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Forecasting the return volatility of energy prices: A GARCH-MIDAS approach

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Abstract

This paper offers an extension to the literature on energy prices by forecasting the return volatility of these prices using the GARCH-MIDAS approach. In addition to the realized volatility, it also evaluates the predictability of relevant macroeconomic information such as industrial growth and consumer prices (with and without energy components) in the predictive model for the return volatility of energy prices. The analyses are distinctly conducted for full-sample, pre-GFC and post-GFC periods. On average, the findings support the inclusion of these macroeconomic information particularly output growth and realized volatility as they yield good in-sample and out-of-sample predictability results for the return volatility. However, the paper finds contrasting evidence between the pre-GFC and post-GFC periods.

JEL Classification: C53; Q47
Key words: GARCH-MIDAS; energy prices; return volatility; realized volatility, industrial production, inflation

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1.0 Introduction

The traditional and common approach of modeling and forecasting in econometrics involves the use of data sampled at the same frequency. The choice of variables in the forecast model in this case is often restricted to those that meet this condition which may affect forecast performance (see Ghysels *et al*., 2015). However, with the emergence of the Mixed Data Sampling (MIDAS) regression and its variants, allowing for macroeconomic (low frequency) variables when forecasting (high frequency) financial series such as stock price, bond price, exchange rate and interest rate, for example, is realizable (see Ghysels *et al*., 2006; Clements and Galvão, 2010; and Ghysels *et al*., 2015, for a review). The computational advantages of using the MIDAS regressions are well documented in Andreou *et al*. (2013).

In this paper, we employ the univariate GARCH-MIDAS approach proposed by Engle, Ghysels and Sohn (2013) to forecast the return volatility of energy prices. Other variants of the MIDAS regressions are the MIDAS-ADL (MIDAS Autoregressive Distributed Lag) regression, MIDAS Quantile regression, and DCC-MIDAS (the multivariate extension to the GARCH-MIDAS model with dynamic conditional correlations (DCC)). However, we favour the GARCH-MIDAS over other univariate variants of the MIDAS regressions as the former accounts for conditional heteroscedasticity which is a prominent feature of most energy prices (see Narayan and Liu, 2015). Information about the volatility of energy prices is crucial for the valuation of cost of production. In other words, as long as energy continues to serve as input to production, producers of goods and services and by implication, final consumers will be constantly exposed to risk as changes in the volatility of energy prices persist. Also, there is a strong positive link between energy prices and inflation; higher energy prices drive a higher rate of inflation (see Salisu *et al*, 2017). Similarly, there is a high correlation between energy prices and agricultural commodity prices; a rise in energy price increases the price of agricultural commodity (see Koirala *et al*., 2015). Thus, information on the extent of volatility in energy prices is useful for commodity derivatives valuation as well as hedging decisions. In addition, a number of studies examining the link between energy consumption and growth have demonstrated different forms of causality (growth hypothesis, conservation hypothesis and feedback hypothesis) between the two variables and therefore unfavourable trends in energy prices may adversely impact on energy consumption and by extension exert a drag on economic growth (see Omri, 2014). Overall, understanding the extent of changes in volatility of energy prices is important for effective investment and policy decisions.

We utilize daily spot prices of seven US energy commodities namely crude oil, gasoline, heating oil, diesel, jet fuel, propane and natural gas. We also consider monthly data on industrial production index and inflation as proxies for real economic activities and macroeconomic uncertainty respectively; in addition to using the realized monthly volatility of the return series of energy prices. The inclusion of these exogenous factors in the model somewhat follows the Arbitrage Pricing Theory which assumes that asset returns are driven by macroeconomic risks such as output volatility, inflation uncertainty, among others. To the best of our knowledge, this is the first paper to examine the return volatility in the selected energy prices using the GARCH-MIDAS approach with exogenous variables whose inclusion is theoretically motivated. A closely related paper to ours is the Valadkhani and Smyth (2017); however, we differ both in terms of the direction of relationship and methodology. In their paper, the objective was to examine the impact of the movements in high frequency (daily) oil prices on low frequency output variable while the reverse is the case in our paper. We evaluate how low frequency predictors including output can affect the high frequency energy prices including oil price. As the dependent variable is susceptible to conditional heteroscedasticity, the GARCH variant of the MIDAS framework becomes inevitable in our case. This partly explains why the Autoregressive Distributed Lag (ADL) variant of the MIDAS regression, which ignores conditional heteroscedasticity, is employed in the Valadkhani and Smyth (2017) study. The ADL-MIDAS may be valid in the latter case since the dependent variable is of low frequency which is less likely to exhibit conditional heteroscedasticity. In addition, our analyses capture prominently consumed energy commodities in the US including oil price and therefore we are able to offer some meaningful generalizations about the predictability of the selected macroeconomic indices in forecasting the return volatility of energy prices. Thus, the consideration of energy prices in the practical application of GARCH-MIDAS for forecasting constitutes the main contribution of this paper to the literature on energy modeling.

The remaining part of this paper is structured as follows: Section 2 provides a brief review of the literature; Section 3 provides the model set up including estimation procedure and data issues; Section 4 deals with the discussion of preliminary and main results including in-sample and out-of-sample forecast results; and Section 6 concludes the paper.

2.0 A review of the literature on forecasting with energy prices

Contemporary empirical literature on forecasting the energy price volatilities have taken various dimensions. A strand of the literature approach this issue by investigating the forecast of energy price volatilities with other macroeconomic fundamentals (see Kristjanpoller and Minutolo, 2016; Degiannakis and Filis, 2017; Pan *et al*., 2017). Most of these studies however focus on oil price volatilities in isolation of other prominent energy prices. Nonetheless, they differ in terms of methodological approaches adopted. While Degiannakis and Filis, (2017) employ the heterogeneous autoregressive (HAR) model, others adopt multivariate GARCH models such as Artificial Neural Network (ANN)-GARCH model (see Kristjanpoller and Minutolo, 2016) and a regime switching GARCH-MIDAS model (see Pan *et al*., 2017).

Although these studies highlight the importance of macroeconomic variables in predicting future oil return volatility, they examine different macroeconomic fundamentals. For instance, Degiannakis and Filis (2017) confirm that information from four asset classes (that is, stocks, foreign exchange, commodities and bonds) enhance the predictive accuracy of oil price realized volatility at all forecast horizons. Also, Kristjanpoller and Minutolo (2016) show that financial variables such as the Euro/Dollar and Yen/Dollar exchange rates, and the DJIA and FTSE stock market indexes are important to the volatility of oil spot and futures prices. Meanwhile, Pan *et al*. (2017) find that both level and volatility of oil supply and demand have significant impacts on oil price volatility.

Another strand of current empirical literature seeks to tie variations in agricultural commodity prices to volatility in energy prices (see Koirala *et al*., 2015; Cabrera and Schulz, 2016). These studies investigate the nature of linkages between different energy futures prices and agricultural commodities futures prices, albeit in different countries. One is a study on Germany using the Dynamic Conditional Correlation (DCC) - GARCH model (see Cabrera and Schulz, 2016) while the other focuses on the US and adopts the copula modelling technique (see Koirala et al., 2015).

Results from these studies are mixed. Findings from Cabrera and Schulz (2016) establish that the concern that biofuel is the cause of high and volatile food prices is unfounded. On the other hand, Koirala *et al*. (2015) conclude that increases in the energy prices of natural gas, crude oil, motor gasoline, diesel, and biodiesel would increase agricultural future prices of corn, soybean, and cattle. This indicates that higher energy prices lead to higher costs of production for agricultural commodities.

