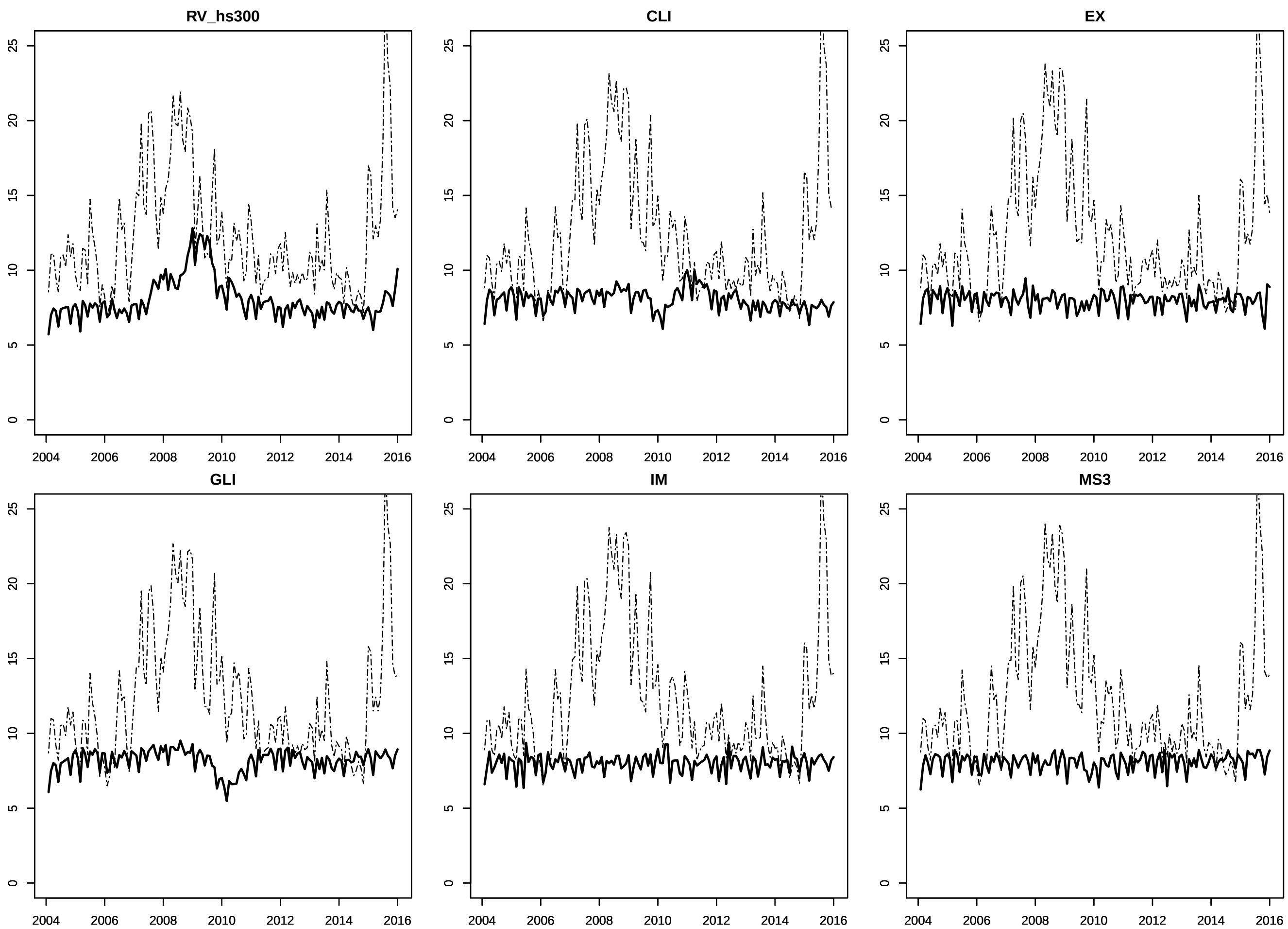


Figure 3: Monthly aggregated conditional volatility $\sqrt{\tau_i^X g_t^X}$(grey line) and long-run volatility components $\sqrt{N^{(t)}\tau_t^X}$(black line) for all GARCH-MIDAS-X models.

variables to develop DCC-MIDAS-X models. In Table 4, we can see that the correlation relationship is highly consistent regardless of how this first-step is configured.

