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Forecasting Oil Volatility Using a GARCH-MIDAS Approach: The Role of Global Economic Conditions

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Abstract

In this study, we offer two main innovations. First, we subject six alternative indicators of global economic activity, including the one recently developed by Baumeister et al. (2020), to empirical tests of their relative predictive powers for crude oil market volatility. Second, we accommodate all the relevant series at their available data frequencies using the GARCH-MIDAS approach, thereby circumventing information loss and any associated bias. We find evidence in support of the ability of global economic activity to predict energy market volatility. Our forecast evaluation of the various indicators places a higher weight on the newly developed indicator of global economic activity by Baumeister et al. (2020), based on a set of 16 variables covering multiple dimensions of the global economy, than other indicators. The results leading to these conclusions are robust to multiple forecast horizons and consistent across alternative energy sources.

Keywords: Energy Markets Volatility, Global Economic Conditions, Mixed-Frequency

JEL Codes: C32, C53, E32, Q41

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1. Introduction

The financialization phenomenon in the crude oil market, and the overall energy market in general, has led to increased participation of hedge funds, pension funds and insurance companies in the oil market, thus rendering crude oil an appealing alternative investment in the portfolio decisions of financial institutions (Bampinas and Panagiotidis, 2015, 2017; Bonato, 2019). Hence, accurate estimates of oil-price volatility are of vital importance to these market participants, including crude oil traders. There is a large body of literature on volatility forecasting in the crude oil market (see Lux et al. (2016), Bonato et al. (2020), and Nguyen and Walter (2020) for detailed reviews of this literature), indicating that a wide array of variables has been used in forecasting oil-price volatility capturing various sectors of the global economy. Notably, given that daily data leads to more precise estimates and forecasts (McAleer and Medeiros, 2008), various types of high-frequency predictors associated with financial and commodity markets, metrics of uncertainties, and behavioural variables have been incorporated into models of conditional and realized volatilities (associated with intraday data). In addition, low frequency explanatory macroeconomic variables have also been used in the generalized autoregressive conditional heteroskedasticity (GARCH) variant of the mixed data sampling (MIDAS) model, i.e., the GARCH-MIDAS model, which avoids the loss of information that would result from averaging the daily volatility to a lower monthly frequency (Clements & Galvão, 2008; Das et al., 2019).

In this paper, we seek to forecast oil-price volatility based on a new measure of global economic conditions developed by Baumeister et al. (2020) to forecast prices and production of oil and energy markets. This index covers conditions of real economic activity, commodity (excluding precious metals and energy) prices, financial indicators, transportation, uncertainty, expectations, weather, and energy market-related indicators, and hence encapsulates the various measures of economic conditions in the overall world economy (not just the United States (US)), as discussed above, for forecasting oil market volatility. Now, given that the global economic conditions index is available at monthly frequency, and we want to predict oil-price volatility on a daily basis (to avoid loss of information), we rely on the GARCH-MIDAS model. Note that the decision to forecast oil market volatility at the daily frequency is not only due to the underlying statistical reason of providing more accurate measures of volatility, but because high frequency forecasts are indeed more important for investors in terms of making timely portfolio decisions. Moreover, while daily data could be aggregated to monthly realized volatilities, which can then be used to examine the link between oil market volatility and economic activity, but, if there are several components to volatility, monthly realized volatility may not be a good measure to consider, and hence, one would like to use the long term component (Engle et al., 2013). At the same time, variability of oil prices is also a concern from the policy perspective, as oil-price volatility has been shown to negatively impact economic activity as well, since it captures macroeconomic uncertainty (Elder and Serletis, 2010; van Eyden et al., 2019). Hence, high-frequency forecasts of oil market uncertainty would help policymakers predict the future path of low-frequency domestic real activity variables using methods of nowcasting (Banbura, 2011), and thus engender appropriate and early policy responses to prevent a possible recession. While the focus is on forecasting the volatility of spot and future price returns of both West Texas Intermediate (WTI) and Brent crude oil markets using the global economic conditions index, we also predict the volatility of natural gas and heating oil price returns. In addition, we forecast the price volatility of all the three energy markets (crude oil, natural gas, and heating oil) using five alternative, but narrower, measures of global economic activity (primarily associated with output) that are used in the literature (see for example, Yin and Zhou (2016), Pan et al. (2017), and Wei et al. (2017)), for comparison.

Given the financialization of the crude oil market, and borrowing from the literature on stock markets, we conjecture a negative relationship between economic conditions and oil-price volatility, just as observed for stock markets (see for example, Engle and Rangel (2008), and Engle et al. (2013)). The underlying theoretical channel can be described as follows. The present value model of asset prices of Shiller (1981a, b) can be used to show that asset market volatility and hence oil volatility due to financialization depends on the volatility of cash flows and the discount factor. Given that worsening global economic conditions (such as crisis periods) affect the volatility of variables that reflect future cash flows by generating economic uncertainty (Bernanke, 1983), and the discount factor (Schwert, 1989), one can hypothesize a negative relationship between economic conditions and oil and energy markets volatilities. To the best of our knowledge, this is the first attempt to forecast daily volatility of energy prices using a broad index of global economic conditions based on a GARH-MIDAS approach.

The remainder of the paper is organized as follows: Section 2 discusses the data, while Section 3 outlines the econometric framework; Section 4 presents the empirical results from the in-sample and out-sample predictive analyses, with Section 5 concluding the paper.

2. Data and Preliminary Analyses

Conventionally, the return rather than price series is used in the analysis of volatility to circumvent the unit root problem. Thus, we employ the spot and future price returns of four energy sources (WTI, Brent, heating oil and natural gas) and six economic activity proxies (the global economic conditions indicator (GECON), real commodity price factor (RCPF), global steel production factor (GSPF), real shipping cost factor (RSCF), Kilian's index (KINDX) and OECD+6NME industrial production (OECDIP)). As stated, the energy returns and economic activities are in daily and monthly frequencies, respectively, spanning a period of May 2005 to May 2020. The energy price data are sourced from DataStream, while the economic activity proxies are obtained from two research databases (https://sites.google.com/site/cjsbaumeister/research and https://econweb.ucsd.edu/~jhamilton/). RCPF, GSPF, and RSCF are directly provided to us by Professor Baumeister. Although the variables have different start and end dates, we restrict our data sample to between April 2006 and August 2018. This ensures a balanced data sample as a basis for comparison of the predictive powers of the six contending economic activities. Our analysis is presented in two phases: the main estimation which entails predicting crude oil (spot and future) price returns for WTI and Brent using each of the six economic activity proxies; and additional analyses which involve the prediction of the remaining two energy, healing oil and natural gas (spot and future), price returns using economic activity proxies. Notably, the additional analyses serve as a form of sensitivity evaluation.