Another focal point of the recent empirical literature in this line of inquiry is the study of the interdependencies among energy prices (see Koto, 2015; Ziel et al., 2015; Manera *et al*., 2016; Baruník and Krehlík, 2016; Serletis and Xu, 2016; Xian *et al*., 2017; Apergis *et* *al*., 2017). These studies however approach the issue from different perspectives, adopting varying methodologies and evaluating different classes of energy prices. For instance, Koto (2015) considers the prices of gasoline, ethanol, natural gas, and crude oil prices with Threshold Autoregressive (TAR) models; Manera *et al*. (2016) focus on crude oil, heating oil, gasoline and natural gas markets, adopting a plethora of GARCH models; Baruník and Krehlík (2016) analyse the crude oil, heating oil, and natural gas and compare the HAR and ARFIMA models against the ANN model; Serletis and Xu (2016) accommodate oil, natural gas, and coal into a trivariate BEKK model; and Ziel *et al*. (2015), Xian *et al*. (2017), and Apergis *et al.* (2017) adopt various GARCH models and divide energy market into renewable and non-renewable energy sources.

In terms of empirical evidence, these studies yield results in support of interactions and spillover effects among the energy prices and their volatilities (see Ziel *et al*., 2015; Manera *et al*., 2016; Baruník and Krehlík, 2016; Serletis and Xu, 2016; Apergis *et al*., 2017). Results from the other side of the divide however do not reveal evidence in support of energy price volatility interdependencies (see Koto, 2015; Xian *et al*., 2017).

In passing, the debilitating effects of the volatility of energy markets have been linked to uncertainties and distrusts among energy companies, investors, consumers, regulators, and legislators (see Baruník and Krehlík, 2016). This has driven researches aimed at modelling and forecasting energy price volatility to aid hedging, derivatives trading and policy decisions. The interdependencies of energy prices volatilities suggesting spillover effects have been explored, but with restricted classes of energy fuels compared with the present study. Also, attempts at forecasting energy prices volatilities with macroeconomic information have largely been limited to oil, excluding other biofuels. Further, findings from these studies have remained inconclusive. The foregoing therefore represents the gap in the literature to which this study attempts to fill.

3.0 Methodology

3.1 The Model

Following the works of Engle *et al.* (2013) and Asgharian *et al.* (2013), we specify the GARCH-MIDAS framework used to forecast the return volatility of energy prices as follows:

$$r_{it} = \mu + \sqrt{\tau_t g_{it} \varepsilon_{it}} \tag{1}$$

$$g_{it} = (1-\alpha-\beta) + \alpha \frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t} + \beta g_{i-1,t} \tag{2}$$

$$\tau_t = m + \theta \sum_{k=1}^{K} \psi_k(\omega) \mathrm{V}_{t-k} \tag{3}$$

$$\mathrm{V}_t = \sum_{i=1}^{N} r_{it}^2 \tag{4a}$$

$$\mathrm{V}_t = \frac{1}{N} \sum_{i=1}^{N} x_{it} \tag{4b}$$

$$\psi_k(\omega) \mu \left(1-\frac{k}{K}\right)^{w-1} \tag{5a}$$

$$\psi_k(\omega) \mu \left(1-\frac{k}{K}\right)^{w_1-1} \left(\frac{k}{K}\right)^{w_2-1} \tag{5b}$$

where r_{it} denotes return series computed as log difference of day i in month t. The conditional variance is partitioned into the short-run component (g_{it}) (see equation (2)) and the long-run component (see equation (3)). Note that the short run component has GARCH (1, 1)-like while the long-run component is determined by the realized volatility or macroeconomic series. The variable V_t in equation (4a) is the realized volatility of the month while the V_t in equation (4b) represents the monthly average of an exogenous variable (such as a monthly macroeconomic variable whose value x_{it} is fixed for i = 1, … , N). As previously mentioned, the macroeconomic series of interest are industrial production index, a proxy for real economic activities and inflation, a proxy for macroeconomic uncertainty. A long history of V_{t-1}, V_{t-2}, V_{t-3}, …, V_{t-K}

weighted by Beta polynomials (see equation (5a) or (5b)) captures the long-run volatility.

3.2 Estimation Procedure

The analyses are partitioned into Full Sample and Sub-Samples. The latter involves the Pre-GFC[1] and the Post-GFC. Indeed, the US energy sector has witnessed significant structural changes since the global financial crisis (see EIA, 2009). As shown in figures 1 to 7, all the energy prices were moderately stable until the period of global financial crisis beyond which the trends became more unsteady and appear to follow irregular patterns. Thus, we further verify whether the chosen predictors matter for forecasting the return volatility of the US energy prices even in the presence of structural shifts (that is, regardless of the sub-periods).

For each of the data samples, we singly include the Realized Volatility, Industrial Production Index and Inflation as predictors of the return volatility of US energy prices. The predictability of each of the predictors under the different data scenarios is evaluated based on the significance of the corresponding coefficient in the conditional variance equation. Thereafter, we evaluate their in-sample and out-of-sample forecast performance. We use the 50% of the observations (see Narayan and Gupta, 2014) and balance forms the scope for the out-of-sample forecast. The rolling window approach, in which the long-run component varies every period, is used to generate the forecast results. This is particularly useful when forecasting series that are susceptible to structural changes such as the energy prices.

For the in-sample analyses, our focus is to essentially test the null hypothesis of no predictability for each of the considered predictors and we further complement this outcome by assessing the in-sample forecast accuracy of the predictive models. In other words, the in-sample forecast evaluation involves testing how the predictive models are

[1] GFC denotes Global Financial Crisis.

able to reproduce the actual data. Nonetheless, the out-of-sample forecast evaluation is also required to ascertain the ability of the model to produce accurate forecasts beyond the estimation period.

3.3 Data Issues

We consider daily spot prices of seven US energy commodities namely Crude Oil (West Texas Intermediate), New York Harbor Conventional Gasoline Regular, New York Harbor Heating Oil, Ultra-Low Sulfur Diesel, Gulf Coast Kerosene-Type Jet Fuel , Texas Propane and Natural Gas. The unit of measurement for all the prices is in US Dollar per Barrel with the exception of Natural Gas price that is quoted in US Dollar per Million Btu. The U.S Energy Information Administration is the main source of all the energy prices considered. Table 1 below shows the distribution of the data in terms of start date and end date. It can be seen from the table that all the series have different start dates but a common end date. This is exactly the way the data are structured in the US EIA database.[2]

As demonstrated under the estimation procedure, the GARCH-MIDAS allows for the inclusion of macroeconomic series usually collected at a low frequency in the modeling and forecasting of high frequency series like the energy prices. The monthly data for the macroeconomic series considered in this study, which are industrial production index and inflation, are available as far back as 1950. However, for the purpose of estimation, the sample data are restricted to the scope of each of the energy prices. For robustness check, we utilize both headline inflation and core inflation in the predictive model for the return volatility. The core inflation excludes the volatile components of the headline inflation such as food and energy and therefore it does make sense to ascertain whether the effect of macroeconomic uncertainty (where inflation serves as a proxy) on the

[2] The same data samples were used in the paper of Narayan and Liu (2015) to illustrate the relevance of using the GARCH-based unit root test when dealing with high frequency and trending time series. However, we have further updated the datasets to account for current realities.

return volatility of energy price is not due to the volatile components. Data for the macroeconomic series are obtained from the Bloomberg terminal.

