University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2024-18
April 2024

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Energy Market Uncertainties and Exchange Rate Volatility: A GARCH-MIDAS Approach

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Abstract

In this paper, we employ the generalized autoregressive conditional heteroscedasticity-mixed data sampling (GARCH-MIDAS) framework to forecast the daily volatility of 19 dollar-based exchange rate returns based on monthly metrics of oil price uncertainty (OPU), and relatively broader global and country-specific energy market-related uncertainty indexes (EUI) over the daily period of January, 1996 to September, 2022. We find that the global EUIs tend to perform better than the OPU, in terms of their respective GARCH-MIDAS-based forecast performances relative to the benchmark (GARCH-MIDAS-realized volatility (RV)) model, highlighting the need to look beyond the oil market to capture energy related uncertainties. This line of reasoning is further enhanced when we observe the relative (to the United States) country-specific EUIs to outperform the benchmark in a statistically significant manner for at least 14 currencies across the short-, medium-, and long-term forecasting horizons. Our findings have important implications for currency traders.

JEL Codes: C32, C53, F31, F37, Q02

Keywords: Monthly Oil Price and Energy Market Uncertainties, Daily Exchange Rate Returns Volatility, GARCH-MIDAS, Forecasting

1. Introduction

In the wake of the integration of financial and commodity markets, due to the financialization of the latter (Tang and Xiong, 2012), quite a few studies have depicted second moment spillovers of oil price on to exchange rates (see, for example, Salisu and Mobolaji (2013), Nouira et al. (2019), Donkor et al. (2022), Ben Salem et al. (2024)). Realizing that, volatility has been traditionally used as a metric of uncertainty (Baker et al., 2016), using the abovementioned in-sample evidence of volatility spillover from oil to currency markets, the objective of this current study is to analyze the ability of recently developed measure of oil price uncertainty (OPU) by Abiad and Qureshi (2023) in forecasting the volatility of United States (US) dollar-based exchange rate returns of 18 developed and developing countries and the Euro area. In addition, recognizing that oil prices are not necessarily a good proxy for pricing of the overall energy market (Salisu et al., 2024), we analyze whether the forecasting performance of exchange rate returns volatility can be improved by the global and country-specific energy-related uncertainty indexes (EUIs) of Dang et al. (2023), which extends the OPU by combining information on the uncertainties associated with the overall

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energy market and the general macroeconomy. These OPU and EUI indexes, as will be discussed in the next section, rely on counts of terms related to the oil or energy markets and uncertainty in the economy from newspapers and country-reports, and, hence, are likely to be exogenous to the volatility in currency markets, by not being model-generated volatilities (Ludvigson et al., 2021).[1] This is important to ensure that our predictive framework does not suffer from the issue of endogeneity bias, given that some of the studies cited above do depict bidirectional volatility spillovers between the oil and currency markets.

As far as the econometric framework is concerned, we use the generalized autoregressive conditional heteroskedasticity (GARCH) variant of the mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model, as originally developed by Engle et al. (2013). The reason behind this is that, while the exchange rate data is at a daily frequency, the OPU and EUI used as predictors are available only at the monthly frequency, and hence, the modelling of volatility requires a MIDAS-based approach, with this aspect ensuring that there is no loss of information by averaging the daily data to a lower frequency (Clements and Galvão, 2008). Technically speaking, the GARCH-MIDAS approach is motivated by the argument that volatility is not just volatility but that there are different components to volatility, namely, one pertaining to short-term fluctuations and the other to a long-run aspect, with the latter likely to be affected by slow-moving predictors, i.e., the OPU and EUI in our case.