We provide a brief description of the real economic activities incorporated in the prediction of energy price returns. The Kilian index (KINDX) is based on single-voyage dry-cargo freight rates (Kilian, 2009). The founding intuition is that deviations from linear time trend changes in real shipping costs capture the cyclical component of industrial commodity demand. The established link between shipment of raw industrial materials and future production of manufacturing goods, KINDX, is used to proxy the state of the global business cycle (Kilian, 2009). Hamilton (2019) faults the isolation of the cyclical component of real shipping costs, by the removal of a deterministic linear time trend, on the basis of lack of data support; hence, our adoption of the month-on-month growth rate of the index. Another proxy of real economic activity, the real shipping cost factor (RSCF), is proposed by Baumeister et al. (2020). RSCF is derived from an unbalanced panel of disaggregated data on a cross-section of 61 freight rates for individual shipping routes, for a set of industrial commodities (coal, iron ore, and fertilizer). The world industrial production index (Baumeister and Hamilton, 2019) is measured by the physical volume of output generated in the industrial sector and considered to be a close representation of the traditional concept of economic activity. An updated monthly version - OECDIP - that includes the OECD countries as well as six emerging markets (Brazil, China, India, Indonesia, the Russian Federation and South Africa) is constructed (Baumeister and Hamilton, 2019) using similar methodology to that used by the OECD. RCPF is an extraction of the global factor relating to business cycle fluctuations from monthly growth rates of real prices of 23 basic industrial and agricultural commodities used as inputs in the production of final goods; excluding precious metals (Alquist et al., 2019). GSPF is obtained from monthly global steel production by taking account of the structural break problem of aggregation caused by alterations in the number of reporting countries. This follows from Ravazzolo and Vespignani's (forthcoming) suggestion of steel being a relevant component of construction, transportation, and manufacturing in many industries, and a relatively homogenous, global and freely traded commodity (see Baumeister et al., 2020: Table 2 for more explanatory details of these indices). Moving away from indices that only capture the cyclical component of real global economic activity, which are thus restricted, we consider a more encompassing index – GECON: the global economic conditions index (Baumeister et al., 2020). This index is derived by applying the expectation-maximization (EM) algorithm to 16 indicators, including commodity prices, economic activity, financial indicators, transportation, uncertainty and expectation measures, weather and energy-related indicators (see Baumeister et al., 2020: Table 7).

Table 1 presents the summary statistics and preliminary analysis of the data used in the study. The energy spot and future price returns are considered in the first and second pane, respectively, while the economic activity is presented in the third pane. WTI spot prices have the highest mean returns while natural gas spot prices have the least mean returns. For future prices, Brent and natural gas have the highest and least returns, respectively. The energy returns have a relatively similar spread, as their standard deviations hover around 0.2 or 0.3 for both spot and future price returns. The energy spot price returns are skewed negatively (Brent, heating oil and natural gas) and positively (WTI), whereas the position is not the same with respect to the future price returns as natural gas and WTI have skewness values different from those for the spot price returns. All the energy spot and future price returns exhibit excess kurtosis and are thus leptokurtic. We find some degree of heteroscedasticity and autocorrelation up to at least lag 20. Of the economic activity proxies, with means ranging from -2.33E-03 to 2.88E-02, KINDX appears to be the most volatile. All the economic activity proxies are negatively skewed and leptokurtic, while all except GECON exhibit some degree of heteroscedasticity and autocorrelation up to at least lag 20. The data characteristics observed are suited for the GARCH-MIDAS framework.

Table 1: Summary Statistics and Preliminary Analysis

	Mean	Standard Deviation	Skewness	Kurtosis	N	$ARCH(5)$	$ARCH(10)$	$ARCH(20)$	$Q(5)$	$Q(10)$	$Q(20)$	$Q^2(5)$	$Q^2(10)$	$Q^2(20)$
ENERGY PRICE RETURNS														
Spot Prices														
BRENT	-1.55E-04	0.03	-2.61	110.08	3915	122.65***	69.61***	51.26***	26.44***	97.55***	208.10***	553.42***	743.84***	1142.90***
Heating Oil	-1.41E-04	0.02	-0.3	9.86	3915	91.89***	53.35***	29.39***	3.35	4.68	21.5	683.23***	1005.20***	1409.30***
Natural Gas	-2.27E-04	0.02	-1.3	101.16	3915	0.37	0.39	4.77***	0.21	0.38	22.88	1.8	3.61	95.48***
WTI	3.71E-06	0.03	1.07	39.73	3913	211.96***	167.03***	140.18***	35.88***	55.93***	98.88***	1456.00***	2877.10***	3880.30***
Future Prices														
BRENT	-1.03E-04	0.02	-0.69	18.57	3915	57.54***	47.72***	38.16***	7.18	22.28**	52.73***	379.89***	804.97***	1626.80***
Heating Oil	-2.22E-04	0.02	-0.15	11.87	3670	94.73***	71.39***	39.69***	23.10***	28.38***	33.56**	626.76***	1225.00***	1606.20***
Natural Gas	-3.52E-04	0.03	0.53	7.92	3915	22.88***	18.94***	11.66***	8.94	14.08	22.9	150.85***	297.21***	475.17***
WTI	-2.14E-04	0.03	-2.27	63.11	3725	63.89***	49.23***	31.90***	38.80***	47.84***	93.61***	421.37***	774.98***	978.21***
ECONOMIC ACTIVITIES														
GECON	-1.26E-01	0.54	-3.41	18.99	180	0.75	0.41	0.31	1.86	7.31	25.77	1.07	1.09	1.18
GSPF	-2.33E-03	0.69	-0.52	5.49	160	19.08***	9.49***	5.11***	20.93***	37.97***	105.67***	57.01***	66.70***	71.39***
KINDX	-5.66E-01	22.65	-0.63	5.25	173	3.28***	2.08**	0.95	7.35	15.65	22.37	17.79***	20.66**	23.27
OECDIP	1.44E-01	0.76	-2.81	17.47	178	1.72	1.17	0.62	16.01***	18.16**	27.74	5.03	5.14	5.5
RCPF	2.88E-02	0.54	-1.32	10.28	160	3.27***	1.62	0.82	10.021*	17.993*	28.11	16.48***	21.27**	23.93
RSCF	-3.36E-02	0.95	-0.75	6.35	160	5.95***	4.17***	1.87**	8.83	25.25***	36.13**	28.99***	48.66***	53.19***