θ_c is significant and positive signed for all macroeconomic varibles of China. Figure 5 shows the volatilities of the two markets switch to exhibiting negative correlations when China's economy goes into recession. According to sections 4.1 and section 4.2, volatilities of BDI are much more sensitive to China's macro economy than China's stock market. Hence, the volatilities of the two markets may not always present the same dynamic trend.

Figure 4 shows estimated dynamics of the short- and long-term correlations on the different DCC-MIDAS specifications. First, the time-varying correlation between bulk commodity and stock was found to be unstable, which fluctuates along with the business cycle of China. Second, the trends of the long-term component are driven by China's macroeconomic variables which confirm that China's economy affects the bulk commodity.

All China's macro variables used in this paper reflect China's economy; imports and money supply are current indicators of China's economy; the China leading index is the leading index of China's economy (Conrad and Loch 2015). Our results suggest that variables which lead the business cycle are also leading with respect to market correlation. Conrad, Loch, and Rittler (2014), Hossein, Charlotte, and Hou (2015) and Asma et al. (2016) suggest similar economic determinants of the oil-stock and bond-stock long-term component of correlation.

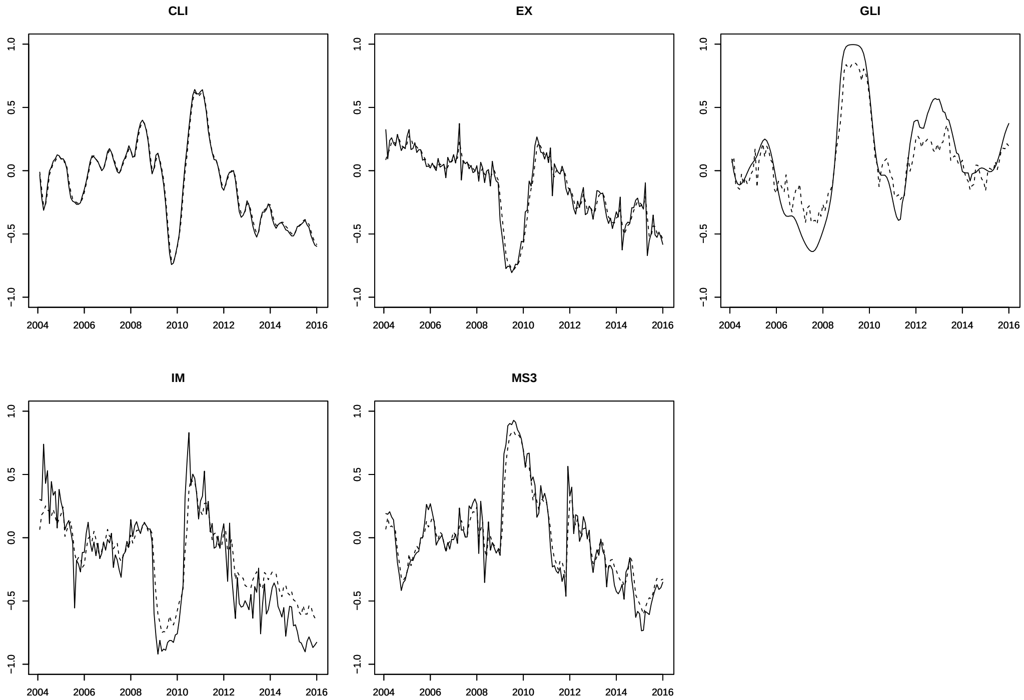
Figure 5 provides an interpretation of the cyclical correlation dynamics, which depicts the secular component along with the China leading index(CLI). We found the long-term correlation in Figure 5 supports our empirical results. During the global financial crisis, China's economy was seriously impeded, and the goverment decided to invest four thousand billion to facilitate economic recovery. Because of the debt problem and the supply-side reforms instituted by the Chinese government since 2011, economic growth rates in China have tended to decline again. The commodity-stock long-term correlation becomes negative consistently when the economy geso into recession. Meanwhile, we can see from Figure 5 that the China leading index basically moves ahead of the trend in the correlation, which confirms the predictive ability of the leading index. Similarly, Nicholas, James, and New (2013) suggest that BDI has a good forecast ability in the context of financial assets and macroeconomic conditions. Therefore, we believe that macroeconomic factors determine the co-movement between the international bulk commodity market and China's financial market.