Table 1: Distribution of US energy price data

Energy Series	Start date	End date	No. of Observations
Diesel	4/17/1996	4/28/2017	5289
Gasoline	6/02/1986	4/28/2017	7781
Heating Oil	6/02/1986	4/28/2017	7777
Jet Fuel	4/02/1990	4/28/2017	6812
Natural Gas	1/13/1994	4/28/2017	5835
Propane	7/09/1992	4/28/2017	6227
WTI	4/04/1983	4/28/2017	8546

4.0 Results

4.1 Preliminary Analyses

In this section, we assess the descriptive properties of the energy return series with statistics such as the mean, skewness, kurtosis and standard deviation to comment on the nature of the distribution of the series. We structure the data into full sample, pre-GFC, and post-GFC. The descriptive statistics are reported in Table 2 while Table 3 presents the results for the serial correlation and heteroscedasticity tests. The descriptive analyses reveal similar mean values for diesel, natural gas and crude oil on one hand and gasoline, heating oil, jet fuel and propane on the other hand for full sample. We do not however obtain the same pattern for the pre-GFC sample period as all the return series have similar average values. For the post-GFC era, the mean energy return values are close except for natural gas and propane that are slightly different. A point that is worthy of note here is that the mean returns are all positive values in full sample and pre GFC while they are all negative in post-GFC era.

Further descriptive analyses from the skewness statistics reveal that majority of the daily energy return series (gasoline, heating oil, jet fuel, propane, and crude oil) are negatively skewed while only diesel and natural gas are positively skewed over full sample. However, during pre-GFC, all except heating oil, propane, and crude oil are positively skewed. In the post-GFC era however, only diesel, gasoline and propane returns are negatively skewed. An inspection of the kurtosis values indicates uniformity in the behaviour of the series as all them have their kurtosis values greater than three; and hence, exhibit leptokurtic distribution across full sample, pre- and post-GFC. The foregoing therefore provides convincing evidence that the energy returns are not normally distributed.

Table 2: Descriptive statistics of the return series

Statistics	Energy Type	Full Sample	Pre-GFC	Post-GFC
Mean	Diesel	0.00969	0.03075	-0.01444
	Gasoline	0.01401	0.04021	-0.01411
	Heating Oil	0.01635	0.04028	-0.01529
	Jet Fuel	0.01397	0.04490	-0.01676
	Natural Gas	0.00687	0.02986	-0.02233
	Propane	0.01042	0.04409	-0.02871
	WTI	0.00604	0.03865	-0.01731
Standard deviation	Diesel	2.36035	2.49375	2.19411
	Gasoline	2.61428	2.87655	2.55570
	Heating Oil	2.51587	2.83568	2.17507
	Jet Fuel	2.55930	2.66741	2.38182
	Natural Gas	3.57324	3.85387	3.08599
	Propane	2.47457	2.61791	2.49171
	WTI	2.39213	2.33502	2.51284
Skewness	Diesel	0.10132	0.32436	-0.29508
	Gasoline	-0.23063	0.09842	-0.34511
	Heating Oil	-1.43258	-1.75531	0.04726
	Jet Fuel	-0.47435	-0.21612	0.31120
	Natural Gas	0.22785	0.37590	0.63787
	Propane	-1.74312	-3.35292	-0.47661
	WTI	-0.71157	-0.27165	0.16746
Kurtosis	Diesel	13.6474	15.37147	9.61252
	Gasoline	10.7110	6.54933	12.2855
	Heating Oil	38.3354	44.5307	7.29701
	Jet Fuel	19.5834	6.23350	28.1943
	Natural Gas	9.88985	7.81420	7.25183
	Propane	50.9006	72.4551	8.15323
	WTI	17.3329	6.10518	7.48704

Having evaluated the distribution of the energy return series, we analyse the standard deviation values to comment on the return volatility of the energy prices. Although the standard deviation values seem to suggest clustering of the volatility, diesel and crude oil are the least volatile while natural gas price seems to most volatile. In between are propane, heating oil, jet fuel and gasoline for the full sample and pre-GFC periods. For the post-GFC period however, heating oil and diesel returns are the least volatile while natural gas is still the most volatile energy fuel. The movements in both the level and return series of energy prices are also rendered graphically (see Figures 1 to 7). It evident that there is a notable shift in the level energy prices which coincides with the period of the global financial crisis and that explains why it may be necessary to partition analyses involving such trends into pre- and post-GFC periods.

We proceed to test for the presence of heteroscedascitity and serial correlation in the data in order to formally justify the suitability of a GARCH-based approach for modelling energy returns (see Table 3). We employ the ARCH-LM test for heteroscedasticity and the Q- and Q^2-Statistics for serial correlation. We run both tests using 5, 10 and 20 lag lengths across the full sample, pre-GFC and post-GFC data samples. The results of the ARCH-LM test reject the null hypothesis of no ARCH effects in the energy price returns at the 1 per cent significance level regardless of the lag order. We complement the ARCH-LM test with the serial correlation test and the results are also reported in Table 3. The results also largely suggest the presence of statistically significant serial correlations regardless of the sample period. This further reinforces the suitability of a GARCH-based framework for modelling and forecasting the return volatility of energy prices.

Table 3: Serial Correlation & Heteroscedasticity Tests

Lag Structure	Energy Type	Full Sample	Pre-GFC	Post-GFC
		ARCH LM Test		
(5)	Diesel	154.539***	117.043***	23.7243***
	Gasoline	174.473***	133.663***	76.0801***
	Heating Oil	248.403***	156.361***	54.0616***
	Jet Fuel	125.614***	69.9640***	122.491***
	Natural Gas	56.440***	24.5140***	17.8240***
	Propane	39.091***	15.2570***	56.7071***
	WTI	106.683***	13.1695***	91.1643***
(10)	Diesel	77.568***	58.3455***	15.9979***
	Gasoline	89.150***	67.4703***	40.6088***
	Heating Oil	136.359***	99.9119***	30.9380***
	Jet Fuel	69.916***	41.9138***	80.4388***
	Natural Gas	30.757***	14.38139***	12.3658***
	Propane	19.630***	7.63607***	31.0950***
	WTI	61.200***	6.74113***	55.0213***
(20)	Diesel	39.585***	29.7945***	11.1356***
	Gasoline	45.943***	34.2455***	22.6261***
	Heating Oil	75.811***	62.4467***	18.7926***
	Jet Fuel	35.930***	27.9428***	41.3318***
	Natural Gas	20.587***	9.28462***	8.99689***
	Propane	10.289***	4.06279***	17.42901***
	WTI	32.965***	3.99354***	33.5791***
		Serial Correlation (Q Stat) Test		
(5)	Diesel	37.021***	35.505***	15.588***
	Gasoline	27.386***	24.921***	20.317***
	Heating Oil	38.164***	50.931***	9.3015*
	Jet Fuel	14.921**	5.8335	11.224**
	Natural Gas	23.221***	7.6319	29.403***
	Propane	28.358***	27.268***	46.607***
	WTI	44.164***	8.0289	17.489***
(10)	Diesel	39.051***	39.736***	19.636*
	Gasoline	53.783***	34.096***	32.477***
	Heating Oil	52.271***	65.266***	12.066
	Jet Fuel	30.190***	14.137	22.694**
	Natural Gas	37.166***	12.283	39.506***
	Propane	36.624***	36.310***	50.535***
	WTI	57.021***	15.549	18.304***
(20)	Diesel	55.082***	51.070***	33.472*
	Gasoline	85.193***	41.801***	53.842***
	Heating Oil	67.821***	84.477***	28.108
	Jet Fuel	57.931***	48.303***	33.225**
	Natural Gas	51.722***	28.500*	54.364***
	Propane	63.495***	57.605***	83.286***
	WTI	69.984***	29.166*	38.265***
		Serial Correlation (Q^2 Stat) Test		
(5)	Diesel	1014.4***	725.25***	160.84***
	Gasoline	1084.1***	832.25***	383.49***