Note: Global Economic Conditions Indicator (GECON), Real Commodity Price Factor (RCPF), Global Steel Production Factor (GSPF), Real Shipping Cost Factor (RSCF), Kilian's index (KINDX) and OECD+6NME Industrial Production (OECDIP). ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

3. Methodology

To analyse the role of global economic conditions in forecasting energy market volatility, we rely on a modelling framework that accommodates mixed data frequencies. Our choice of model is informed by the available data frequency for the relevant series. Daily frequency is available for the energy series considered (i.e. crude oil, heating and natural gas) while the highest available frequency for the various measures of global economic conditions is monthly. We favour the GARCH-MIDAS model as it is suitable for high frequency dependent (energy) and low frequency independent (global economic conditions) variables.[1] Among the attractions of this model is its ability to combine data occurring naturally in different frequencies and thus its ability to overcome the problem of information loss and, consequently, the estimation bias that results from aggregation or dis-aggregation that most models, dependent on uniform frequency, are likely to cause. In other words, the model incorporates all the available information into the estimation process and may therefore offer better predictive power than other models that do not. The GARCH-MIDAS model[2] is therefore considered appropriate given that our predicted variables – WTI, Brent, heating oil, and natural gas – occur daily, while the predictor variable – global economic activity – occurs monthly. As indicated in the introduction, our decision to forecast oil market volatility at the daily frequency is motivated by the fact that high frequency forecasts are more important for market participants in terms of making timely portfolio decisions.

Returns on energy (WTI, Brent, heating oil and natural gas) prices are generated as log returns, technically defined as $r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$, where $P_{i,t}$ is the i^{th} day energy price in the t^{th} month; t ($t = 1,\dots,T$) and i ($i=1,\dots,N_t$) indicate monthly and daily frequencies and N_t indicates the number of days in any given month t. The GARCH-MIDAS model for the daily energy price returns comprises two components - a constant conditional mean and a conditional variance part. It is defined as:

[1] Another variant that incorporates a higher frequency predictor variable for a lower frequency predicted variable also exists and is shown to have some computational advantages over a model employing uniform frequencies (see Salisu and Ogbonna, 2019).
[2] Engle et al. (2013) technically presents details of the multiplicative decomposition of conditional variance into the high- and low-frequency components of the MIDAS model.

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \qquad \forall \ i = 1,...,N_t \tag{1}$$

and

$$\varepsilon_{i,t} \big| \Phi_{i-1,t} \sim N(0,1) \tag{2}$$

where μ denotes the unconditional mean of the energy price return. The conditional variance part of Eq. (1) is decomposed into short- and long-run components, such that the short-run component $(h_{i,t})$ is characterised by a higher frequency and follows the $\text{GARCH}(1,1)$ process, while the long-run component is captured by τ_i in a rolling window framework. The notation $\Phi_{i-1,t}$ denotes the information that is available at day $i-1$ of period t. The conditional variance is therefore defined by:

$$h_{i,t} = (1-\alpha-\beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_i} + \beta \overline{h}_{i-1,t} \tag{3}$$

where α and β represent ARCH and GARCH terms, respectively, satisfying the following conditions: $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The long-term component, originally varying monthly, is structured to daily frequency and is given by:

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{i-k}^{(rw)} \tag{4}$$

where the superscript *rw* indicates the rolling window framework being implemented; m_i denotes the long-run component constant; θ_i represents the MIDAS slope coefficient that indicates the predictability of the incorporated predictor variable X_{i-k}; and the weighting scheme $\phi_k(\omega_1, \omega_2) \geq 0, \ k = 1,...,K$ must sum to one for model parameter identification. Hinging on flexibility and popularity, as portrayed by Colacito et al. (2011), the one-parameter beta polynomial weighting scheme and is defined by:

$$\phi_k(\omega_1,\omega_2)=\frac{\left[k/(K+1)\right]^{\omega_1-1}\times\left[1-k/(K+1)\right]^{\omega_2-1}}{\sum_{j=1}^{K}\left[j/(K+1)\right]^{\omega_1-1}\times\left[1-j/(K+1)\right]^{\omega_2-1}} \tag{5}$$

For the in-sample predictability analysis, we test whether θ_i is significantly different from zero, such that a rejection of the null would imply that future energy volatility can be influenced by the current state of economic conditions. The sign obtained after estimation tells us the direction of the relationship and can be explained either way. For instance, a positive relationship suggests that an improvement in economic activity increases trading in the energy market which, by extension, increases its volatility. Conversely, a negative relationship implies that higher economic activity reduces overall uncertainty and reduces energy market volatility. We also examine the comparative forecast performance of the GARCH-MIDAS model for the alternative economic activity indices, using a 50% in- and out-of-sample split of the data and the conventional root mean square error (RMSE) statistic.

4. Results and Discussion

We begin our analysis with the crude oil volatility and thereafter extend it to the other energy sources. The results comprise the predictive power of the economic activity proxies for crude oil volatility (using both spot and future prices for WTI and Brent) and forecast evaluation using the conventional RMSE statistic. The predictive power results (see Table 2) are based on the full data sample, while a 50% in- and out-of-sample split of the data is used for forecast performance evaluation (see Table 3). We also provide predictive power results based on a 50% data sample in the appendix (see Tables A1 & A2). Three out-of-sample forecast horizons ($h=60$, $h=120$ and $h=180$ days ahead) are considered for the forecast evaluation. Upon confirmation of the predictive power, the performance of the contending economic activity proxies is examined.

4.1 The Role of Economic Conditions in Crude Oil Market Volatility

As noted, we begin the analysis with the crude oil market. Table 2 presents the GARCH-MIDAS parameters where each economic activity proxy is incorporated into the volatility of the crude oil market, for both spot (upper pane) and futures (lower pane) of WTI and Brent. These parameters are the unconditional mean for crude oil (μ); ARCH term (α); GARCH term (β); the slope coefficient (θ) which gives an indication of the predictive power of monthly economic activity for daily crude oil volatility; adjusted beta polynomial weight (w); and the long run constant term (m). With the exception the unconditional mean, we find all the parameters to be statistically significant across the various economic activities (except for the θ coefficient of KINDX in the WTI spot and RSCF in Brent futures), crude oil spot and future prices. In the ARCH and GARCH terms, which give some information on the short-run component of the model in terms of persistence, we find a high degree of volatility persistence, which also exhibits mean reverting characteristics since the sum of the ARCH and GARCH terms is less than unity. Imperatively, while the impact of shocks to crude oil (WTI and Brent) volatility is likely to take a longer time to completely decay, the impact of such shocks are not permanent. We confirm this position consistently across the economic activity proxies and crude oil spot and future prices. The adjusted beta weight coefficients are found to be statistically significant and greater than one across the two crude oil prices and economic activity proxies, which is an indication that immediate past observations are assigned larger weights than far apart lag observations.