5 Model comparison

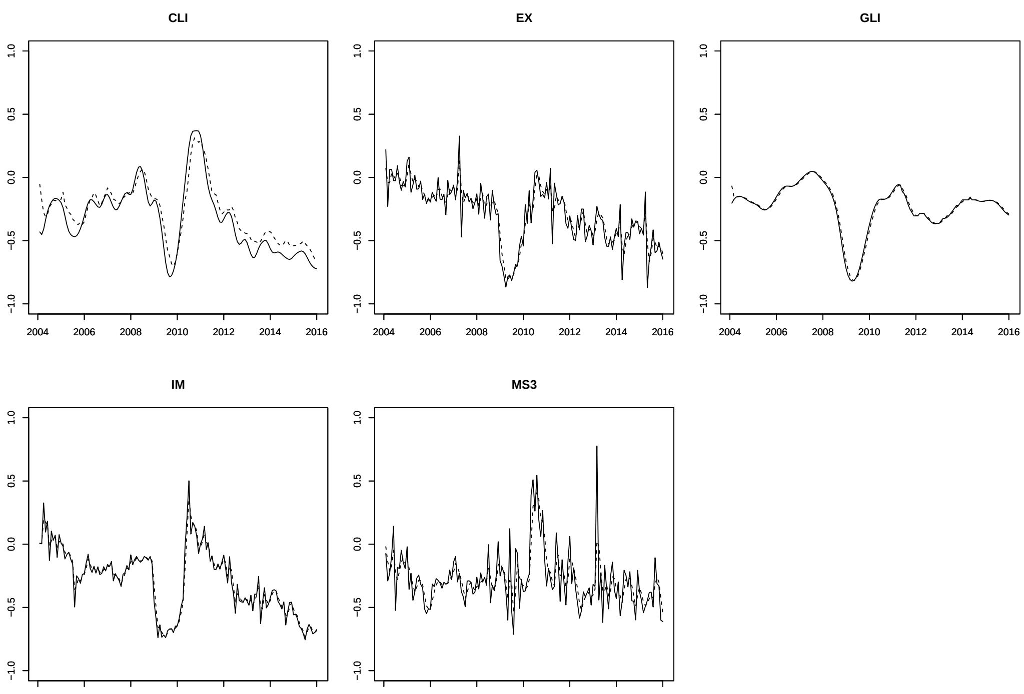
In this section we compare the in-sample predictive ability of the DCC-MIDAS models using the MCS procedure proposed by Hansen, Lunde, and Nason (2011). The comparison methods are based on the choices of loss functions. In this paper, we use the Euclidean distance and Frobenius distance loss function (Laurent., Rombouts, and Violante 2013):

$$L_t^E = (r_{1,t}^2 - \hat{h}_{11,t})^2 + (r_{2,t}^2 - \hat{h}_{22,t})^2 + (r_{1,t} \cdot r_{2,t} - \hat{h}_{12,t})^2$$

$$L_t^F = (r_{1,t}^2 - \hat{h}_{11,t})^2 + (r_{2,t}^2 - \hat{h}_{22,t})^2 + 2(r_{1,t} \cdot r_{2,t} - \hat{h}_{12,t})^2$$



(a) GARCH-MIDAS-RV



(b) GARCH-MIDAS-EX

Figure 4: The figure shows the DCC-MIDAS estimates of the conditional bulk commodity-stock correlation (dashed line) and its long-term component (bold black line).

