Global Financial Cycle and the Predictability of Oil Market Volatility: Evidence from a GARCH-MIDAS Model

Afees A. Salisu[*], Rangan Gupta[**] and Riza Demirer[***]

Abstract

This study examines the predictive power of the global financial cycle (GFCy) over oil market volatility using the GARCH-MIDAS framework. The GARCH-MIDAS model provides an appropriate setting to forecast high frequency oil market volatility using global predictors that are only available at low frequency. We show that the global financial cycle carries significant predictive information over both oil market volatility proxies, both in- and out-of-sample. The predictive relationship is found to be positive, more strongly during the pre-GFC period, suggesting that rising global asset prices coupled with improved cross-border capital flows are associated with rising volatility in the oil market. While the GARCH-MIDAS model incorporating GFCy or any other proxy of global financial/economic conditions yields economic gains compared to the conventional GARCH-MIDAS-RV specification, especially in the pre-GFC period; the stance is found to be robust to risk aversion and leverage ratio. The economic gains observed from the GFCy-based model particularly during the pre-GFC period when world markets experienced a steady rise in global asset prices and cross-border capital flows underline the potential role of risk appetite (or behavioural factors) in forecasting applications. Overall, our results suggest that incorporating low frequency proxies of global asset market conditions can provide significant forecasting gains for energy market models, with significant implications for both investors and policymakers.

Keywords: Global Financial Cycle, Oil Volatility, Predictability, MIDAS models
JEL Codes: C32, C53, G15, Q02

[*] Corresponding author. Centre for Econometric & Allied Research, University of Ibadan, Ibadan, Nigeria. Email: adebare1@yahoo.com.
[**] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: rangan.gupta@up.ac.za.
[***] Department of Economics and Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1102, USA. Email: rdemire@siue.edu.

1. Introduction

There is growing evidence that a single common factor explains a significant percentage of variability in global asset prices (Miranda-Agrippino and Rey, 2020). The so-called global financial cycle is shown to respond to U.S. monetary policy actions that drive liquidity conditions and global capital flows, which in turn, drives volatility in global risky assets. Against this backdrop, this study contributes to this emerging literature from a novel perspective by examining the predictive role of the global financial cycle over perhaps the most strategic commodity in the world, i.e. crude oil, via the GARCH-MIDAS framework. The predictive relationship between the global financial cycle and oil market volatility is justified considering the recent financialization of commodities which has led to increased participation of hedge funds, pension funds, and insurance companies in the oil market, thus rendering oil a profitable alternative investment in the portfolio decisions of financial institutions (Bampinas and Panagiotidis, 2015, 2017; Bonato, 2019). If the global financial cycle explains the common variation in global risky asset prices, one can argue that such variations in global asset markets will in part be driven by liquidity conditions that drive cross-border capital flows and/or risk appetite among global traders. Considering that these market dynamics reflect expectations of economic fundamentals or changes in risk preferences, the oil market will certainly not be immune from the spillover effects, thus establishing a link between the global financial cycle and volatility in the oil market.

The literature offers primarily three prominent approaches to volatility forecasting: In the traditional approach, oil market volatility has been modelled through univariate and multivariate versions of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, as well as the Markov-switching multifractal (MSM) model (see for example, Lux et al., (2016), Degiannakis and Filis, (2017), Gkillas et al., (2020) for detailed reviews). In general, studies in this literature find that the univariate GARCH-type models perform better than their multivariate counterparts, and also models which includes daily exogenous predictors. Moreover, within the univariate GARCH models, more often than not, the standard version is found to outperform other more complicated variations within this category. However, the MSM model, in general, is the preferable framework majority of the times, across forecasting horizons and sub-samples relative to the various univariate GARCH models considered. The second approach builds on a common feature of the above line of research that these studies rely on oil-price returns at a daily frequency, and forecast the daily conditional oil-price volatility. However, as pointed out by McAleer and

Medeiros (2008), intraday data containing rich information can lead to more accurate estimates and forecasts of daily volatility. Given this, various types of high-frequency predictors associated with financial and commodity markets, metrics of uncertainties, and behavioural variables have been incorporated into the Heterogeneous Autoregressive (HAR) model of Corsi (2009) to improve forecasts of the realized volatility of oil relative to the benchmark HAR model (see for example, Bonato et al., (2020), Bouri et al., (2020), Luo et al., (2020) for detailed discussion of this literature). Finally, borrowing from the recent literature on the role of low frequency variables on the volatility of stock markets (Asgharian, 2013; Engle et al., 2013; Conrad and Loch, 2015), a parallel literature has also emerged for forecasting daily oil volatility based on monthly or quarterly predictors using the GARCH variant of mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model (see for example, Yin and Zhou, 2016; Pan et al., 2017; Wei et al., 2017; Nguyen and Walther, 2020; Salisu et al., forthcoming). The GARCH-MIDAS model avoids loss of information that would have resulted by averaging the daily volatility to a lower monthly frequency (Clements and Galvão, 2008; Das et al., 2019). Instead, the main idea behind this model is that volatility is modelled in terms of various components, one pertaining to short-term fluctuations and the other to a long-run component, with the latter likely to be affected by the low-frequency predictors.