The foreign exchange market is the largest and most liquid financial market in the world. As reported in the Triennial Survey of global foreign exchange market volumes of the Bank for International Settlement (BIS), the average daily turnover was 7.5 trillion US dollars in April of 2022 (up from 6.6 trillion US dollars three years earlier). Naturally, in light of the size of this market, real-time forecasts are important to multinational firms, financial institutions, and traders aiming to hedge currency risks (Rapach and Strauss, 2008). Naturally, the decision to forecast currency returns volatility at a daily frequency is not only due to the underlying statistical need to provide more accurate measures of volatility (Ghysels et al., 2019), but also because high-frequency forecasts are important for traders of foreign-currency options looking to make profits by buying (selling) options if they expect volatility to rise above (fall below) of what is implied in currency option premiums (Balcilar et al., 2016). Hence, a real-time forecasting analysis, being a well-established stronger test of predictability, should be of immense value to investors than in-sample analyses thus far conducted in the context of the volatility-nexus involving energy and currency markets.

While, the existing literature on forecasting exchange rate volatility, based on alternative types of models and various predictors, is huge (see, Christou et al., (2018), Liu et al., (2020) and Bonato et al. (2023), for detailed reviews), to the best of our knowledge, this is the first paper to compare the role of narrow and broad measures of uncertainties in the energy sector in terms of forecasting international currency returns volatility. The rest of the paper is structured as follows: Section 2

[1] Theoretically, (oil and energy) uncertainty can cause an appreciation or depreciation of the exchange rate via the hedging motive, depending on whether the currency is relatively (to the US dollar) safer or not when bad news arrives (Benigno et al., 2011). But, as has been shown by Musa et al. (2022), energy market-related uncertainties in general tends to depreciate dollar based exchange rates globally (possibly indicative of the safe-haven nature of the US dollar), and given the well-known “leverage effect” (Black, 1976) to be widely operating in the currency market (Abdullah et al., 2017), the depreciating exchange rates are likely to be associated with increased volatility.

provides an overview of the data, while Section 3 outlines the basics of the methodology. Section 4 presents the results, and Section 5 concludes the paper.

2. Data

As pointed out earlier, the GARCH-MIDAS model is used to assess the out-of-sample predictability of daily dollar-based nominal exchange rate returns volatility due to monthly measures of oil- and energy market-related uncertainties, i.e., OPU and EUI. The exchange rates, from which we compute the log returns, are derived from the BIS.[2] Besides the Eurozone, the economies considered in this regard, based on the availability of country-specific EUI-indexes, are: Australia, Brazil, Canada, Chile, China, Colombia, Denmark, India, Japan, Mexico, New Zealand, Pakistan, Russia, Singapore, South Korea, Sweden, the United Kingdom (UK), and Vietnam.

Abiad and Qureshi (2023) construct their OPU index based on frequency counts of newspaper articles. In constructing their index, Abiad and Qureshi (2023) consider the set of English-language articles with at least 100 words published in 50 newspapers around the world lodged in the Factiva database. For this set of articles, and for each newspaper and month, these authors count the ones that contain the words: "oil", "petrol", "petroleum", "gas" or "gasoline" within two words of "pric*", and in which "pric*" appears within two words of "uncert*", "volatil*", "fluct*", "erratic", "unstable", "unsteady", "chang*", "unpredict*", "vary*", "swing*" or "move*". They scale these raw OPU counts by the number of articles in the same newspaper and month. Next, they standardize each newspaper's scaled frequency counts to have a unit standard deviation during the period of its data coverage. Finally, they average over the resulting newspaper-level series by month and normalize the average OPU index value to a mean of 100 over the associated sample size.[3]