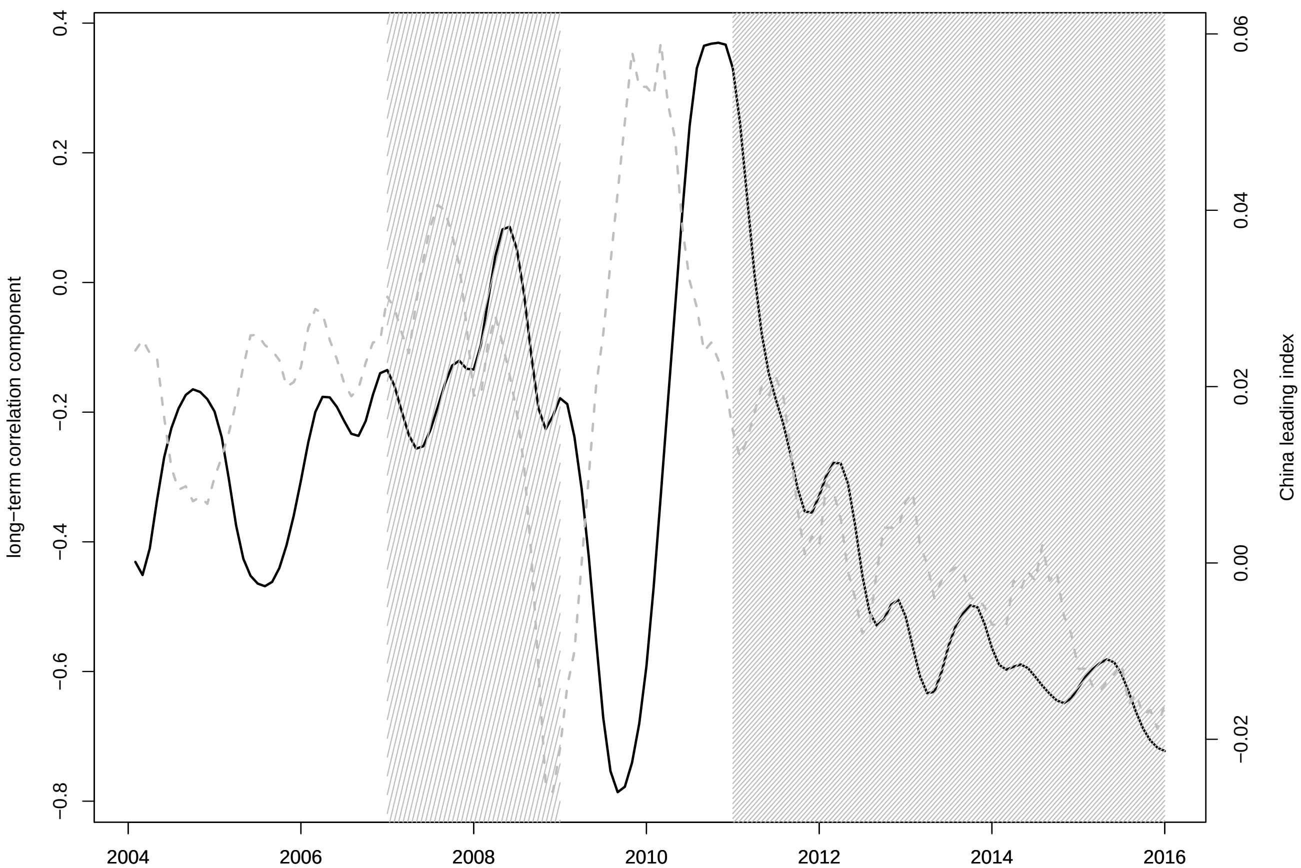


Figure 5: The bold black line (left scale) represents the DCC-MIDAS-CLI estimate of the long-term commodity-stock correlation. The dash line(right scale) corresponds to the China Leading index(CLI). Shaded areas represent respectively the global financial crisis period and the supply-side reform period.

with $\hat{h}_{11,t}$, $\hat{h}_{22,t}$ and $\hat{h}_{12,t}$ estimated by the GARCH-MIDAS and DCC-MIDAS models. L_t^F differs from L_t^E by double counting the loss associated to the conditional covariances.