	Heating Oil	1791.0***	1078.1***	316.97***
	Jet Fuel	782.80***	514.72***	645.58***
	Natural Gas	374.41***	160.71***	114.33***
	Propane	254.20***	92.180***	454.51***
	WTI	730.76***	78.261***	764.27***
(10)	Diesel	1041.9***	727.20***	278.56***
	Gasoline	1192.1***	844.73***	443.97***
	Heating Oil	1975.8***	1168.2***	452.96***
	Jet Fuel	888.67***	820.72***	659.57***
	Natural Gas	472.91***	222.21***	205.17***
	Propane	265.09***	94.354***	647.66***
	WTI	995.27***	86.931***	1401.9***
(20)	Diesel	1078.7***	728.96***	278.56***
	Gasoline	1358.6***	869.67***	443.97***
	Heating Oil	2160.3***	1261.4***	783.35***
	Jet Fuel	1044.5***	1383.7***	690.84***
	Natural Gas	746.79***	329.64***	370.12***
	Propane	287.39***	101.88***	896.22***
	WTI	1378.4***	107.93***	2501.5***

Note: *, **, * represent significance at 1%, 5%; and 10% respectively.**

Figure 1: Trends in U.S Diesel Spot Prices and Returns

Figure 1.1: Daily Diesel Spot Prices

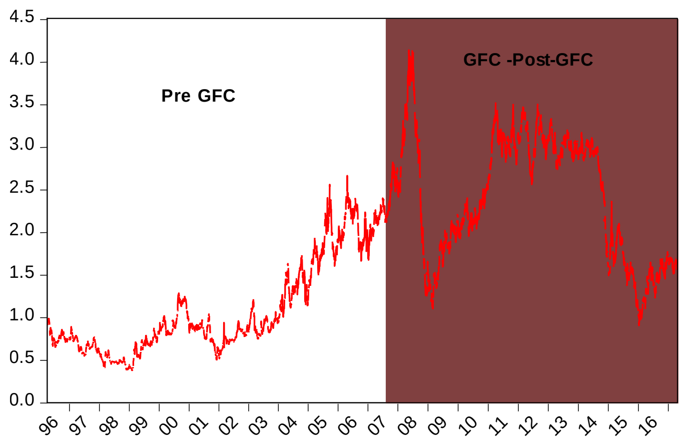


Figure 1.2: Daily Diesel Spot Returns

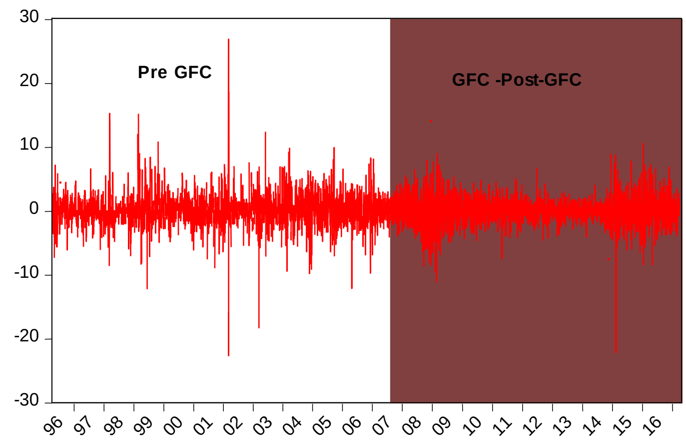


Figure 2: Trends in U.S Gasoline Spot Prices and Returns

Figure 2.1: Daily Gasoline Spot Prices

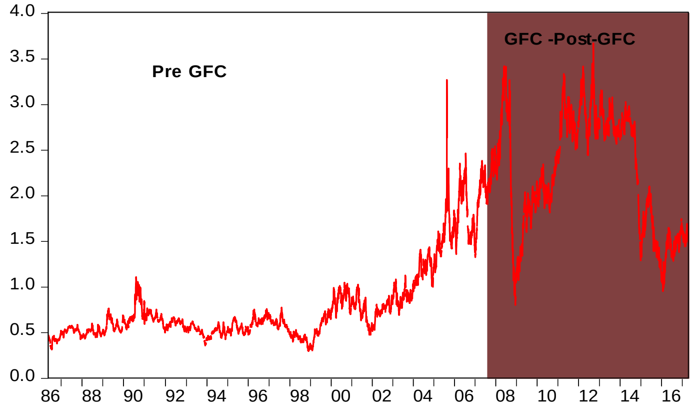


Figure 2.2: Daily Gasoline Spot Returns

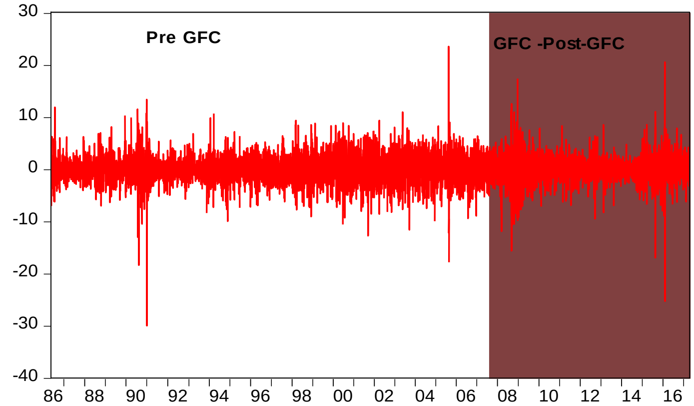
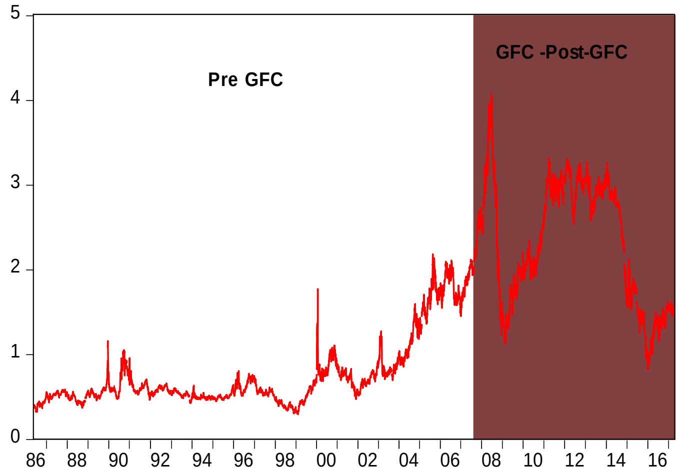