Dang et al. (2023) develop monthly EUI indexes in three steps. First, they construct an economic uncertainty index for each country by counting the frequency of terms like "uncertain," "uncertainty," and "uncertainties" in each monthly country report of the Economist Intelligence Unit. They then divide that count by the number of words in the same report and normalize each resulting country-level index to a mean of 100 over time. In the second step, the authors take the same approach to construct an energy-related index for each country from the same source. For this purpose, they use the energy-related keywords listed in Table 1 of their paper. Finally, in the third step, they compute the monthly country-level EUI values as the simple mean of the economic uncertainty index and the energy-related index. Note that, we take the equal-weighted average of the EUI indexes of Croatia, France, Germany, Greece, Ireland, Italy, the Netherlands, and Spain to come up with our overall Euro area measure of EUI. Dang et al. (2023) also compute two Global EUI series as the equal-weighted (GEUI_EQ) and GDP-weighted (GEUI_GDP) means of the country-specific EUI series, which we also utilize given that they would be capturing global energy market related uncertainty and would be comparable to the OPU, which can be considered as a measure of worldwide oil price uncertainty.[4]

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[2] The daily US dollar bilateral nominal exchange rates can be downloaded from: https://data.bis.org/topics/XRU.
[3] The data is available for download at: https://policyuncertainty.com/oil_uncertainty.html.
[4] The data for 28 countries (18 stated in the first paragraph of Section 2 plus the 9 comprising the Euro zone and the US) can be accessed from: https://policyuncertainty.com/energy_uncertainty.html.

Based on data availability, the first exercise involving the OPU along with the two Global EUIs, covers the period of (2nd) January 1996 to (31st) December 2019, while the sample period associated with the country-specific EUIs is (2nd) January 1996 to (30th) September 2022. For the second analysis, since exchange rates are expressed is relation to the dollar, we compute a relative measure of country or region-specific EUI (REUI), by the taking log difference between the EUI of each country or area and that of the US.[5]

3. Methodology

Due to observed conditional heteroscedasticity in all the currency returns (details of which are available upon request from the authors), and mixed frequency characteristics in our data, we utilize the GARCH-MIDAS model. Engle et al. (2013) introduced this model framework, consisting of two main components: an unconditional mean and a conditional variance, which is multiplicatively decomposed into high- and low-frequency components. Equations (1) to (5) define the specification of the GARCH-MIDAS model.

$$r_{i,t} = \mu + \sqrt{h_{i,t} \times \tau_t} \times \varepsilon_{i,t}, \qquad \forall\ i = 1,2,...,N_t \tag{1}$$

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

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k(\omega) X_{i-k}^{(rw)} \tag{3}$$

$$\phi_k(w) = \frac{\left[1-k/(K+1)\right]^{w-1}}{\sum_{j=1}^{K}\left[1-j/(K+1)\right]^{w-1}} \tag{4}$$

$$\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1) \tag{5}$$

where $exr_{i,t}$ is the i^{th} day of the month t percentage change in the exchange rate (domestic currency per US dollar) for the selected countries, with N_t indicating the number of days in month t; μ is the unconditional mean of the percentage change in the exchange rate; $h_{i,t}$ is the short-run that is assumed to follow a GARCH(1,1) process; τ_t is the long-run components of the conditional variance $\left(\sqrt{h_{i,t} \times \tau_t}\right)$ part of Equation (1); α and β in Equation (2) represent the ARCH and GARCH terms, respectively, which are constrained by the following restrictions, $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$; in Equation (3) m is the long-run constant, θ is the slope coefficient that indicates the impact of the realized volatility (RV) or the incorporated exogenous variable (OPU, GEUI_EQ, GEUI_GDP or REUI) for the exchange rate volatility of a particular country; $\phi_k(w)$ is a flexible

[5] Our forecasting analysis compared to the usage of REUIs got weaker when we just utilized the country-specific EUIs, thus justifying the usage of the former metric from an econometric perspective as well. Complete details of these results are available upon request from the authors.

(Colacito et al., 2011) one parameter beta polynomial weighting scheme[6], such that $\phi_k(w) \geq 0,\ k = 1,2,\ldots,K$ and $\sum_{k=1}^{K} \phi_k(w) = 1$, for the model identification condition to be satisfied; a constraint $(w > 1)$ is also imposed to ensures that more recent observation lags are assigned larger weights than distant observation lags, X_{i-k} represents the exogenous predictor (OPU, GEUI_EQ, GEUI, GDP or REUI); and the superscript "*rw*" denotes that a rolling window framework is employed for the estimation exercise; while $\varepsilon_{i,t} \mid \Phi_{i-1,t}$ is the information set that is available at the $(i-1)^{th}$ day of the month t is normally distributed.