We test the hypothesis that the MIDAS slope coefficient (θ) is statistically different from zero, such that a rejection of the null implies the predictive power of the corresponding economic activity for crude oil volatility, otherwise, there is no predictability. Consequently, we find the economic activity proxies to have predictive power for the volatility of crude oil returns regardless of whether spot or future price returns are used, given that the slope parameter (θ) is found to be statistically significant. Cases of unconfirmed predictive power of economic activity for crude oil price volatility are only evident for KINDX and RSCF in the volatility of WTI spot and Brent futures, respectively. We find the relationship between economic activity and crude oil volatility to be negative, which is observed consistently across the paired variables, regardless of whether the spot price or future price is considered. Interestingly, where we find positive relationships they are not statistically significant (the case of KINDX for WTI spot and RSCF for Brent futures). Overall, the relationship between price volatility and economic activity is negative, which is in line with the channels identified in the introduction, associated with cash flow and discount factors.

Table 2: The Predictive Power of Economic Conditions for Crude Oil Market Volatility

Energy Price	Economic Activity	μ	α	β	θ	w	m
SPOT PRICES							
WTI	GECON	0.0004	0.0326***	0.9611***	-0.0691***	41.9030***	0.0005***
		[0.0003]	[0.0046]	[0.0053]	[0.0109]	[9.8617]	[0.0001]
	RCPF	0.0004	0.0480***	0.9513***	-0.1938**	15.3520***	0.0019**
		[0.0003]	[0.0047]	[0.0047]	[0.0913]	[4.1162]	[0.0009]
	GSPF	0.0004	0.0556***	0.9435***	-0.1034*	39.9360**	0.0020**
		[0.0003]	[0.0053]	[0.0054]	[0.0589]	[19.7860]	[0.0010]
	RSCF	0.0004	0.0601***	0.9354***	-0.1272**	1.0685***	0.0007***
		[0.0003]	[0.0056]	[0.0060]	[0.0562]	[0.1978]	[0.0002]
	KINDX	0.0004	0.0602***	0.9383***	0.0136	35.2910	0.0016**
		[0.0003]	[0.0057]	[0.0058]	[0.0098]	[23.7570]	[0.0008]
	OECDIP	0.0005	0.0545***	0.9398***	-0.0386***	7.0035***	0.0006***
		[0.0003]	[0.0050]	[0.0052]	[0.0110]	[2.0153]	[0.0001]
BRENT	GECON	0.0002	0.0333***	0.9643***	-0.0641***	41.5550***	0.0005***
		[0.0003]	[0.0049]	[0.0052]	[0.0168]	[14.6170]	[0.0001]
	RCPF	0.0002	0.0401***	0.9595***	-0.1408***	15.5960***	0.0014***
		[0.0003]	[0.0046]	[0.0046]	[0.0542]	[3.5143]	[0.0005]
	GSPF	0.0001	0.0484***	0.9513***	-0.1271***	29.6920*	0.0030***
		[0.0003]	[0.0054]	[0.0055]	[0.0463]	[18.0370]	[0.0010]
	RSCF	0.0000	0.0392***	0.9606***	-0.5508*	1.3821***	0.0023**
		[0.0003]	[0.0045]	[0.0045]	[0.2951]	[0.2496]	[0.0009]
	KINDX	0.0001	0.0418***	0.9560***	-0.0272**	1.3142***	0.0004***
		[0.0003]	[0.0048]	[0.0049]	[0.0128]	[0.2775]	[0.0001]
	OECDIP	0.0002	0.0365***	0.9614***	-0.0257**	5.4539***	0.0005***
		[0.0003]	[0.0039]	[0.0040]	[0.0101]	[1.8185]	[0.0001]
FUTURE PRICES							
WTI	GECON	0.0003	0.0367***	0.9576***	-0.0696***	40.2450***	0.0005***
		[0.0003]	[0.0051]	[0.0060]	[0.0138]	[11.0360]	[0.0001]
	RCPF	0.0002	0.0514***	0.9481***	-0.2235**	14.6570***	0.0021*
		[0.0003]	[0.0049]	[0.0050]	[0.1133]	[3.6960]	[0.0011]
	GSPF	0.0002	0.0550***	0.9443***	-0.1161*	36.7810**	0.0022**
		[0.0003]	[0.0056]	[0.0057]	[0.0669]	[18.4960]	[0.0011]
	RSCF	0.0002	0.0568***	0.9401***	-0.1338*	1.0011***	0.0007**

		[0.0003]	[0.0060]	[0.0063]	[0.0806]	[0.1243]	[0.0003]
	KINDX	0.0002	0.0567***	0.9393***	-0.0389*	1.1736***	0.0006***
		[0.0003]	[0.0058]	[0.0063]	[0.0199]	[0.3002]	[0.0002]
	OECDIP	0.0003	0.0499***	0.9461***	-0.0385***	7.8415***	0.0006***
		[0.0003]	[0.0050]	[0.0051]	[0.0110]	[1.7999]	[0.0001]
BRENT	GECON	0.0002	0.0333***	0.9604***	-0.0494***	22.0480***	0.0003***
		[0.0003]	[0.0045]	[0.0055]	[0.0086]	[6.7654]	[0.0000]
	RCPF	0.0002	0.0441***	0.9555***	-0.1615**	15.9490***	0.0016**
		[0.0003]	[0.0045]	[0.0046]	[0.0751]	[4.4025]	[0.0008]
	GSPF	0.0005	0.0559***	0.9001***	0.0252***	5.0726***	0.0002***
		[0.0003]	[0.0044]	[0.0084]	[0.0011]	[0.0032]	[0.0000]
	RSCF	0.0001	0.0530***	0.9450***	-0.0186	9.0366	0.0008***
		[0.0003]	[0.0055]	[0.0059]	[0.0246]	[11.8910]	[0.0002]
	KINDX	0.0003	0.0502***	0.9004***	0.0159***	4.9996***	0.0003***
		[0.0003]	[0.0045]	[0.0095]	[0.0015]	[1.1950]	[0.0000]
	OECDIP	0.0003	0.0433***	0.9526***	-0.0245***	4.7650***	0.0004***
		[0.0003]	[0.0044]	[0.0047]	[0.0084]	[1.6730]	[0.0001]