Against this backdrop, the objective of our analysis is to forecast West Texas Intermediate (WTI) and Brent crude oil returns volatility based on a new monthly measure of global financial cycle (GFCy), developed by Miranda-Agrippino et al., (2020). The GFCy metric is derived from a global common factor estimated via a Dynamic Factor Model (DFM) applied to a large cross-section of 1,004 global risky assets. Building on a theoretical framework of heterogeneous financial intermediaries that differ in their propensity to take on risk, Miranda-Agrippino and Rey (2020) show that, higher (lower) values of the GFCy are associated with lower (higher) degree of risk aversion. Given this result, one can argue that a rising trend in the GFCy would be associated with greater trading activity by oil traders, more likely by financial investors participating in oil trades due to rising risk appetite, thus contributing to volatility in the oil market. These arguments are further supported by the Mixture of Distribution Hypothesis (MDH) introduced by Clark (1973) and the Sequential Information Arrival Hypothesis (SIAH) developed by Copeland (1976) in that price volatility can be potentially predictable through trading volume patterns and that the relationship of volume and volatility is positive.[1]

These arguments are further supported graphically in Figure A1 (in the Appendix) where we observe a positive association between the global financial cycle and global economic conditions. For instance, the index exhibits a declining pattern during all recessionary periods, while it remains relatively stable until the beginning of the 90s, when a sharp and sustained increase is recorded. The rise in the global financial cycle series lasts until 1997–1998 when capital markets experienced several shocks including the Russian default, the LTCM bailout, the East Asian Crisis and finally, the burst of the dot-com bubble, reversing the upward pattern in the GFCy series. Starting with 2003, the index takes on a positive trend again until the beginning of the third quarter of 2007. At that point, with the collapse of the subprime market, the first signals of increased vulnerability in financial markets became visible. This led to an unprecedented plunge. Since 2010, the factor picks up other important global events such as the Eurozone sovereign crisis; the global equity sell-off at the beginning of 2016, triggered by fears that the Chinese growth slowdown may have spiralled out of control, and by the dramatic plunge in oil prices; and the slowdown at the end of 2018, which the commentators attribute to the combined effect of the withdrawal of some monetary stimuli, and of the escalation in the US-China trade conflict. Overall, a visual inspection of the GFCy series suggests that the global financial cycle is likely to be positively correlated with global economic activity leading to higher demand for oil, and hence more trading and volatility in the market. Accordingly, whether it is via the risk aversion channel or global economic conditions channel, we can hypothesize a positive relationship between GFCy and oil volatility.

For our empirical analysis, the GARCH-MIDAS framework provides an appropriate setting to forecast high frequency oil market volatility using global predictors that are only available at low frequency. Given that the GFCy index is available at a monthly frequency, we rely on the

[1] The MDH postulates that the innovation on returns is a linear combination of the intraday return movements. The intraday return increment incorporates the number of information flows arrived into the market in a given day. Since the intraday price movement is random, daily returns follow a mixture of normally distributed random variables with the information flow into the market as a mixing variable. To sum up, daily price changes are driven by a set of information flow and the arrival of unexpected news is accompanied by the above average trading activity. On the other hand, the SIAH questions the instantaneous relationship as predicted by MDH and provides a different explanation. It argues that each trader observes the information signal differently and not necessarily simultaneously, thereby generating a series of incomplete equilibria. Market equilibrium can be established provided that all traders receive the same set of information simultaneously. Thus, the shift of new information is not immediate as considered in the MDH.

GARCH-MIDAS model to help predict oil market volatility on a daily basis (to avoid loss of information). The decision to forecast oil market volatility at a daily frequency is premised not only on the underlying statistical need to provide more accurate measures of volatility (Ghysels et al., 2019), but also because high-frequency forecasts are important for investors in terms of making timely portfolio decisions, given that daily volatility forecasts are featured prominently in the context of Value-at-Risk (VaR) estimates (Ghysels and Valkanov, 2012).[2] At the same time, the variability of oil prices is also a concern from a policy perspective, as oil-price volatility has been shown to impact economic activity negatively, since it captures information related to macroeconomic uncertainty (van Eyden et al., 2019). Hence, high-frequency forecasts of oil market uncertainty can help policymakers to predict in real time, i.e., nowcast, the future path of low-frequency domestic real activity variables, using MIDAS models (Banbura, 2011), and in the process, allow them to develop appropriate and early policy responses to prevent possible recessions. To the best of our knowledge, this study is the first attempt to forecast the daily volatility of the oil market using a broad index of the global financial cycle (GFCy) based on a GARCH-MIDAS approach.

Our findings provide significant support for the predictive role played by the global financial cycle over oil market volatility, both in- and out-of-sample. As hypothesized, the predictive relationship is found to be positive, more strongly during the pre-GFC period, suggesting that rising global asset prices coupled with improved cross-border capital flows and rising risk appetite are associated with rising volatility in the oil market. The superiority of the GARCH-MIDAS model that incorporates GFCy over the conventional GARCH-MIDAS-RV alternative transcends oil market volatility proxies and forecast horizons, given the consistency of outperformance. Finally, while the GARCH-MIDAS model incorporating GFCy or any other proxy of global financial/economic conditions yields some economic gains than the conventional GARCH-MIDAS-RV, especially in the pre-GFC period; the stance is robust to the risk aversion and leverage ratio. This further confirms the statistical significance of the outperformance of our predictive model, highlighting the predictive information and economic value of the global financial cycle over energy market volatility forecasts. Overall, the results suggest that a common factor that

[2] Ghysels et al. (2019) compare the GARCH and RV methodologies by producing multiperiod-ahead forecasts to show that the MIDAS-based model yields the most precise forecasts of volatility, both in-and out-of-sample.

describes fluctuations in global asset prices can be utilized to accurately forecast the volatility of energy market returns at low frequencies.