We compare the out-of-sample forecast accuracies of our alternative GARCH-MIDAS-energy uncertainty-based models with those of the GARCH-MIDAS-RV (benchmark) framework. We utilize the modified Diebold-Mariano test, denoted by *DM**, as developed by Harvey et al. (1997), which extends the conventional Diebold and Mariano (DM, 1995) test for paired non-nested model evaluations. The statistical formulations are delineated in Equations (6) and (7) below:

$$DM^* = \left(\sqrt{\frac{T + 1 - 2h + T^{-1} h(h-1)}{T}} \right) DM \tag{6}$$

$$DM = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{7}$$

where DM^* denotes the modified DM statistic; T represents the number of the out-of-sample periods of the forecast errors and h represents the forecast horizon; $\bar{d} = 1/T \left[\sum_{t=1}^{T} d_t \right]$ indicates the average of the loss differential, $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$; $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ are loss functions of the forecast errors (ε_{it} and ε_{jt}, respectively) from the paired competing models; while $V(d_t)$ is the unconditional variance of the loss differential d_t. The DM^* null hypothesis asserts equality in the forecast precision of the paired non-nested contending models $(H_0 : d = 0)$ against a mutually exclusive alternative, $(H_1 : d \neq 0)$. Non-rejection of the null hypothesis would indicate that the forecast accuracies of the paired models are equivalent, whereas rejection would imply inequality. The sign of the DM^* statistic determines the direction of preference: a negative value indicates superiority of a particular GARCH-MIDAS-energy uncertainty-based model over the GARCH-MIDAS-RV, whereas a significant positive value suggests the converse. The out-of-sample forecast assessment is performed on the last 25% of the observations for forecast horizons of h = 20-, 60-, and 120-days ahead.

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6 This is obtained from the two-parameter beta weighting scheme $\phi_k(w_1, w_2) = \left[k/(K+1) \right]^{w_1 - 1} \times \left[1 - k/(K+1) \right]^{w_2 - 1} \Big/ \sum_{j=1}^{K} \left[j/(K+1) \right]^{w_1 - 1} \times \left[1 - j/(K+1) \right]^{w_2 - 1}$ by constraining w_1 to 1 and setting $w = w_2$.

4. Empirical Results

In this section, we first present the out-of-sample predictability outcomes concerning exchange rate returns volatility from a global perspective, based on modified Diebold-Mariano test statistics, which compares the GARCH-MIDAS-OPU, GARCH-MIDAS-GEUI_EQ, and GARCH-MIDAS-GEUI_GDP with the benchmark model of GARCH-MIDAS-RV. As can be seen from Table 1, barring one case of equal performance with the benchmark, the OPU-based model significantly outperforms the corresponding model with RV in 13 cases, and is outperformed significantly for the remaining 5 exchange rates, with this result being consistent across the three forecasting horizons. As far as the GEUIs are concerned, the GARCH-MIDAS models with GEUI_EQ (GEUI_GDP) significantly performs better than the GARCH-MIDAS-RV in 14 (14), 13 (14), and 13 (12) instances at h = 20, 60 and 120, respectively, with the benchmark doing significantly outperforming in 4 (3) cases for the corresponding three forecast horizons. At the same time, equal performance is observed under 1 (2), 2 (2), and 2 (3) cases between the GARCH-MIDAS-GEUI_EQ (GARCH-MIDAS-GEUI_GDP) with the GARCH-MIDAS-RV at h = 20, 60 and 120, respectively. In sum, the importance of energy market related uncertainties cannot be ignored in accurately forecasting the volatility of the majority of the currencies considered here, with the broader energy uncertainty indexes found to be better suited in this regard compared to oil price uncertainty in the short- and medium-term horizons.