Figure 3: Trends in U.S Heating Oil Spot Prices and Returns

Figure 3.1: Daily Heating Oil Spot Prices



Fogure 3.2: Daily Heating Oil Spot Returns

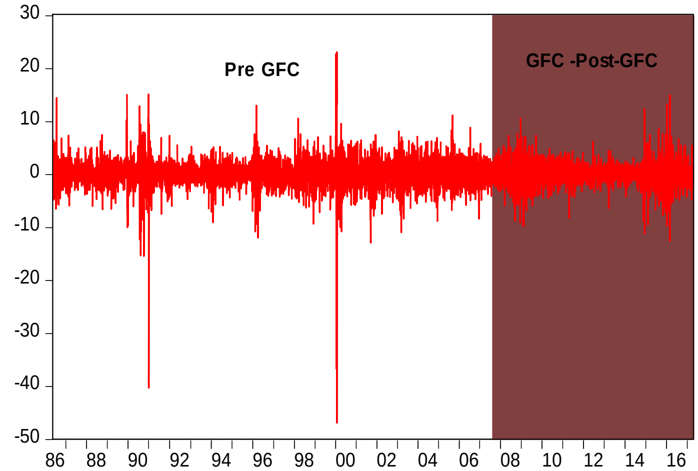


Figure 4: Trends in U.S Jet Fuel Spot Prices and Returns

Figure 4.1: Daily Jet Fuel Spot Prices

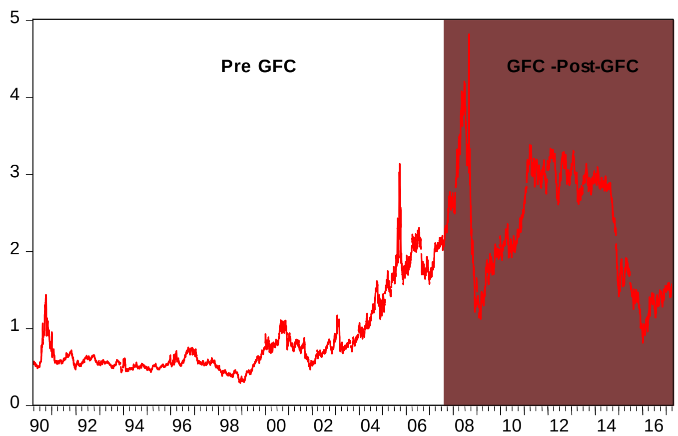


Figure 4.2: Daily Jet Fuel Spot Returns

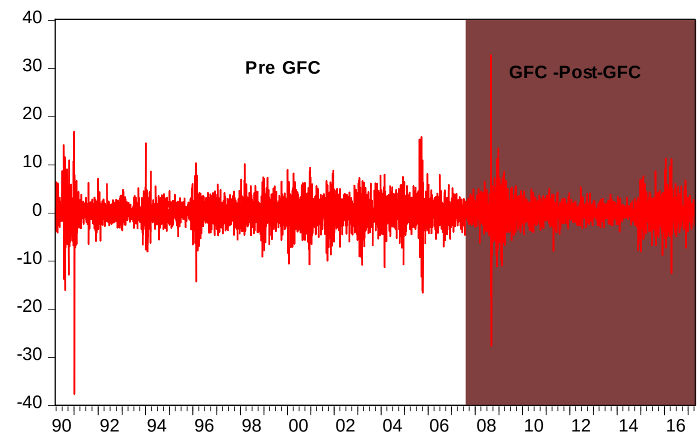


Figure 5: Trends in U.S Natural Gas Spot Prices and Returns

Figure 5.1: Daily Natural Gas Spot Prices

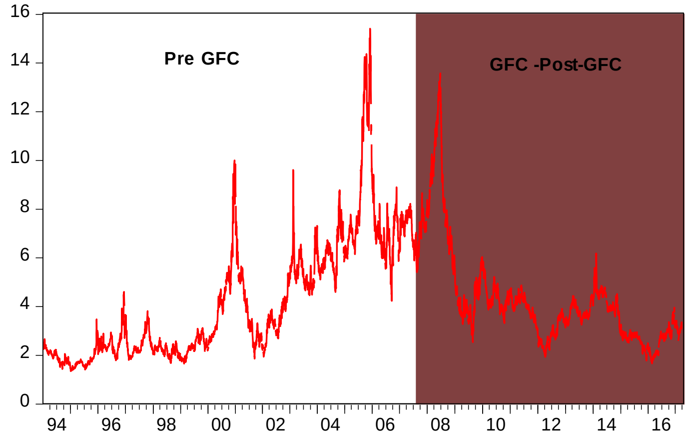


Figure 5.2: Daily Natural Gas Spot Returns

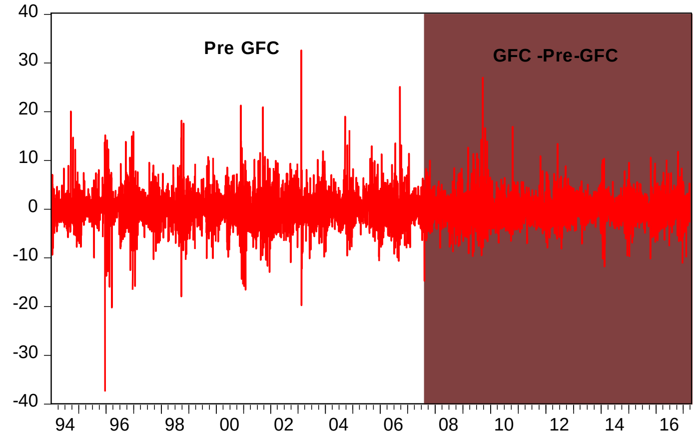


Figure 6: Trends in U.S Propone Spot Prices and Returns

Figure 6.1: Daily Propane Spot Prices

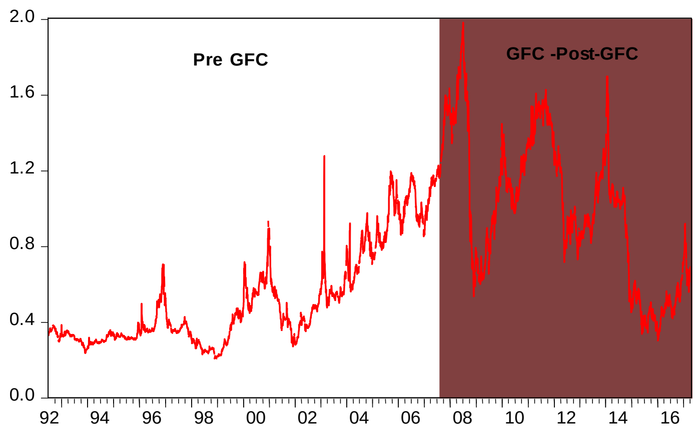


Figure 6.2: Daily Propane Spot Returns

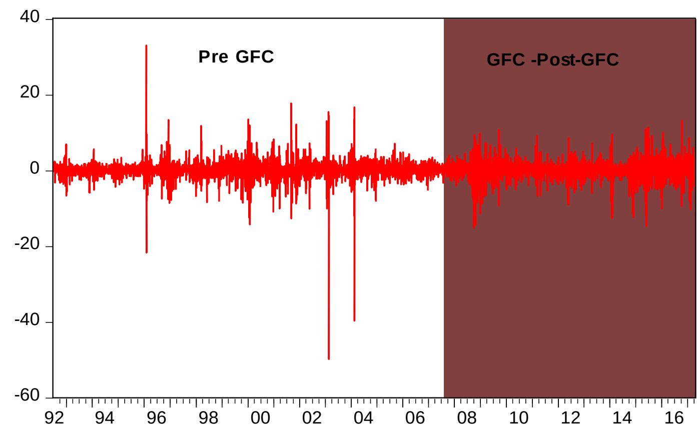


Figure 7: Trends in WTI Crude Oil Spot Prices and Returns

Figure 7.1: Daily Crude Oil Spot Prices

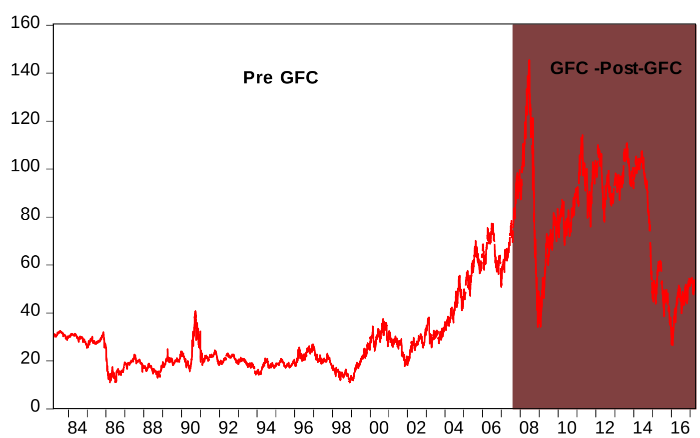
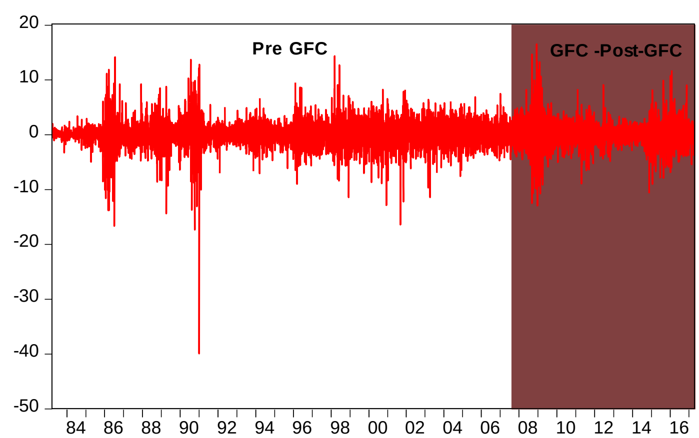


Figure 7.2: Daily Crude Oil Spot Returns



4.2 Predictability Test Results

4.2.1 Full Sample

Given the motivation of this study, we obtain information from realized volatility and two prominent macroeconomic variables namely growth in industrial production and inflation to test whether these variables can help predict the return volatility of energy prices. Although, the realized volatility is used measure macroeconomic volatility in the GARCH-MIDAS framework, however, the additional exogenous variables included become necessary as the former could be a noisy proxy (see Engle et al., 2013). We also test whether the return volatility is sensitive to the choice of measure for inflation. In other words, we consider both headline inflation and core inflation and thereafter we test the significance of the two measures in predicting energy prices. The tests are conducted for the full sample as well as for the pre-GFC and post-GFC sub-periods. The predictability performance results are contained in Table 6. These are evaluated based on the significance or otherwise of the respective coefficients of each of the predictors.

Our results are mixed for the three time periods studied. For the full sample (see Table 4), our results reveal that virtually all the macroeconomic information considered; realized volatility, output, headline, and core inflation appear as consistent potential predictors of diesel, jet fuel, natural gas, propane and crude oil volatility returns. This evidence is not unexpected since increased productive activities imply a higher consumption of energy products that are used in the production process such as those that are found to respond significantly to the movements in industrial output. Similarly, the co-movement between inflation (both headline and core) and energy prices captures the demand side of the energy in which case increased demands for goods and services may cause the demand for energy products to increase (and by extension energy prices) in order to increase supply to meet such demands. The nexus between CPI-inflation and energy prices in our study particularly for crude oil and diesel prices is consistent with findings from Koirala *et al*. (2015); Cabrera and Schulz (2016); and Al-Madid et