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

2. Methodology and Data

2.1 Methodology

We employ a GARCH-MIDAS framework to examine the predictive role of the global financial cycle (GFCy) on oil market volatility. As our goal is to examine high-frequency predictability (daily in our case) of return volatility in the oil market, the choice of the MIDAS framework is primarily driven by the unavailability of the GFCy index at a higher frequency as this index is only available at monthly frequency. This is a common issue in forecasting applications that employ macro-level predictors that are only available at lower frequencies. To that end, the GARCH-MIDAS framework is well suited for model settings that involve high-frequency dependent (oil) and low-frequency independent (GFCy) variables.[3] A major advantage of the MIDAS specification is that it circumvents the problem of information loss and biases resulting from data aggregation or disaggregation through data splicing, as the case may be. The model simultaneously allows for the incorporation of variables in their natural frequencies, thereby harnessing all possible information that may be inherent in the original data. This has proved to outperform alternative models that assume uniformity in terms of frequency of the variables included in the forecasting model [see Salisu and Ogbonna (2019) for the ADL-MIDAS variant and Salisu et al., (forthcoming) for a recent application that involves global economic conditions-based indexes].[4]

Accordingly, in our context, the GARCH-MIDAS model is the preferred framework, since MSM-MIDAS models have not yet been developed, though would be ideal to forecast oil market volatility, given the superior performance of the MSM models relative to the GARCH framework.

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[3] Alternatively, ADL-MIDAS variants that incorporate higher frequency predictors with low frequency predicted variables have also been shown to have some computational advantages over models that employ uniform frequencies.
[4] Engle et al. (2013) provide technical details of the multiplicative decomposition of conditional variance into high- and low-frequency components of the MIDAS model.

At the same time, daily data-based HAR-type models too, where realized volatility (RV) estimates are derived from intraday data, does not allow for predictors at lower frequency, as would be the case in our context. This, in turn, would require the use of reverse-MIDAS regressions recently developed by Foroni et al., (2018), which could indeed be an area of future research (when the computer codes to implement such a method become publicly available). Of course, we could obtain RV at monthly frequency from daily data, and use a monthly version of the HAR-RV model, but then this would not allow us to produce daily forecasts. In light of these issues, high-frequency forecasting of the volatility of the oil market based on the GFCy index, does indeed make the GARCH-MIDAS approach preferable over alternative methods.

We define the returns of the predicted series as $r_{i,t} = ln\left(P_{i,t}\right) - ln\left(P_{i-1,t}\right)$, where $P_{i,t}$ represents the price for day *i* in month *t* with $t = 1, \ldots, T$ and $i = 1, \ldots, N_t$ denoting the monthly and daily frequencies, respectively, and N_t is the number of days in a given month *t*. The GARCH-MIDAS model for the return series has two components representing the mean and conditional variance separately and is specified as:

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

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

where the first component, μ is the unconditional mean of the return series. The conditional variance part comprises a short-run component $\left(h_{i,t}\right)$ that follows the $\text{GARCH}(1,1)$ process and is of a higher frequency, and a long-run component that is captured by τ_t with $\Phi_{i-1,t}$ in (2) representing the available information at day *i-1* of month *t*. The conditional variance is then formulated as:

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

where α and β are the ARCH and GARCH terms, respectively, conditioned to be positive and/or at least zero ($\alpha > 0$ and $\beta \geq 0$) and sum up to less than unity $(\alpha + \beta < 1)$. The model specification by Engle et al. (2013) puts everything in the daily frequency, without loss of the GARCH-MIDAS features, such that the initial monthly varying long-term component $\left(\tau_t\right)$ is transformed to daily frequency (τ_i). This is simply because the days in month t are rolled back without keeping track of it, which in turn yields the daily long-term component defined as:

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \phi_k (w_1, w_2) X_{i-k}^{(rw)} \tag{4}$$

where the superscript "(rw)" denotes the implementation of a rolling window framework (which allows the secular long-run component to vary daily) and m represents the long-run component intercept. The focus of our analysis is the MIDAS slope coefficient (θ) that indicates the predictability of the incorporated exogenous predictor X_{i-k} where $\phi_k (w_1, w_2) \geq 0,\ \ k = 1, \ldots, K$ is the weighting scheme that must sum to one for the parameters of the model to be identified; and K is chosen based on the log-likelihood statistic for each pair of the predicted and the predictor series in order to filter the secular component of the MIDAS weights.