Note: Values in square brackets are the associated standard errors of the estimated parameters, while ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

4.2. Out-of-Sample Forecast Evaluation

Following from the established predictive power of economic activity for crude oil volatility, we consider the out-of-sample performance of the GARCH-MIDAS predictive model that incorporates at each point any pair of crude oil (spot or future) volatility and economic activity. This is a bid to ascertain which of the economic activity proxies predicts the corresponding crude oil volatility more precisely, with the least forecast error. Consequently, for each crude oil volatility proxy, there are six GARCH-MIDAS models, thus a total of 48 models comprising pairs of predicted and predictor variables. The forecast horizons considered are $h = 60$, $h = 120$ and $h = 180$ days ahead. The conventional RMSE statistic is used for comparison, where the GARCH-MIDAS model with the smallest value is judged the most preferred. We consider only 50% of the data sample for the forecast evaluation. The results of the model predicting WTI and Brent spot and future volatility are presented in Table 3. We find the GARCH-MIDAS model with RCPF as the predictor variable for WTI (both for spot and futures) to have the least RMSE when a 60 days ahead forecast horizon is used. However, this out-performance is not sustained when the forecast horizon increases to 120 or 180 days. The GECON proxy shows higher precision in predicting the WTI spot and future volatility at higher forecast horizons. Like WTI, besides the out-performance of RSCF over other economic activity proxies in predicting 60 days ahead for Brent spot volatility, the GECON predictor consistently out-performs all economic activity proxies at the specified out-of-sample forecast horizons. Overall, we find the GECON to be the most preferred economic activity proxy for predicting spot and future WTI and Brent volatility, while KINDX is the least preferred. This is in addition to its confirmed in-sample predictive power, which is not sensitive to the crude oil volatility being modelled. Consequently, it provides a more precise estimate of the relationship between crude oil volatility and economic activity. This finding is confirmatory of the standpoint of Baumeister et al. (2020), attributable to the GECON. They not only argue against using previous indices that capture only the cyclical component of economic activity (and therefore do not measure the global economic conditions properly), but also construct an alternative index that reasonably reflects global economic activity. It is therefore not surprising to find that the GECON of Baumeister et al. (2020) consistently outperforms other indices and therefore possesses a higher precision in the predicting of oil volatility. In summary, our study provides empirical evidence to support the preference of the GECON over other indices particularly for the predicting of global variables such as oil volatility and possibly others, the behaviours of which are susceptible to global macroeconomic shocks. Our findings complement a similar work by Baumeister et al. (2020) focusing on the energy market and global economic activity, albeit with a different approach and objective. We focus on energy market volatility rather than returns, using a mixed frequency approach, as the former measures the uncertainty in the market which is a more important factor for making investment decisions.

Table 3: Forecast Evaluation using RMSE Results (WTI and Brent)

Energy	Economic Activity	Spot Prices			Future Prices		
		$h=60$	$h=120$	$h=180$	$h=60$	$h=120$	$h=180$
WTI	GECON	2.599E-04	**2.368E-04**	**2.099E-04**	2.547E-04	**2.274E-04**	**2.020E-04**
	RCPF	**2.597E-04**	2.371E-04	2.104E-04	**2.544E-04**	2.277E-04	2.024E-04
	GSPF	2.624E-04	2.393E-04	2.137E-04	2.576E-04	2.301E-04	2.058E-04
	RSCF	2.644E-04	2.420E-04	2.171E-04	2.572E-04	2.309E-04	2.064E-04
	KINDX	2.644E-04	2.426E-04	2.212E-04	2.580E-04	2.319E-04	2.082E-04
	OECDIP	2.630E-04	2.396E-04	2.137E-04	2.582E-04	2.307E-04	2.057E-04
BRENT	GECON	3.119E-04	**2.497E-04**	**2.192E-04**	**2.467E-04**	**2.177E-04**	**2.021E-04**
	RCPF	3.108E-04	2.508E-04	2.198E-04	2.477E-04	2.192E-04	2.031E-04
	GSPF	3.115E-04	2.508E-04	2.206E-04	2.668E-04	2.322E-04	2.180E-04
	RSCF	**3.105E-04**	2.503E-04	2.202E-04	2.507E-04	2.205E-04	2.058E-04
	KINDX	3.109E-04	2.513E-04	2.211E-04	2.510E-04	2.208E-04	2.067E-04
	OECDIP	3.118E-04	2.504E-04	2.201E-04	2.683E-04	2.332E-04	2.190E-04

4.3. Additional Analysis

We follow trends in the estimation to examine two additional energy sources, heating oil and natural gas, as a robustness check for the sensitivity of the predictive performance of the six economic activity proxies. In this case, we only consider 50% of the data sample for the predictive power (see Tables A1 & A2 in the appendix) and forecast evaluation (Table 4). We do not discuss the predictive power results in detail here as the sections corresponding to WTI and Brent crude volatility are similar to those of the full sample discussed in the main estimation, showing the predictive power of economic activity for crude oil volatility. Thus, we focus on which economic activity produces the most precise out-of-sample forecast for the volatility of the energy markets considered – in this case, heating oil and natural gas. The RMSE results, presented in Table 4, are also similar to those in the main estimation for spot and future return volatility of heating oil and natural gas, under 60, 120 and 180 days ahead forecast horizons.

For all three specified out-of-sample forecast horizons, we find an overwhelming out-performance of GECON over the other economic activity proxies in forecasting the volatility of heating oil (whether spot or futures). Except in the case of the 60 days ahead forecast horizon for naturals gas spot price where RCPF is found to have the least RMSE, the GECON again proves to be the most preferred proxy for global economic activity for modelling energy (spot and future) market volatility, as it consistently out-performs other economic activity proxies across the specified out-of-sample forecast horizons. This confirms its preferability over all other proxies as it hinges on the incorporation of all possible information as against variants of economic activity proxies that only capture the cyclical component. Our predictability results, in addition to the observed forecast performance, show the importance of accommodating all plausible economic activity information when modelling energy market volatility and hence, the preference for the GECON.