Following Hansen, Lunde, and Nason (2011), we test the null hypothesis of equal predictive abilities which employ the statistics $T_{R,M}$ and T_{Max}[2]. If the initial model set M_0 rejects the null hypothesis, we remove the worst model i ($i \in M_0$) using the elimination rule e_M. In other words, models in set M_0 are statistically equivalent if the null hypothesis can not be rejected. The EPA can compute the p-value corresponding to T_R and T_{Max}. The larger the p-value, the better the corresponding model is in the superior set of models (SSMs). Again following Hansen, Lunde, and Nason (2003), we set the confidence level for the MCS to $\alpha = 0.25$ and the number of bootstrap samples to 10000.

The results based on Euclidean distances and Frobenius distances loss function are presented in Tables 5 and 6. The p-values for the $T_{R,M}$ and $T_{max,M}$ are reported in the fourth and seventh columns,respectively. We can see that the estimated SSMs based on the Euclidean distance loss function equal those from the Frobenius function. The benchmark models (GARCH-DCC and DCC-MIDAS-RC) are all eliminated from the SMMs according to the elimination rule. The results suggest that the DCC-MIDAS-X models are superior to the benchmark models.

6 Conclusion

In this paper, GARCH-MIDAS-X model and DCC-MIDAS-X model are used to overcome the problem that financial market data and macroeconomic data do not have the same frequencies. The effects of China's macroeconomic context on the volatility of commodity markets, the volatility of China's stock market, and the relationship between two markets is explored. By using MIDAS models, we classify volatilities and market correlations as long-term and short-term components. The long-term component is relatively stable, which reflects China's macroeconomy. The short-term components are mainly affected by current information vis-a-vis market immediacy.

The results suggest that the long-term component of BDI index volatilities is relatively stable, which is related to China's macroeconomic cycle. In the long-term, the volatility of the BDI index is counter-cyclical to China's macroeconomy. The better the macroeconomic situation in China, the lower the volatility of the commodity market. China is a large importer of large markets, ergo China's macroeconomic environment determines the stability of commodity demand and prices.

The correlation between the commodity market and the Chinese stock market also changes according to the macroeconomy of China. The results show that the linkage between the commodity market and the Chinese stock market is procyclical. China's macroeconomic better, the two markets tend to have no correlation. The international financial crisis and supplyoside reform enhance the relevance between two markets. The results show

[2] See more details in the appendix.

that as a result of the global financial crisis, China's macroeconomic environment was negatively shocked, the linkage between the two markets rapidly enhanced and exhibits a negative correlation. In the relative stability following from the recent supply-side reforms in China (2011-current), the correlation between the two markets has tended to weaken and then negative too.

Furthermore, the GARCH-DCC-MIDAS-X model is compared with benchmark GARCH models by using the MCS method. The results show that MIDAS models perform better than benchmark GARCH models. Compared with traditional methods according to a single market, the study of commodity markets according to the macroeconomic cycle can better explain the trend and risks of the commodity market and also help optimize risk management and hedging operations of financial assets.

Appendix: MCS approach

The procedure starts from an initial set of models M_0 of dimension m encompassing all the model specifications described in our paper, and delivers, for a given confidence level $1-\alpha$, a smaller set, the superior set of models, SSM, $\hat{M}_{1-\alpha}$ of dimension $m^* < m$. The ideal is $m^* = 1$ when the final set $\hat{M}_{1-\alpha}$ consists of a single model.Let $d_{ij,t}$ denote the loss differential between models i and j:

$$d_{ij,t} = L_{i,t} - L_{j,t}, t = 1, 2, \ldots, T$$

and let

$$d_{i.,t} = \frac{1}{m-1} \sum_{j \in M \setminus \{i\}} d_{ij,t}$$

be the simple loss of model i relative to the other models in model set M.