We draw from the documented flexibility and popularity of the beta weighting scheme (Colacito et al., 2011) and transform the two-parameter- to one-parameter- beta polynomial weighting scheme. This means that w_1 is set to one, $w_2 = w$, so that an optimal weighting function that is monotonically decreasing is obtained (Engle et al. 2013). The weighting function is thus defined as:

$$\phi_k (w_1, w_2) = \frac{\left[k/(K+1) \right]^{w_1 - 1} \times \left[1 - k/(K+1) \right]^{w_2 - 1}}{\sum_{j=1}^{K} \left[j/(K+1) \right]^{w_1 - 1} \times \left[1 - j/(K+1) \right]^{w_2 - 1}} \Leftrightarrow \phi_k (w) \frac{\left[1 - k/(K+1) \right]^{w-1}}{\sum_{j=1}^{K} \left[1 - j/(K+1) \right]^{w-1}} \tag{5}$$

where the weights are positive, sum to one, and $w>1$ is imposed so that higher weights are assigned to recent observations. The model is subjected to in-sample predictability, wherein we test the statistical significance of the MIDAS slope coefficient, θ (i.e. whether θ differs from zero significantly). A statistically significant slope coefficient would indicate that return volatility can be influenced by GFCy, while the sign of the estimated slope coefficient ascertains the direction of predictive the relationship.

In the case of out-of-sample forecast performance evaluation, we compare the forecasts of our proposed GARCH-MIDAS predictive model (involving GFCy) with that of the conventional GARCH-MIDAS specifications that include realized volatility (GARCH-MIDAS-RV). The out-of-sample forecast performance is evaluated using three data samples (i.e. the full sample and two sub-samples partitioned as pre- and post-Global Financial Crisis samples) and four forecast horizons that correspond to short- and long-run predictability (h = 5, 10, 20, 30). Given that the contending models are not nested, the Diebold and Mariano (1995) test is employed to formally ascertain whether the forecast errors associated with the contending models differ significantly. Specifically, the test statistic is formulated as:

$$DM\ Stat = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{6}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the mean 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) that are associated with the return forecasts ($\hat{r}_{it}$ and $\hat{r}_{jt}$, respectively); and $V(d_t)$ is the unconditional variance of the loss differential d_t. The null hypothesis of relative equality of the forecast precision of the contending model pairs is tested by examining $E[d_t] = 0$; with statistical significance implying a statistically significant difference in the forecast precision of the contending model pairs.

2.2 Data

Conventionally, return, rather than price, series is used in the analysis of volatility to circumvent the unit root problem. Thus, in this study, we employ daily spot price returns for WTI and Brent crude oil and monthly data for the GFCy index. As stated earlier, the MIDAS framework allows us to employ high frequency oil return data with the lower frequency global financial cycle series that is only available at monthly frequency. The data for WTI and Brent crude oil prices are derived from the Global Financial Data (https://globalfinancialdata.com/), covering 17th January, 1980 to 30th April, 2019, and 12th June, 1987 to 30th April, 2019, respectively. The data for the monthly GFCy index series is obtained from the website of Professor Silvia Miranda-Agrippino at: http://silviamirandaagrippino.com/code-data, and covers 1980:01 to 2019:04. The GFCy index is based originally on the work of Miranda-Agrippino and Rey (2020), and was available until 2012, but has now been updated by Miranda-Agrippino et al., (2020) to 2019, by extending the cross-section of risky assets included in the computation of the index from 858 to 1,004 to reflect a compositional change addressing greater visibility of Eastern (Chinese) markets, in line with the composition of the S&P Global index (https://us.spindices.com/indices/equity/sp-global-1200). The GFCy index is essentially generated as the common global factor extracted from a dynamic factor model (DFM) that involves a comprehensive panel of global risky assets including equity and corporate bond indices that represent Europe, North America, Latin America, Asia-Pacific, and Australia as well as commodity prices excluding precious metals. Miranda-Agrippino and Rey (2020) show that this single common global factor alone accounts for over 20% of the common variation in the price of risky assets globally despite the heterogeneity of the asset markets included in the panel.

3. Empirical Results

Our forecasting analysis is performed in several steps. First, we examine the in-sample predictive power of the global financial cycle (GFCy) over the full sample as well as the pre- and post-global financial crisis (GFC) periods.[5] The assessment by data sample is to ascertain whether the nexus is time-varying and more importantly to see whether the global financial crisis has played a role in the predictive relationship between oil market volatility and the global financial cycle. Next, we proceed with the evaluation of the out-of-sample forecasts across four forecast horizons: h = 5, 10, 20, 30 and compare the forecasting performance of the GARCH-MIDAS model that incorporates GFCy as a predictor against the conventional GARCH-MIDAS-RV specification via the Diebold and Mariano (1995) test. We also adopt the rolling window approach to iteratively generate a one-day ahead forecast over the specified forecast horizons. Finally, we examine the economic significance of incorporating GFCy in the forecasting models for oil market volatility.