Table 1: Modified Diebold-Mariano Test Results for Oil Price Uncertainty (OPU) and Global Energy Uncertainty Indexes: 1996 - 2019

	GEUI_EQ			GEUI_GDP			OPU		
	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
Australia	-11.89***	-11.32***	-11.52***	-12.73***	-12.17***	-12.33***	-9.01***	-8.58***	-8.96***
Brazil	-7.68***	-7.83***	-7.44***	-7.94***	-8.08***	-7.68***	-7.13***	-7.29***	-6.94***
Canada	-12.49***	-13.31***	-12.92***	-9.58***	-10.40***	-10.11***	-4.03***	-4.10***	-3.75***
Chile	-6.99***	-7.32***	-7.51***	-7.09***	-7.43***	-7.61***	-4.44***	-4.87***	-5.11***
China	7.36***	7.38***	7.40***	13.19***	13.25***	13.29***	3.77***	3.86***	4.00***
Colombia	-11.15***	-11.20***	-11.22***	-11.45***	-11.49***	-11.48***	-8.30***	-8.46***	-8.57***
Denmark	-7.32***	-6.58***	-6.01***	-2.97***	-2.17**	-1.64	-16.89***	-16.25***	-15.10***
Euro	-13.35***	-12.63***	-12.00***	-0.30	0.57	1.16	-15.67***	-15.06***	-13.94***
India	-6.06***	-8.54***	-7.85***	-3.34***	-1.70*	-9.05***	-5.76***	-6.74***	-7.44***
Japan	-2.39**	-1.48	1.23	-3.79***	-2.68***	-0.002	4.73***	5.62***	8.10***
Mexico	-5.75***	-5.80***	-5.52***	-5.80***	-5.85***	-5.56***	-4.94***	-5.04***	-4.80***
New Zealand	13.47***	14.97***	16.73***	22.22***	23.49***	24.51***	13.15***	14.34***	16.76***
Pakistan	-8.97***	-8.74***	-8.27***	-9.13***	-9.09***	-9.00***	-11.99***	-11.89***	-11.74***
Russia	-5.09***	-5.07***	-5.06***	-5.08***	-5.07***	-5.06***	-5.08***	-5.07***	-5.05***
Singapore	-8.92***	-8.41***	-7.65***	-13.09***	-12.55***	-11.56***	4.69***	4.18***	4.61***
South Korea	1.35	1.51	1.56	1.30	1.46	1.50	1.45	1.60	1.62
Sweden	11.65***	14.35***	17.57***	26.08***	27.67***	28.46***	-7.03***	-5.97***	-4.74***
UK	-6.10***	-6.11***	-6.09***	-6.38***	-6.43***	-6.41***	-7.98***	-7.93***	-7.76***
Vietnam	17.49***	17.11***	16.47***	-9.04***	-9.06***	-9.09***	31.89***	30.80***	29.01***
Sig. Neg. DM*	**73.68%**	**68.42%**	**68.42%**	**73.68%**	**73.68%**	**63.16%**	**68.42%**	**68.42%**	**68.42%**
Sig. Pos. DM*	**21.05%**	**21.05%**	**21.05%**	**15.79%**	**15.79%**	**15.79%**	**26.32%**	**26.32%**	**26.32%**

Note: The figures in each cell are the modified Diebold-Mariano test statistics (Harvey et al., 1997) with ***, **, and * indicating statistical significance at 1%, 5%, and 10%, respectively. The significant negative test statistics (*Sig. Neg. DM**) imply the outperformance of the global energy uncertainty-based GARCH-MIDAS model over the RV-variant, while significant positive test statistics (*Sig. Pos. DM**) denote the outperformance of the latter over the former.