The null hypothesis is that all the models in the set exhibit equal predictive abilities(EPA):

$$H_{0,M} : c_{ij} = 0, \forall i, j \in \{1, 2, \ldots, m\}$$

$$H_{1,M} : c_{ij} \neq 0, \exists i, j \in \{1, 2, \ldots, m\}$$

or

$$H_{0,M} : c_{i.} = 0, \forall i \in \{1, 2, \ldots, m\}$$

$$H_{A,M} : c_{i.} \neq 0, \exists i \in \{1, 2, \ldots, m\}$$

where $c_{ij} = E(d_{ij})$,$c_{i.} = E(d_{i.})$.

Hansen, Lunde, and Nason (2011) proposes two statistics, t_{ij} and $t_{i.}$, in order to test the null hypothesis:

$$t_{ij} = \frac{\bar{d}_{ij}}{\sqrt{\widehat{var}(\bar{d}_{ij})}}$$

$$t_{i.} = \frac{\bar{d_{i.}}}{\sqrt{\widehat{var}(\bar{d_{i.}})}}$$

where $\bar{d}_{i.} = (m-1)^{-1}\sum_{j\in M\setminus\{i\}} \bar{d}_{ij}$ and $\bar{d}_{ij} = m^{-1}\sum_{t=1}^{m} d_{ij,t}$. $\widehat{var}(\bar{d}_{ij})$ and $\widehat{var}(\bar{d}_{i.})$ are obtained by a bootstrap procedure. Given t_{ij} and $t_{i.}$ the two EPA null hypotheses can be tested by the two following test statistics:

$$T_R = \max_{i,j\in M} \mid t_{ij} \mid$$

and

$$T_{Max} = \max_{i\in M} t_{i.}$$

The distribution of T_R and T_{Max} is not standard but can be obtained by the bootstrap approach(Hansen, Lunde, and Nason 2003).

The MCS procedure consists of a sequential testing procedure,which eliminates the worst performing model at each step according to the elimination rule:

$$e_{max,M} = arg\max_{i\in M} \frac{\bar{d}_{i,.}}{\widehat{var}(\bar{d}_{i,.})}$$

or

$$e_{R,M} = arg\max_{i}\{\sup_{j\in M} \frac{\bar{d}_{ij}}{\widehat{var}(\bar{d}_{ij})}\}$$

until the hypothesis of equal predictive ability(EPA)is accepted for all the models belonging to the superior set of models(SSM). Summarizing, the MCS procedure to obtain the SSM, consists of the following steps:

(1) Set $M = M_0$

(2) Test for EPA-hypothesis:if EPA is accepted terminate the algorithm and set $M^*_{1-\alpha} = M$, otherwise use the elimination rules to determine the worst model.

(3) Remove the worst model and proceed to step 2.