3.1 Does GFCy predict oil return volatility?

In-sample results. Table 1 presents the in-sample predictability results for the full sample as well as the pre- and post-global financial crisis periods. Note that January 2008 is used as the cutoff point for the pre- and post-GFC samples. In each cell, we report the estimates of the GARCH-MIDAS-GFCy model described in Equation 4, including the unconditional mean for the selected returns (μ); ARCH term (α); GARCH term (β); MIDAS slope coefficient (θ); adjusted beta polynomial weight (w); and the long-run constant term (m). While we consider the statistical significance of the GARCH-MIDAS model parameters, the parameter that is of utmost importance

[5] Please note for the purpose of emphasis, the abbreviations for global financial cycle (GFCy) and Global Financial Crisis (GFC) are used in this paper.

is the MIDAS slope coefficient (θ) as it provides an indication of predictability of oil return volatility due to GFCy. We observe that all parameters, except the unconditional mean, are statistically significant, consistently across the three data samples. The adjusted beta polynomial weight (w) is greater than one and statistically significant across the three samples, indicating that more recent observations are assigned higher weights than those at longer lags. There is also evidence of high volatility persistence with mean-reverting characteristics, indicated by the sums of the statistically significant ARCH (α) and GARCH (β) terms of the short-run component less than unity in all cases. This suggests that the impact of shocks to oil return volatilities would be transient, only taking a longer time to completely fizzle out.

Examining the MIDAS slope coefficient (θ) which gives an insight into the predictive power of the included exogenous variable, i.e. the global financial cycle, we observe positive and statistically significant estimates for the slope coefficients, consistently across all samples. The positive slope coefficients imply a positive predictive relationship between the global financial cycle and future volatility in the oil market, associating positive trends in the common component of global risky asset prices with rising volatility in the oil market. Miranda-Agrippino and Rey (2020) note that the global financial cycle is closely related to global risk aversion such that periods of increasing cross-border capital flows and rising global asset prices are associated with declines in global risk aversion. It can thus be argued that the positive predictive relationship between the global financial cycle and oil market volatility is partially driven by rising risk appetite among global investors implied by high GFCy values, which in turn, results in greater trading activity by financial investors in the oil market and thus a rise in volatility. It can also be argued that high GFCy values imply favourable expectations on global economic fundamentals, which means greater demand for oil globally, leading oil hedgers and speculators to build up their positions, thus resulting in greater volatility in the oil market. These arguments are indeed supported by greater θ values observed during the pre-GFC period than the post-GFC period when global asset prices suffered from a sustained slump along with a rise in global risk aversion (Figure A1 in the Appendix). Nevertheless, our in-sample analysis points to a robust predictive relationship between the global financial cycle and oil market volatility, which is also evident graphically in Figure 1 where we plot the tracking power of the GFCy-based predictive model.

Out-of-sample results: Clearly, in-sample predictability does not guarantee out-of-sample forecasting gains (Campbell, 2008) and a full-fledged forecasting exercise would not be considered a robust econometric test to determine the suitability of econometric methods and predictors without the out-of-sample analysis. In Table 2, we compare the out-of-sample forecast performance of the GARCH-MIDAS-GFCy model with that of the conventional GARCH-MIDAS-RV model. Specifically, we report the estimated Diebold and Mariano (1995) test statistics that compare the predictive performance of the GARCH-MIDAS-GFCy model against the GARCH-MIDAS-RV benchmark. A significantly negative test statistic implies that the GARCH-MIDAS-GFCy specification is preferred over the GARCH-MIDAS-RV alternative, while positive and statistically significant test statistics indicate preference for the latter. The results reported in Table 2 yield overwhelming support for the GARCH-MIDAS-GFCy model over the GARCH-MIDAS-RV benchmark, consistently for both oil series and across all three sample periods. The forecasting model that incorporates the global financial cycle as a predictor yields more precise forecasts than the conventional GARCH-MIDAS-RV model across all four out-of-sample forecast horizons, while forecast accuracy is found to be generally stronger at shorter horizons during the post-GFC period. Thus, these results further confirm the predictive information captured by the global financial cycle over oil market volatility, both in- and out-of-sample.[6]

3.2 How does GFCy compare with an index of global economic conditions?

In a recent paper, utilizing a broad measure of monthly global economic conditions (GECON), developed by Baumeister et al., (forthcoming), Salisu et al., (forthcoming) show that global economic conditions contain predictive ability for WTI and Brent crude oil market volatility in a GARCH-MIDAS setting. The GECON index is derived by applying the expectation-maximization algorithm to 16 indicators associated with commodity prices (excluding precious metals and energy), economic activity, financial indicators, transportation, uncertainty and expectation measures, weather and energy-related indicators. Baumeister et al., (forthcoming) show that this

[6] Just like oil, gold is an equally important commodity from the perspective of investment decisions due its safe-haven properties, and hence, the literature on forecasting gold returns volatility is massive [see Salisu et al., (2020) for a detailed review of this literature]. Given this, we present in Table A1 in the Appendix, the results for out-of-sample forecastability of gold return volatility due to GFCy based on the GARCH-MIDAS-GFCy model. Similar to the findings for oil, we observe in Table A1 that GFCy indeed possesses predictive information for out-of-sample forecasting of gold volatility as well.

new index of global economic conditions serves as an important predictor of real oil prices and global petroleum consumption. Against this background, we next examine whether or not the global financial cycle captures predictive information over and above that is captured by global economic conditions. Considering that the global financial cycle is in part driven by changes in global risk preferences, the comparison of predictive performance against global economic conditions can enlarge our understanding of the role of behavioral factors in oil market volatility over and above real economic fundamentals.