Next in Table 2, we now turn our attention to evaluate the ability of the country-specific EUIs relative to that of the US EUI (REUI), again based on the modified Diebold-Mariano test statistics. As can be seen, the GARCH-MIDAS-REUI outperforms the GARCH-MIDAS-RV for 15, 14 and 14 exchange rates in a statistically significant manner at h = 20, 60, and 120, respectively. The benchmark stands out statistically in only 2, 2 and 3 cases for the short-, medium-, and long-horizons, with corresponding equal performances between the GARCH-MIDAS-REUI and

GARCH-MIDAS-RV registered in 2, 3, and 2 instances. Clearly then, barring the cases of New Zealand, South Korea and Vietnam (in the long-horizon), the importance of the country-specific relative energy uncertainties in accurately forecasting exchange rate volatility cannot be overlooked, irrespective of whether a country is a net oil exporter or importer. While looking for reasons as to why in New Zealand, South Korea and Vietnam, the information content of relative energy uncertainty does not seem to matter in forecasting exchange rate volatility, we found that these countries depict relatively lower mean and volatility associated with the REUI, when compared to the currencies for which REUI matters.

Table 2: Modified Diebold-Mariano Test Results for Country-Specific Relative Energy Uncertainty Indexes: 1996 - 2022

	REUI		
	$h = 20$	$h = 60$	$h = 120$
Australia	-8.781***	-8.852***	-8.767***
Brazil	-8.018***	-7.896***	-6.625***
Canada	-11.952***	-11.622***	-11.555***
Chile	-4.138***	-4.115***	-4.051***
China	-5.586***	-5.03***	-5.04***
Colombia	-6.855***	-6.434***	-6.248***
Denmark	-10.035***	-10.001***	-11.241***
Euro	-10.755***	-10.535***	-11.851***
India	-8.94***	-8.836***	-8.694***
Japan	-2.39**	-2.058**	-2.365**
Mexico	-6.506***	-6.587***	-6.599***
New Zealand	2.637***	2.998***	3.594***
Pakistan	-4.665***	-4.627***	-4.504***
Russia	-5.755***	-5.686***	-5.582***
Singapore	-0.872	-0.911	-0.199
South Korea	2.782***	2.765***	2.64***
Sweden	-2.351**	-1.239	-0.241
UK	-7.024***	-7.009***	-6.967***
Vietnam	0.582	1.598	5.066***
Sig. Neg. DM*	**78.95%**	**73.68%**	**73.68%**
Sig. Pos. DM*	**10.53%**	**10.53%**	**15.79%**

Note: The figures in each cell are the modified Diebold-Mariano test statistics (Harvey et al., 1997) with ***, and **, indicating statistical significance at 1%, and 5%, respectively. The significant negative test statistics (*Sig. Neg. DM**) imply the outperformance of the country-specific energy uncertainty-based GARCH-MIDAS model over the RV-variant, while significant positive test statistics (*Sig. Pos. DM**) denote the outperformance of the latter over the former.

5. Conclusions

In this paper, we forecast daily dollar-based exchange rate returns volatility of 19 currencies using monthly measures of oil price uncertainty (OPU), and relatively broader global and country-specific energy market-related uncertainty indexes (EUI) using the GARCH-MIDAS framework over the period of January 1996 to September 2022. When compared to the GARCH-MIDAS-RV, we find that, while both OPU and global level EUIs can accurately forecast exchange rate returns volatility relative to the benchmark, the worldwide metrics of energy uncertainty is relatively more important statistically, especially at short- and medium-run. And this finding becomes more obvious when we obtain the result that, relative (to the US) country-specific EUIs outperform the GARCH-MIDAS-RV in a statistically significant manner for at least 14 currencies across the short-, medium-, and long-term forecast horizons.

On the basis of our findings, we can conclude that currency traders should rely more on elaborate indexes of energy market uncertainty, especially those that are country-specific rather than the same for just the oil market while making their portfolio decisions.

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