al. (2017). Koirala et al. (2015) adopt copula modeling approach; Cabrera and Schulz (2016) employ the DCC-GARCH model; while Al-Madid *et al*. (2017) apply the VAR-GARCH framework to establish the significant linkages between volatilities in energy and other prices (i.e. food & agricultural prices). These studies are however less encompassing compared to our study given that we assess return volatilities in energy prices and thereafter evaluate the forecast performance of relevant predictors for a broader number of energy commodities.

In addition, the significance of both realized volatility and industrial growth seems to be in tandem with the results from contemporary researches such as Antonakakis et al. (2014); Karali and Ramirez (2014); Degiannakis and Filis (2017) and Pan et al. (2017). These studies highlight the importance of realized volatility, production and the level of global economic activities in providing information for predicting energy volatility. However, a major drawback in comparing our study with these previous works is that they restricted their analysis to oil price volatility excluding other energy prices.

4.2.2 Pre-GFC vs Post-GFC

Results obtained in the pre-GFC sample period stand in contrast with those of the full sample (see Table 4). For the pre-GFC sample, all the four variables appear as potential predictors of diesel, gasoline and propane return volatilities. Realized volatility, headline and core inflation are the likely predictors of heating oil and natural gas return volatilities. While our results show output, headline and core inflation as potential predictors of jet fuel, only endogenous shocks (realized volatility) and core inflation could likely predict crude oil return volatility in the period before the global financial crisis. Core inflation is the only consistent potential predictor of all the energy returns in this period. This implies that the return volatility of energy prices responds more prominently to volatility in non-energy consumer prices during the pre-GFC period (see also Koirala et al., 2015; Cabrera and Schulz, 2016; and Al-Madid *et al.,* 2017)

Contrary to the pre GFC but in unison with the full sample results, realized volatility and output emerge as consistent potential predictors of all the seven energy returns in the post-GFC. We can therefore safely infer that the findings of Antonakakis, *et al* (2014); Karali and Ramirez (2014); Pan *et al.* (2017); Degiannakis and Filis (2017) are relevant in the post GFC era. Further in this period, headline inflation (which contains information about energy prices) is shown as a more consistent potential predictor of energy returns than core inflation. This finding also indicates that the submissions of Koirala et al. (2015); Cabrera and Schulz (2016); and Al-Madid et al. (2017) are valid for the post-GFC period.

In sum, three major conclusions are distinct from the in-sample predictability results. First, on average, the realized volatility and output offer more useful information for predicting energy return volatility than inflation. Second, the impact of these predictors tends to be more pronounced in the post-GFC period than the pre-GFC period. Third, the information about energy prices contained in headline inflation enhances its predictability of energy returns.