For this purpose, we consider two other predictors, i.e. GECON index of Baumeister et al., (forthcoming) and a principal component factor (PCA) that combines the information content in both the GFCy and GECON series. Table 3 presents the estimated Diebold and Mariano (1995) test statistics that compare the predictive power of the GARCH-MIDAS-GFCy model (as the benchmark) against the GARCH-MIDAS-GECON (Panel A) and GARCH-MIDAS-PCA (Panel B) alternatives. A significantly negative value in each cell implies that the GARCH-MIDAS-GFCy specification is preferred over the GARCH-MIDAS (GECON or PCA factor) model, while positive and statistically significant test statistics indicate preference for the latter specification. The findings in Table 3 confirm the superiority of the GFCy-based model over the GECON and the PCA-based specifications for Brent volatility across all three sub-samples. While this result also holds for all cases associated with WTI volatility, we find that GECON is the preferred predictor during the post-GFC period, highlighting the dominance of the predictive information captured by real economic conditions on the US economy over and above financial market dynamics. Nevertheless, the additional results confirm the predictive role played by the global financial cycle over and above real economic dynamics, possibly as the GFCy captures the dynamics of market liquidity and global risk aversion that govern cross-border capital flows globally.

3.3 Economic Significance

An issue of high interest in any forecasting application is whether or not forecasting gains translate into gains in an economic sense. To that end, following Liu et al. (2019), we examine the economic significance of the forecast performance of the contending GARCH-MIDAS model that incorporates the global financial cycle as an exogenous predictor relative to the model variant that ignores the same. Assuming a typical mean-variance utility investor who holds investment positions in a risky and a risk-free asset, the optimization procedure yields the optimal weight, ψ_t, allocated to the risky asset formulated as

$$\psi_t = \frac{1}{\gamma} \frac{\lambda \hat{r}_{t+1} + (\lambda - 1)\hat{r}^f_{t+1}}{\lambda^2 \hat{\sigma}^2_{t+1}} \tag{7}$$

where γ is the risk aversion coefficient; λ is the leverage ratio (Zhang et al. 2018) that is set to 6 and 8, premised on the assumption of a margin account at 10% level usually maintained by investors; $\hat{r}_{t+1}$ is the commodity return forecast at time $t+1$; $\hat{r}^f_{t+1}$ is the risk-free rate (Treasury bill rate in our case); and $\hat{\sigma}^2_{t+1}$ is a 30-day moving window estimate of daily return volatility. Using the investor's optimal weight (ψ_t) obtained in (7), we then formulate the certainty equivalent return (CER) as

$$CER = \overline{R}_p - 0.5(1/\gamma)\sigma^2_p \tag{8}$$

where $\overline{R}_p$ and σ^2_p denote the mean and variance, respectively, of the out-of-sample period portfolio return that is formulated as $R_p = \psi\,\lambda\left(r - r^f\right) + (1-\psi)r^f$ and its variance formulated as $Var\left(R_p\right) = \psi^2\lambda^2\sigma^2$, where σ^2 indicates excess return volatility. The economic significance is then assessed by maximizing the objective utility function formulated as

$$\begin{aligned} U\left(R_p\right) &= E\left(R_p\right) - 0.5(1/\gamma)Var\left(R_p\right) \\ &= \psi\lambda\left(r - r^f\right) + (1-\psi)r^f - 0.5(1/\gamma)\psi^2\lambda^2\sigma^2 \end{aligned} \tag{9}$$

Table 4 presents the economic gains from incorporating the GFCy index as a predictor in the GARCH-MIDAS model over the alternative specification that excludes GFCy as a predictor, along the lines of Liu et al. (2019). We report in the table mean portfolio returns, volatility, certainty equivalent returns, as well as the corresponding risk-adjusted returns, i.e. Sharpe ratios, formulated as $SP = \left(R_p - r^f\right)\Big/\sqrt{Var\left(R_p\right)}$. Economic gains are then assessed based on the model that yields the maximum return, CER and risk-adjusted returns (SP); and minimum volatility (see Liu et al., 2019). When the level of risk aversion and leverage ratio are set to 3 and 6, respectively, we find that at a relatively similar risk level; GARCH-MIDAS-GFCy model provides greater economic gains than the GARCH-MIDAS-RV alternative across both oil markets, particularly during the pre-GFC sample. The risk-adjusted returns obtained from the GFCy-based model are particularly superior for WTI during the pre-crisis period. However, these economic gains seem to have disappeared during the post-GFC sample period as the GARCH-MIDAS-GFCy model yields lower risk-adjusted returns compared to the GARCH-MIDAS-RV alternative. The results do not differ markedly from the stance earlier reported when the leverage parameter is set to 8 and the risk aversion set to 3, suggesting that the performance results are robust to model parameters.

Overall, our results suggest that while incorporating the global financial cycle as a predictor of oil market volatility indeed yields more accurate volatility forecasts, both in- and out-of-sample, the economic gains from utilizing GFCy in the forecasting model is largely limited to the pre-GFC sample period. Accordingly, the findings highlight the predictive value of the global financial cycle from an economic sense during periods of rising global asset prices and credit flows. Accounting for financial cycles during such periods does not only statistically improve out-of-sample forecasts, but also presents some economic gains that qualifies the incorporation of this variable as an important predictor. The economic gains observed from the GFCy-based model particularly during the pre-GFC period when world markets experienced a steady rise in global asset prices and cross-border capital flows further underline the potential role of risk appetite (or behavioural factors) in forecasting applications. The fact that the GFCy-based model does not necessarily yield economic gains during economic downturns suggests that real economic fundamentals play a more dominant role during such periods, thus rendering the role of financial cycle relatively less important as a predictor.