Table 4: Forecast Evaluation using RMSE Results (Heating Oil and Natural Gas)

Energy	Economic Activity	Spot Prices			Future Prices		
		$h=60$	$h=120$	$h=180$	$h=60$	$h=120$	$h=180$
HEATING OIL	GECON	**3.428E-04**	**2.684E-04**	**2.334E-04**	**2.103E-04**	**1.742E-04**	**1.627E-04**
	RCPF	3.485E-04	2.748E-04	2.391E-04	2.129E-04	1.774E-04	1.655E-04
	GSPF	3.525E-04	2.763E-04	2.408E-04	2.135E-04	1.774E-04	1.661E-04
	RSCF	3.549E-04	2.783E-04	2.426E-04	2.127E-04	1.770E-04	1.655E-04
	KINDX	3.524E-04	2.780E-04	2.432E-04	2.120E-04	1.771E-04	1.658E-04
	OECDIP	3.557E-04	2.825E-04	2.489E-04	2.118E-04	1.763E-04	1.647E-04
NATURAL GAS	GECON	1.107E-03	**8.296E-04**	**7.496E-04**	**8.508E-04**	**6.677E-04**	**5.912E-04**
	RCPF	**1.101E-03**	8.420E-04	7.684E-04	8.895E-04	7.349E-04	6.697E-04
	GSPF	1.106E-03	8.359E-04	7.573E-04	8.707E-04	7.011E-04	6.306E-04
	RSCF	1.111E-03	8.321E-04	7.510E-04	8.644E-04	6.841E-04	6.079E-04
	KINDX	1.116E-03	8.355E-04	7.538E-04	8.646E-04	6.846E-04	6.090E-04
	OECDIP	1.104E-03	8.339E-04	7.546E-04	8.819E-04	7.173E-04	6.474E-04

5. Conclusion

The significant role of global economic activity in the prediction of the future path of energy demand is not new in energy economic literature. What is understudied, however, is how to determine the best indicator, among various alternatives, for global economic activity. Meanwhile, the related literature on the subject is limited by the fact that it mainly relies on world industrial production as a proxy for global economic activity which does not seem to capture this activity properly. In this paper, we contribute to the academic literature by examining the role of global economic activity in the prediction of energy market volatility using six alternative indicators, including the one recently developed by Baumeister et al. (2020). Our interest lies in the volatility of the energy market rather than returns, as the former measures the extent of uncertainty in the market which is a crucial factor for making investment decisions and, by extension, determining expected/risk-adjusted returns on investment. Given the available data frequencies for the variables of interest (daily energy prices for crude oil, heating oil and natural gas and monthly data for global economic activity), we adopt the GARCH-MIDAS approach. We begin the analysis with crude oil and thereafter extend it to other energy sources, namely heating oil and natural gas, for robustness. The relative predictive powers of the six alternative indicators of global economic activities are evaluated using multiple out-of-sample forecast horizons based on a 50% data split between the in-sample and out-of-sample forecasts, relying on the rolling window approach to forecasting.

Our results lend support to the negative relationship between global economic activity and crude oil market volatility, regardless of whether the spot price or future price is considered. Further analyses involving heating oil and natural gas offer the same conclusion. Our forecast evaluation of the various indicators validates the use of the newly developed indicator of global economic activity by Baumeister et al. (2020) for forecasting energy market volatility. These conclusions are robust to multiple forecast horizons and alternative measures of energy sources.

Our results have important implications for both investors and policymakers. In particular, using the information content of the broad measure of economic conditions around the world, investors could accurately forecast energy market volatility, which would, in turn, help them design optimal portfolios, especially under the current extreme situation of deteriorating economic conditions due to the COVID-19 outbreak. Moreover, given that oil market volatility captures economic uncertainty, accurate forecasting would provide information about the future path of the domestic economy contingent on the evolution of uncertainty, which can then be incorporated into mixed-frequency models to produce forecasts of wide ranges of low-frequency variables measuring domestic economic activity, and thus allow the design of appropriate policy responses to prevent the possibility of economic downturns.

As part of future research, it would be interesting to use the new measure of global economic conditions to forecast the price volatility of cryptocurrencies that have recently emerged as important alternative investment options for economic agents, relative to traditional financial assets. This could be compared to the results of Walther et al. (2019) in which only two economic measures are used namely, economic policy uncertainty and global real economic activity.

References

Alquist, R., Bhattarai, S., and Coibion, O. (2019). Commodity-Price Comovement and Global Economic Activity. Journal of Monetary Economics. DOI: https://doi.org/10.1016/j.jmoneco.2019.02.004.

Bampinas, G., and Panagiotidis, T. (2017). Oil and stock markets before and after financial crises: A local Gaussian correlation approach. The Journal of Futures Markets, 37(12), 1179-1204.

Bampinas, G., and Panagiotidis, T. (2015). On the relationship between oil and gold before and after financial crisis: linear, nonlinear and time-varying causality testing. Studies in Nonlinear Dynamics & Econometrics, 2015, 19(5), 657-668.

Banbura, M., D. Giannone, L. Reichlin (2011). Nowcasting. Oxford Handbook on Economic Forecasting, Edited by Michael P. Clements and David F. Hendry, pages 63-90. Oxford University Press.

Baumeister, C., and Hamilton, J.D. (2019). Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. American Economic Review, 109(5), 1873-1910.

Baumeister, C., Korobilis, D., and Lee, T.K. (2020). Energy Markets and Global Economic Conditions. NBER Working Paper No. 27001.

Bernanke, B.S. (1983). Nonmonetary Effects of the Financial Crises in the Propagation of the Great Depression. American Economic Review, 73, 257-76.

Bonato, M. (2019). Realized correlations, betas and volatility spillover in the agricultural commodity market: What has changed? Journal of International Financial Markets, Institutions and Money, 62, 184-202.

Bonato, M., Gkillas, K., Gupta, R., and Pierdzioch, C. (2020). Investor Happiness and Predictability of the Realized Volatility of Oil Price. Sustainability, 12, 4309.

Clements, M.P., and Galvão, A.B. (2008). Macroeconomic forecasting with mixed-frequency data. Journal of Business and Economic Statistics, 26(4), 546-554.

Colacito, R., Engle, R. F., & Ghysels, E. (2011). A component model for dynamic correlations. Journal of Econometrics, 164(1), 45-59.