Table 4: In-sample predictability performance results

Energy	**Full Sample**				**Sub-Sample**							
					Pre-GFC				**Post-GFC**			
	V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}	
			CPI	CPIC			CPI	CPIC			CPI	CPIC
Diesel	-0.00305***	-0.05237***	-0.2372***	0.0732**	0.01856***	0.02010**	-0.46328***	-0.40439**	0.01021***	-0.03364***	-0.06264**	-0.007567
	(0.00057)	(0.01000)	(0.05568)	(0.03266)	(0.004850)	(0.008349)	(0.05496)	(0.20177)	(0.003277)	(0.01073)	(0.02817)	(0.04213)
Gasoline	0.03087***	0.10003***	0.05527	0.02677	0.01714***	0.08803***	0.11375**	0.09224**	0.03564***	-0.04204***	-0.0861**	-0.05548
	(0.003477)	(0.031926)	(0.03422)	(0.02297)	(0.006173)	(0.03394)	(0.05052)	(0.03963)	(0.00498)	(0.01162)	(0.04088)	(0.1211)
Heating Oil	-0.0012025***	-0.05157**	0.06843	-0.0746	0.03015***	-0.01352	0.14369***	0.04683***	0.04032***	-0.03346***	0.00809	-0.1250**
	(0.00018163)	(0.02124)	(0.05089)	(0.04556)	(0.003556)	(0.010788)	(0.04462)	(0.01445)	(0.00399)	(0.01202)	(0.03288)	(0.0585)
Jet Fuel	0.033492***	-0.01165*	0.02775*	-0.2952***	0.00515	0.082766**	-0.45319**	0.02753**	0.05067***	-0.06033***	-0.2416*	1.9334*
	(0.0027475)	(0.006143)	(0.01455)	(0.05973)	(0.005818)	(0.03808)	(0.21985)	(0.01305)	(0.00414)	(0.009236)	(0.1264)	(1.0376)
Natural Gas	0.032009***	-0.20835***	-0.4660***	-1.6943***	0.03040***	-0.73158	-0.66013*	-2.5808***	0.02550**	-0.02326**	-0.0759**	-0.14552**
	(0.0028233)	(0.05172)	(0.1738)	(0.36769)	(0.003956)	(0.67392)	(0.37557)	(0.73202)	(0.01207)	(0.01100)	(0.03052)	(0.06106)
Propane	-0.003961***	0.09997***	-0.6423***	0.19637***	-0.00396***	-0.22277***	0.18651***	0.19264***	0.04071***	-0.47608***	0.05916**	0.1118**
	(0.0009048)	(0.00107)	(0.1184)	(0.03573)	(0.0009048)	(0.04743)	(0.03490)	(0.03061)	(0.00651)	(0.16047)	(0.02986)	(0.05291)
WTI	0.052445***	0.31545*	-0.17792**	-0.31202***	0.05608***	0.04217	0.002186	-0.50548***	0.03589***	-0.44146***	0.09665**	0.11822***
	(0.002221)	(0.16875)	(0.08125)	(0.10488)	(0.003740)	(0.03769)	(0.01872)	(0.17002)	(0.00567)	(0.12021)	(0.04474)	(0.04507)

Note: For brevity, we report only the results for the predictors in the predictive regression model. Thus, the parameter of interest in the GARCH-MIDAS regression is the θ in equation 3. Values in parentheses – () denote standard errors, while ***, ** and * imply significance at 1%, 5% and 10% respectively.

4.3 In-Sample Forecast Evaluation

4.3.1 Full Sample

The predictability test results have shown that, on average, realized volatility and output can consistently predict at least five of the energy prices while headline and core inflation play a marginal role. To validate these results, we explore the forecast performance using a simple forecast measure involving the Root Mean Square Error (hereafter, RMSE)[3]. The conventional value of the RMSE is zero and as such, the closer the RMSE value due to a particular predictor to zero, the better the forecasting accuracy of such predictor. The in-sample forecast results of the GARCH-MIDAS for the data samples are presented in Table 5.

The in-sample performance evaluation of the full sample period reveals that the predictors provide more accurate in-sample forecasts for gasoline return volatility and least accurate in-sample forecasts for propane return volatility. Based on this, the predictors are less accurate in predictive abilities for forecasting heating oil and natural gas. In this light, after gasoline, the predictors provide good in-sample forecast accuracy for diesel, jet fuel and crude oil return volatility, in that order. Our finding that the forecast performance of the macroeconomic information is relatively lower for heating oil and natural gas returns compared to other energy price returns has been previously established by Karali and Ramirez (2014). Further, the evidence in support of good in-sample forecast accuracy for gasoline, diesel, jet fuel and crude oil return volatility is partly corroborated by Pan et al. (2017) who model WTI and Brent oil return volatility with a regime switching GARCH-MIDAS model. The study finds good in-sample of macroeconomic variables in the volatility forecasting. Other studies that find that the inclusion of macroeconomic information improve in-sample of energy returns are Kristjanpoller and Minutolo (2016); Manera *et al*. (2016); and Degiannakis and Filis

[3] We do acknowledge other prominent measures of evaluating forecast performance measures such as the Diebold and Mariano (1995) and Campbell-Thomson (2008), among others. However, all these measures are suppressed in this paper since our mean square errors are consistently found to be very small for all the considered energy prices.

(2017). These studies however include macroeconomic information different from the present study like financial speculation, exchange rate, stock market indices, and commodity prices to predict return volatility in energy prices.

4.3.2 Pre-GFC vs Post-GFC

In the pre-GFC sample period, the predictors record the highest forecast performance for diesel return volatility while the least for natural and propane return volatilities. In between are gasoline, heating oil, jet fuel and crude oil returns with the predictors providing better in-sample forecasts for gasoline after diesel return volatility. These results differ for the post GFC sample period. Based on the RMSE values, the predictors have more accurate in-sample predictive ability for forecasting heating oil returns followed by diesel, propane, gasoline and crude oil return volatility, in that order.

In comparison, the predictors offer a lower forecast performance for natural gas and jet fuel return volatilities in the post-GFC compared with the pre-GFC. This stands in contrast with Barunik and Krehlik (2016) who establish in-sample predictability for natural gas in the post-crisis. However, the difference between Barunik and Krehlik (2016) and the present study is that the former adopts a different methodology – the Artificial Neural Networks (ANN) approach and include only realized volatility in the forecasting model. Nonetheless, our predictors give better in-sample forecast results on the energy return volatility for the post GFC period compared with the pre GFC period.

Table 5: In-Sample Forecast Evaluation of GARCH-MIDAS sample using Root Mean Square Error

Energy	Full Sample				Sub-Sample							
					Pre-GFC				Post-GFC			
	V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}	
			CPI	CPIC			CPI	CPIC			CPI	CPIC
Diesel	2.294e-03	2.313e-03	2.311e-03	2.321e-03	1.454e-03	1.464e-03	1.469e-03	1.463e-03	1.129e-03	1.032e-03	1.038e-03	1.036e-03
Gasoline	1.943e-03	1.931e-03	1.933e-03	1.928e-03	2.172e-03	2.159e-03	2.155e-03	2.156e-03	1.672e-03	1.671e-03	1.683e-03	1.674e-03
Heating Oil	5.011e-03	5.115e-03	5.113e-03	5.116e-03	3.582e-03	3.488e-03	3.492e-03	3.482e-03	8.896e-04	8.861e-04	9.552e-04	9.769e-04
Jet Fuel	2.866e-03	2.861e-03	2.861e-03	2.864e-03	3.430e-03	3.433e-03	3.432e-03	3.428e-03	3.910e-03	3.882e-03	4.749e-03	4.751e-03
Natural Gas	4.599e-03	4.599e-03	4.598e-03	4.602e-03	4.622e-03	1.379e-02	4.607e-03	4.613e-03	2.957e-03	2.957e-03	2.957e-03	2.974e-03
Propane	5.932e-03	5.885e-03	6.023e-03	6.057e-03	5.932e-03	6.095e-03	6.032e-03	6.041e-03	1.421e-03	1.839e-03	1.503e-03	1.501e-03
WTI	2.915e-03	2.971e-03	2.890e-03	2.888e-03	3.437e-03	3.375e-03	3.357e-03	3.364e-03	1.793e-03	2.071e-03	2.021e-03	2.016e-03

4.4 Out-of-sample Forecast Performance Evaluation

4.4.1 Full Sample

The fact that good in-sample forecast results does not necessarily translate to quality out-of-sample forecast performance has been established. On this note, we consider the out-of-sample forecast performance of the GARCH-MIDAS energy returns predictive model. We report the 30-day and the 60-day periods ahead forecast horizons. Consequently, we evaluate the accuracy of each of the predictors for the out-of-sample forecast. The results are reported in Tables 6 and 7 respectively for 30-day and 60-day forecast horizons.