4. Conclusion

This study contributes to the emerging evidence that a single common factor explains a significant percentage of variability in global asset prices. The so-called global financial cycle is examined from a novel perspective by exploring its predictive role over a strategic commodity that is globally traded, i.e. crude oil, via the GARCH-MIDAS framework. The GARCH-MIDAS framework provides an appropriate setting to forecast high frequency oil market volatility using global predictors that are only available at low frequency. The decision to forecast oil market volatility at a daily frequency is premised on the underlying statistical need to provide more accurate measures of volatility (Ghysels et al., 2019) as well as the dire need of high-frequency forecasts for investors to make timely portfolio decisions, given that daily volatility forecasts are featured prominently in the context of Value-at-Risk (VaR) estimates (Ghysels and Valkanov, 2012). The GARCH-MIDAS model framework naturally circumvents the problem of information loss and aggregation/disaggregation biases by allowing variables of mixed frequencies to be simultaneously accommodated; thus, preserving the data in its original form.

We examine the predictive information captured by the global financial cycle (GFCy) via in- and out-of-sample test at both the short and long forecast horizons and compare the accuracy of the forecasts with those obtained from the conventional GARCH-MIDAS specification with realized volatility (GARCH-MIDAS-RV). The forecast evaluation is performed over three data samples (full, pre- and post-global financial crisis samples) via Diebold and Mariano (1995) tests, since the contending models are non-nested. Four main findings emerge from the empirical analysis. First, we find evidence of high but mean-reverting volatility persistence with respect to the crude oil proxies considered, which is indicative of the transient nature of shock impacts. Second, we find predictability of the global financial cycle for both oil market volatility proxies, an indication of the relevance of the GFCy as a robust predictor of oil market volatility. The predictive relationship is found to be positive, more strongly during the pre-GFC period, suggesting that rising global asset prices coupled with improved cross-border capital flows are associated with rising volatility in the oil market. Third, the outperformance of the GARCH-MIDAS-GFCy model over the conventional GARCH-MIDAS-RV transcends oil market volatility proxies and forecast horizons, given the consistency of outperformance. Finally, while the GARCH-MIDAS model incorporating GFCy or any other proxy of global financial/economic conditions yields some economic gains than the conventional GARCH-MIDAS-RV, especially in the pre-GFC period; the stance is robust to the risk aversion and leverage ratio. This further confirms the statistical significance of the outperformance of our predictive model, highlighting the predictive information and economic value of the global financial cycle.

Our results have important implications for both investors and policymakers. Considering that most proxies for global economic conditions or financial/macro uncertainty are available at low frequencies, our findings suggest that the GARCH-MIDAS specification can be successfully utilized to generate improved volatility forecasts at high frequencies without loss of valuable data. The results also suggest that a common factor that describes fluctuations in global asset prices can be utilized to accurately forecast the volatility of energy market returns. This is indeed an important consideration for corporations and policy makers who rely on accurate volatility forecasts in energy markets in order to better monitor tail risks and the impact on the economy. Given that oil market volatility captures economic uncertainty, accurate forecasting would provide information about the future path of the macroeconomy contingent on the evolution of uncertainty, which can then be incorporated into mixed-frequency models to produce forecasts of a wide range of low-frequency variables measuring economic activity, thus allowing the design of appropriate policy responses to prevent the possibility of unfavourable outcomes. The results also have important implications from a valuation perspective in the pricing of energy derivatives and suggest that low frequency proxies of global uncertainty or asset market trends can be incorporated into forecasting model in order to identify mispriced derivatives that are used in investment portfolios or as part of hedging programs. In future research, it would be interesting to use GFCy to forecast the volatility of cryptocurrencies, along the lines of Walther et al., (2019), which have recently emerged as an important alternative investment option for economic agents, relative to traditional financial assets.

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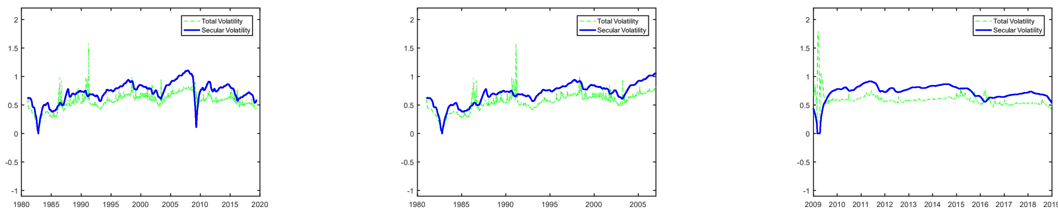
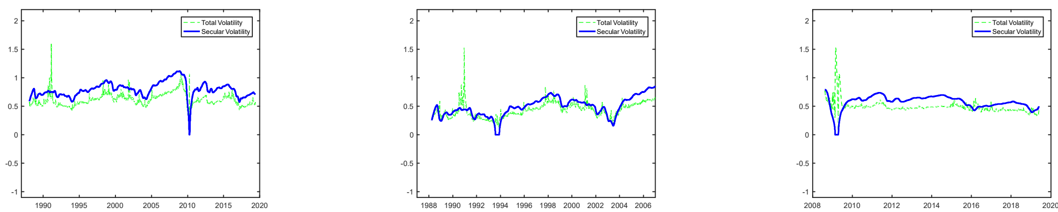
Figure 1. In-sample predictability graphs.