Das, S., Demirer, R., Gupta, R., and Mangisa, S. (2019). The Effect of Global Crises on Stock Market Correlations: Evidence from Scalar Regressions via Functional Data Analysis. Structural Change and Economic Dynamics, 50, 132-147.

Elder, J., and Serletis, A. (2010). Oil price uncertainty. Journal of Money, Credit and Banking, 42, 1137-1159.

Engle, R.F., Ghysels, E., and Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. Review of Economics and Statistics 95, 776-797.

Engle, R.F., and Rangel, J.G. (2008). The Spline-GARCH Model for Low Frequency Volatility and its Global Macroeconomic Causes. Review of Financial Studies, 21(3), 1187-1222.

Gkillas, K., Gupta, R., and Pierdzioch, C. (2020). Forecasting realized oil-price volatility: The Role of financial stress and asymmetric loss. Journal of International Money and Finance, 104, 102137.

Hamilton, J.D. (2019). Measuring Global Economic Activity. Journal of Applied Econometrics. DOI: https://doi.org/10.1002/jae.2740.

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. American Economic Review, 99(3), 1053-1069.

Lux, T., Segnon, M., and Gupta, R. (2016). Forecasting crude oil price volatility and value-atrisk: Evidence from historical and recent data. Energy Economics, 56, 117-133.

McAleer, M., and Medeiros, M.C. (2008). Realized volatility: A review. Econometric Reviews, 27, 10-45.

Nguyen, D.K., and Walther, T. (2020). Modeling and forecasting commodity market volatility with long-term economic and financial variables. Journal of Forecasting, 39(2), 126-142.

Pan, Z., Wang, Y., Wu, C., and Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model. Journal of Empirical Finance, 43, 130–142.

Ravazzolo, F., and Vespignani, J. (Forthcoming). World Steel Production: A New Monthly Indicator of Global Real Economic Activity. Canadian Journal of Economics.

Salisu, A.A., and Ogbonna, A.E. (2019). Another look at the energy-growth nexus: New insights from MIDAS regressions. Energy, 174(C), 69-84.

Schwert, G.W. (1989). Why does stock market volatility change over time. Journal of Finance 44, 1115-1153.

Shiller, R.J. (1981a). Do Stock Prices Move Too Much to Be Justified by Subsequent Changes in Dividends. American Economic Review, 75, 421-36.

Shiller, R.J. (l981b) The Use of Volatility Measures in Assessing Market Efficiency. Journal of Finance, 36, 291-304.

Walther, T., Klein, T., & Bouri, E. (2019). Exogenous drivers of bitcoin and cryptocurrency volatility–a mixed data sampling approach to forecasting. Journal of International Financial Markets, Institutions and Money, 63, 101133.

van Eyden, R., Difeto, M., Gupta, R., andWohar, M.E. (2019). Oil price volatility and economic growth: Evidence from advanced OECD countries using over one century of data. Applied Energy, 233/234, 612-621.

Wei, Y., Liu, J., Lai, X., & Hu, Y. (2017). Which determinant is the most informative in forecasting crude oil market volatility: Fundamental, speculation, or uncertainty? Energy Economics, 68, 141–150.

Yin, L., and Zhou, Y. (2016). What Drives Long-term Oil Market Volatility? Fundamentals versus Speculation. Economics: The Open-Access, Open-Assessment E-Journal, 10, 1–26.

APPENDIX

Table A1: Predictive power of Economic Activity for Energy Spot Volatility (50% Sample)

Energy Price	Economic Activity	μ	α	β	θ	w	m
WTI	GECON	0.0006[0.0005]	0.0322***[0.0070]	0.9668***[0.0075]	-0.0958***[0.0334]	49.9150***[17.6760]	0.0007***[0.0003]
	RCPF	0.0006[0.0005]	0.0469***[0.0071]	0.9528***[0.0072]	-0.2001**[0.0996]	18.6610***[6.0805]	0.0022**[0.0011]
	GSPF	0.0006[0.0005]	0.0614***[0.0099]	0.9376***[0.0102]	-0.1164[0.0737]	48.7440[31.9490]	0.0023*[0.0012]
	RSCF	-0.0009*[0.0005]	0.0479***[0.0038]	0.9000***[0.0059]	0.0904***[0.0049]	4.9939***[0.0089]	0.0005***[0.0000]
	KINDX	0.0006[0.0005]	0.0851***[0.0079]	0.8855***[0.0113]	0.0189***[0.0070]	5.0248[3.4143]	0.0004***[0.0000]
	OECDIP	0.0105***[0.0006]	0.0472***[0.0027]	0.9002***[0.0078]	0.0160***[0.0006]	5.0289***[0.0161]	0.0004***[0.0000]
BRENT	GECON	0.0006[0.0005]	0.0334***[0.0085]	0.9657***[0.0092]	-0.0642***[0.0212]	49.9940*[26.7230]	0.0006***[0.0002]
	RCPF	0.0006[0.0005]	0.0268***[0.0064]	0.9733***[0.0066]	-0.0861***[0.0246]	15.9250***[3.6242]	0.0009***[0.0003]
	GSPF	0.0005[0.0005]	0.0448***[0.0102]	0.9546***[0.0105]	-0.0445[0.0327]	39.6850[41.3490]	0.0014***[0.0005]
	RSCF	0.0003[0.0005]	0.0369***[0.0072]	0.9629***[0.0073]	-0.4858*[0.2778]	1.3659***[0.3105]	0.0021**[0.0009]
	KINDX	0.0006[0.0005]	0.0594***[0.0115]	0.9403***[0.0116]	0.0181[0.0261]	49.5780[90.2370]	0.0043***[0.0013]
	OECDIP	0.0007[0.0004]	0.0269***[0.0049]	0.9717***[0.0056]	-0.0248***[0.0084]	5.9691***[1.6369]	0.0004***[0.0001]
HEATING OIL	GECON	0.0006[0.0005]	0.0242***[0.0057]	0.9740***[0.0061]	-0.0528***[0.0167]	47.1340**[23.4540]	0.0004***[0.0001]
	RCPF	0.0006[0.0005]	0.0344***[0.0062]	0.9650***[0.0062]	-0.0853*[0.0438]	29.3550**[12.4600]	0.0013**[0.0006]
	GSPF	0.0005[0.0005]	0.0439***[0.0071]	0.9549***[0.0073]	-0.0332[0.0280]	44.7640[46.5880]	0.0011**[0.0005]
	RSCF	0.0002[0.0004]	0.0340***[0.0058]	0.9653***[0.0058]	-0.1444[0.1064]	1.3608***[0.5229]	0.0010**[0.0004]
	KINDX	0.0008[0.0005]	0.1455***[0.0180]	0.8476***[0.0115]	0.0592[0.1067]	5.2042[5.7346]	0.0015[0.0024]
	OECDIP	0.0006[0.0004]	0.0232***[0.0049]	0.9737***[0.0051]	-0.0177***[0.0063]	4.4694***[1.6373]	0.0004***[0.0001]
NATURAL GAS	GECON	0.0000[0.0004]	0.0000[0.0003]	0.9987[178.9600]	-0.0658***[0.0013]	3.7817***[0.0281]	0.0001***[0.0000]
	RCPF	0.0000[0.0003]	0.0000[0.0075]	0.2959[237.8500]	-0.0656***[0.0014]	1.9424***[0.0187]	0.0002***[0.0000]
	GSPF	-0.0003[0.0004]	0.0001[0.0069]	0.3309[45.9520]	-0.1309***[0.0030]	2.2933***[0.0073]	0.0002***[0.0000]
	RSCF	-0.0005[0.0005]	0.0084***[0.0003]	0.9912***[0.0003]	-0.1203***[0.0062]	4.4691***[0.2447]	0.0010***[0.0000]
	KINDX	-0.0004[0.0006]	0.0032***[0.0003]	0.9968***[0.0005]	-0.0420***[0.0027]	2.3141***[0.1084]	0.0002***[0.0000]
	OECDIP	-0.0001[0.0004]	0.0040***[0.0003]	0.9934***[0.0005]	-0.0176***[0.0004]	4.5097***[0.2159]	0.0003***[0.0000]