Our out-of-sample forecast evaluation result for full-sample is consistent with in-sample forecast performance results. These predictors give relatively more accurate out-of-sample forecast for jet fuel and crude oil, and this is consistent for 30-day and 60-day forecast horizons. They are also consistently less-accurate in out-of-sample forecast of natural gas and heating oil in the 30-day and 60-day forecast horizons. In tandem with Haugom et al. (2014) and Pan et al. (2017) that also adopt the GARCH-MIDAS approach; and Barunik and Krehlik (2016) that adopt the ANN modeling framework, we establish that macroeconomic variables offer useful information that can be exploited in order to enhance the out-of-sample predictability of return volatility of energy prices.

4.4.2 Pre-GFC vs Post-GFC

The in-sample forecast evaluation results reveal that the predictors produce least RMSE values for gasoline and diesel and relatively higher RMSE values for natural gas and propane in the pre-GFC. Conversely in the post GFC era, the predictors provide more accurate in-sample forecasts for all the energy returns except natural gas and jet fuel. Like the in-sample case, our results are also slightly different for the out-of-sample predictability evaluation between the pre-GFC and post-GFC era. The predictors are shown to offer good out-of-sample forecast predictability for gasoline, heating oil and crude oil consistently for 30-day and 60-day forecast horizons in the pre-GFC. However, in the post-GFC period, the predictors consistently offer good out-of-sample forecast predictability for all the energy returns except natural gas. Notwithstanding the mixed results for pre-GFC and post-GFC periods, the predictors have the least out-of-sample forecast predictability for natural gas returns. This further confirms the findings of Manera *et al* (2016); Kristjanpoller and Minutolo (2016); and Degiannakis and Filis (2017) and equally corroborates our in-sample predictability evaluation result that find relatively lower predictability performance for natural gas returns when compared with the forecast performance of other return volatilities.

Table 6: Out-of-Sample Forecast Evaluation of GARCH-MIDAS with h=30

Energy	Full Sample				Sub-Sample							
					Pre-GFC				Post-GFC			
	V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}	
			CPI	CPIC			CPI	CPIC			CPI	CPIC
Diesel	1.030e-03	1.004e-03	1.018e-03	1.015e-03	1.586e-03	1.564e-03	1.516e-03	1.566e-03	3.215e-04	3.346e-04	3.350e-04	3.377e-04
Gasoline	1.906e-03	1.928e-03	1.927e-03	1.924e-03	4.007e-04	4.021e-04	3.979e-04	3.955e-04	3.361e-04	3.630e-04	3.510e-04	3.628e-04
Heating Oil	2.050e-03	2.050e-03	2.051e-03	2.050e-03	3.683e-04	3.680e-04	3.780e-04	3.751e-04	3.161e-04	3.189e-04	3.172e-04	3.129e-04
Jet Fuel	7.582e-04	7.595e-04	7.574e-04	7.612e-04	2.105e-03	2.104e-03	2.086e-03	2.103e-03	2.970e-04	3.493e-04	2.765e-04	2.751e-04
Natural Gas	3.844e-03	3.829e-03	3.864e-03	3.806e-03	9.268e-03	9.094e-03	9.157e-03	9.100e-03	1.720e-03	1.714e-03	1.710e-03	1.711e-03
Propane	1.748e-03	1.742e-03	6.023e-03	1.753e-03	1.748e-03	1.763e-03	1.755e-03	1.780e-03	7.233e-04	7.134e-04	7.049e-04	7.006e-04
WTI	9.774e-04	9.707e-04	9.703e-04	9.692e-04	2.883e-04	2.879e-04	2.847e-04	2.877e-04	5.982e-04	5.937e-04	5.392e-04	5.407e-04

Table 7: Out-of-Sample Forecast Evaluation of GARCH-MIDAS with h=60

Energy	Full Sample				Sub-Sample							
					Pre-GFC				Post-GFC			
	V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}		V_t	y_{it}	π_{it}	
			CPI	CPIC			CPI	CPIC			CPI	CPIC
Diesel	2.082e-03	2.083e-03	2.083e-03	2.088e-03	1.114e-02	1.153e-02	1.196e-02	1.155e-02	3.691e-04	3.830e-04	3.790e-04	3.828e-04
Gasoline	1.697e-03	1.705e-03	1.710e-03	1.708e-03	3.968e-04	4.062e-04	3.963e-04	3.986e-04	6.152e-04	6.102e-04	6.118e-04	6.129e-04
Heating Oil	1.622e-03	1.622e-03	1.622e-03	1.622e-03	3.888e-04	3.881e-04	3.923e-04	3.901e-04	2.743e-04	2.776e-04	2.729e-04	2.624e-04
Jet Fuel	1.083e-03	1.075e-03	1.070e-03	1.070e-03	1.842e-03	1.840e-03	1.829e-03	1.837e-03	2.623e-04	3.268e-04	2.454e-04	2.456e-04
Natural Gas	3.028e-03	3.017e-03	3.045e-03	2.993e-03	8.163e-03	8.148e-03	8.126e-03	8.111e-03	1.355e-03	1.362e-03	1.348e-03	1.355e-03
Propane	1.748e-03	1.291e-03	1.262e-03	2.315e-05	1.229e-03	1.238e-03	1.263e-03	1.256e-03	8.725e-04	8.726e-04	8.721e-04	8.709e-04
WTI	1.144e-03	1.126e-03	1.122e-03	1.122e-03	3.036e-04	3.009e-04	2.963e-04	2.996e-04	4.679e-04	5.781e-04	4.299e-04	4.315e-04

5.0 Conclusion

Several studies in the literature have focused on energy prices to study the volatility and factors responsible for such. Even so, there are still several issues of concern. One of these is that most of the studies that seek to forecast energy prices are limited to oil returns excluding other classes of energy fuels. More so, findings from these studies are not unanimous. Further, many of those that consider various energy prices majorly explore the interdependencies of spillover effects among the energy prices volatilities while the role of macroeconomic factors in such spillovers is not analyzed from a forecasting perspective. This study offers evidence on the modeling of different classes of energy prices in the periods before and after the global financial crisis given the likely impact of the financial crisis on the macroeconomic predictors of energy prices.

We examine the predictive power of such macroeconomic predictors as realized volatility, output, headline inflation and core inflation and adopt the GARCH-MIDAS modelling framework to model and forecast return volatilities in diesel, gasoline, jet fuel, heating oil, natural gas, propane and crude oil. We conduct relevant descriptive statistics and pre-test on the series to reveal the volatilities, serial correlation and autoregressive conditional heteroscedasticity in the energy returns. We conduct the predictability performance tests, the in-sample and out-of-sample forecast performance evaluations for the full-sample, pre GFC and post GFC time bounds.

Our findings show that the macroeconomic information considered in the model are good predictors of energy return volatilities and these predictors have more reliable in-sample and out-of-sample forecast performances especially in the post-GFC period. In all, this study reveals that realized volatility and output offer more useful information for predicting energy return volatility than inflation.

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