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Table 4: DCC-MIDAS model

	a	b	m	θ_c	ω_1	ω_2	LLF
First-step MIDAS Filtering Variable:realised volatility							
CLI	0.009	0.86***	-0.423***	20.957***	498.58***	305.28***	11395.40
	(0.011)	(0.078)	(0.049)	(1.751)	(49.59)	(39.643)	
EX	0.000	0.946***	-0.498***	28.256***	1.24**	1.663**	11395.05
	(0.003)	(0.034)	(0.089)	(7.353)	(0.576)	(0.74)	
GLI	0.056***	0.906***	0.275*	-73.29***	2e-4	21.908	11368.42
	(0.002)	(0.007)	(0.159)	(21.524)	(10.904)	(71.445)	
IM	0.028*	0.946***	-0.762***	43.806***	1.164***	1.097***	11391.74
	(0.016)	(0.036)	(0.168)	(13.257)	(0.424)	(0.268)	
MS3	0.025***	0.927***	-2.094***	163.7***	0.763	2.17	11379.38
	(0.004)	(0.011)	(0.29)	(19.97)	(0.57)	(1.432)	
First-step MIDAS Filtering Variable:export							
CLI	0.012	0.961***	-0.652*	19.075**	25.687	21.578	11388.29
	(0.039)	(0.156)	(0.381)	(9.617)	(60.596)	(46.379)	
EX	0.004	0.931***	-0.605***	23.659***	0.818	1.526***	11377.07
	(0.004)	(0.054)	(0.029)	(2.798)	(0.744)	(0.437)	
GLI	0.000	0.929***	-0.269**	22.474***	13.774	386.46	11389.88
	(0.042)	(0.077)	(0.129)	(6.583)	(23.571)	(241.5)	
IM	0.001	0.905***	-0.585***	24.358***	1.211***	1.05***	11373.36
	(0.002)	(0.082)	(0.04)	(3.362)	(0.328)	(0.242)	
MS3	0.000	0.948***	-0.95***	48.831***	26.103	1.16	11401.39
	(0.006)	(0.028)	(0.194)	(13.234)	(71.967)	(9.727)	
Benchmark model							
GARCH-DCC	0.0250	0.3976					
	(0.0210)	(0.2602)					
DCC-MIDAS-RC	0.0237	0.4116			296.82***	499.72***	
	(0.0204)	(0.2685)			(20.7650)	(64.0490)	

This table reports estimation results for the DCC-MIDAS-X specifications. DCC-MIDAS-X models are based on standardized residuals from from the GARCH-MIDAS-RV and GARCH-MIDAS-EX models from tables 2 and 3. The estimations are based on daily standardized residuals from January 2004 to November, 2015.

The numbers in brackets are Bollersev-Wooldridge robust standard errors. ***, ** and *indicate the significances at 1%, 5% and 10% level respectively.

Table 5: Comparison of the SSMs for DCC-MIDAS models based on L_t^E function

Model	$Rank_R$	t_{ij}	p_R	$Rank_{\max}$	$t_{i.}$	$p_{\max}$	Loss
RV_CLI	3	-1.09	1.00	3.00	0.20	1.00	180.60
RV_EX	8	0.95	0.62	8.00	1.45	0.14	183.07
RV_GLI	5	-0.02	1.00	5.00	0.90	0.91	181.92
RV_IM	10	1.06	0.38	10.00	1.50	0.08	183.24
RV_MS3	4	-0.60	1.00	4.00	0.55	1.00	181.22
EX_CLI	2	-1.18	1.00	2.00	0.12	1.00	180.47
EX_EX	7	0.74	0.91	7.00	1.35	0.29	182.81
EX_GLI	9	0.98	0.55	9.00	1.50	0.10	183.19
EX_IM	6	0.55	0.99	6.00	1.24	0.47	182.57
EX_MS3	1	-1.32	1.00	1.00	-0.13	1.00	180.26

Table 6: Comparison of the SSMs for DCC-MIDAS models based on L_t^F function

Model	$Rank_R$	t_{ij}	p_R	$Rank_{\max}$	$t_{i.}$	$p_{\max}$	Loss
RV_CLI	3	-1.09	1.00	3.00	0.20	1.00	180.60
RV_EX	8	0.95	0.62	8.00	1.46	0.15	183.07
RV_GLI	5	-0.02	1.00	5.00	0.90	0.91	181.92
RV_IM	10	1.06	0.38	10.00	1.51	0.09	183.24
RV_MS3	4	-0.61	1.00	4.00	0.55	1.00	181.22
EX_CLI	2	-1.18	1.00	2.00	0.13	1.00	180.47
EX_EX	7	0.74	0.91	7.00	1.36	0.30	182.81
EX_GLI	9	0.98	0.55	9.00	1.50	0.10	183.19
EX_IM	6	0.55	0.99	6.00	1.24	0.49	182.57
EX_MS3	1	-1.32	1.00	1.00	-0.13	1.00	180.26