Table A2: Predictive power of Economic Activity for Energy Future Volatility (50% Sample)

Energy Price	Economic Activity	μ	α	β	θ	w	m
WTI	GECON	0.0006[0.0006]	0.0291***[0.0068]	0.9698***[0.0074]	-0.0922***[0.0303]	49.9310***[17.4030]	0.0007***[0.0002]
	RCPF	0.0006[0.0005]	0.0428***[0.0069]	0.9569***[0.0069]	-0.1999**[0.0944]	20.1340***[6.1457]	0.0023**[0.0011]
	GSPF	0.0006[0.0005]	0.0517***[0.0088]	0.9475***[0.0091]	-0.1171*[0.0661]	49.6140*[29.4870]	0.0022**[0.0011]
	RSCF	0.0002[0.0006]	0.0500***[0.0044]	0.9000***[0.0073]	0.0997***[0.0054]	4.9999***[0.0085]	0.0006***[0.0000]
	KINDX	0.0006[0.0004]	0.0714***[0.0066]	0.9263***[0.0071]	0.0068[0.0161]	4.9650***[1.7631]	0.0001[0.0003]
	OECDIP	0.0006[0.0005]	0.0410***[0.0065]	0.9543***[0.0068]	-0.0372***[0.0101]	8.0848***[1.8927]	0.0005***[0.0001]
BRENT	GECON	0.0006[0.0005]	0.0314***[0.0071]	0.9675***[0.0078]	-0.0748***[0.0259]	42.2450**[18.9600]	0.0006***[0.0002]
	RCPF	0.0006[0.0005]	0.0373***[0.0065]	0.9625***[0.0066]	-0.1535**[0.0683]	22.4450***[6.9654]	0.0018**[0.0008]
	GSPF	0.0008[0.0005]	0.1495***[0.0156]	0.8306***[0.0208]	0.0872*[0.0497]	5.7990[4.7231]	0.0006*[0.0003]
	RSCF	0.0003[0.0005]	0.0554***[0.0083]	0.9440***[0.0084]	-0.4385[0.4090]	1.1562***[0.2759]	0.0020[0.0014]
	KINDX	0.0007[0.0005]	0.0595***[0.0101]	0.9116***[0.0155]	0.0674***[0.0164]	1.3660***[0.1271]	0.0005***[0.0001]
	OECDIP	0.0007[0.0004]	0.0341***[0.0059]	0.9617***[0.0065]	-0.0222***[0.0066]	6.0327***[1.8901]	0.0004***[0.0001]
HEATING OIL	GECON	0.0006[0.0005]	0.0156***[0.0047]	0.9843***[0.0051]	-0.0582***[0.0166]	48.9100**[24.3190]	0.0005***[0.0001]
	RCPF	0.0007[0.0005]	0.0252***[0.0061]	0.9747***[0.0063]	-0.0872**[0.0348]	19.5870**[7.9019]	0.0012***[0.0005]
	GSPF	0.0006[0.0005]	0.0294***[0.0079]	0.9702***[0.0081]	-0.0405[0.0249]	38.0760[37.3390]	0.0012***[0.0004]
	RSCF	0.0005[0.0005]	0.0503***[0.0054]	0.9001***[0.0091]	0.0279***[0.0017]	4.9969***[0.0159]	0.0004***[0.0000]
	KINDX	0.0006[0.0005]	0.0243***[0.0068]	0.9754***[0.0070]	0.0124*[0.0067]	26.9230*[14.7480]	0.0011***[0.0003]
	OECDIP	0.0010[0.0007]	0.0504***[0.0024]	0.9000***[0.0048]	0.0902***[0.0072]	5.0000***[0.0048]	0.0012***[0.0001]
NATURAL GAS	GECON	-0.0001[0.0009]	0.0331***[0.0100]	0.9314***[0.0222]	-0.1899***[0.0334]	3.0133***[0.3328]	0.0006***[0.0001]
	RCPF	-0.0001[0.0009]	0.0452***[0.0095]	0.9388***[0.0133]	-0.2745**[0.1303]	1.4823***[0.2406]	0.0013***[0.0002]
	GSPF	-0.0001[0.0009]	0.0466***[0.0096]	0.9318***[0.0148]	-0.3121***[0.0963]	1.8025***[0.2326]	0.0010***[0.0001]
	RSCF	-0.0006[0.0008]	0.0444***[0.0091]	0.9418***[0.0120]	-0.0108[0.0077]	37.1620[41.1980]	0.0009***[0.0001]
	KINDX	-0.0002[0.0009]	0.0483***[0.0095]	0.9396***[0.0121]	0.0121[0.0267]	4.8895[11.2620]	0.0011***[0.0002]
	OECDIP	-0.0001[0.0006]	0.0478***[0.0082]	0.9373***[0.0107]	-0.0114[0.0093]	45.0050[126.5200]	0.0009***[0.0001]