Whole sample	**Pre-GFC period**	**Post-GFC period**

Panel A: WTI and GFCy



Panel B: Brent and GFCy



Note: The figure presents the findings for in-sample predictability by plotting the tracking power of the GFCy-based predictive model for the volatility of WTI (Panel A) and Brent (Panel B) oil returns across the whole, pre- and post-GFC samples.

Table 1. Predictability results of the GARCH-MIDAS-GFCy model.

	μ	α	β	θ	w	m
Full Sample						
WTI	4.80E-05 [3.01E-04]	5.00E-02*** [5.25E-03]	9.00E-01*** [1.08E-02]	1.00E-01*** [6.29E-05]	5.00E+00*** [9.54E-02]	2.16E-03*** [1.25E-06]
BRENT	1.70E-04 [5.69E-04]	5.00E-02*** [4.35E-03]	9.00E-01*** [1.69E-02]	9.99E-02*** [8.98E-03]	5.00E+00*** [1.41E-02]	2.26E-03*** [2.03E-04]
Pre-GFC Sample						
WTI	1.27E-04 [3.49E-04]	5.00E-02*** [6.87E-03]	9.00E-01*** [1.46E-02]	1.00E-01*** [1.83E-03]	5.00E+00*** [1.74E-01]	2.16E-03*** [4.00E-05]
BRENT	-3.29E-04 [2.83E-04]	4.98E-02*** [2.52E-03]	9.00E-01*** [5.30E-03]	9.90E-02*** [2.24E-03]	5.00E+00*** [2.09E-03]	7.93E-04*** [1.79E-05]
Post-GFC Sample						
WTI	1.59E-04 [9.31E-04]	5.00E-02*** [8.61E-03]	9.00E-01*** [2.13E-02]	9.65E-02*** [5.90E-03]	5.00E+00*** [1.67E-02]	2.17E-03*** [1.33E-04]
BRENT	2.37E-04 [7.41E-04]	5.01E-02*** [2.28E-03]	9.00E-01*** [5.21E-03]	6.56E-02*** [3.32E-03]	5.00E+00*** [1.33E-02]	1.38E-03*** [6.98E-05]

Note: This table presents the in-sample predictability results for the whole, pre- and post-GFC samples. The figures in each cell are the estimates of the GARCH-MIDAS-GFCy model in Equation 4 and their corresponding standard errors in square brackets. January 2008 is used as the cutoff point for the pre- and post-GFC samples. *** indicates statistical significance at 1% level.

Table 2. Out-of-sample forecast evaluation of the GARCH-MIDAS-GFCy model via Diebold and Mariano (1995) test.

Forecast Horizon	Panel A: WTI			Panel B: Brent		
	Full sample	**Pre-GFC**	**Post-GFC**	**Full sample**	**Pre-GFC**	**Post-GFC**
$h = 5$	-51.310***	-48.265***	-101.737***	-53.989***	-91.464***	-109.390***
$h = 10$	-66.358***	-41.133***	-112.703***	-77.735***	-110.716***	-80.486***
$h = 20$	-54.562***	-53.471***	-72.226***	-86.110***	-92.241***	-41.457***
$h = 30$	-46.793***	-73.071***	-58.694***	-51.949***	-97.028***	-40.253***

Note: This table reports the estimated Diebold and Mariano (1995) test statistics that compare the predictive power of the GARCH-MIDAS-GFCy model against the GARCH-MIDAS-RV specification. January 2008 is used as the cutoff point for the pre- and post-GFC samples. A significantly negative value in each cell implies that the GARCH-MIDAS-GFCy specification is preferred over the GARCH-MIDAS-RV alternative, while positive and statistically significant Diebold and Mariano (1995) test statistics indicate preference for the latter. *** denotes statistical significance at 1% level.

Table 3. Out-of-sample forecast evaluation via Diebold and Mariano (1995) test (GARCH-MIDAS-GFCy as the benchmark model).

Forecast Horizon	**Panel A:** GARCH-MIDAS-GECON			**Panel B:** GARCH-MIDAS-PCA		
	Full sample	**Pre-GFC**	**Post-GFC**	**Full sample**	**Pre-GFC**	**Post-GFC**
			WTI			
$h=5$	-92.21***	-106.93***	495.24***	-28.62***	-144.25***	-285.07***
$h=10$	-93.31***	-84.37***	739.41***	-23.68***	-127.79***	-247.48***
$h=20$	-99.35***	-100.36***	248.86***	-16.03***	-157.64***	-57.55***
$h=30$	-64.10***	-123.21***	78.35***	-13.07***	-211.96***	-27.43***
			Brent			
$h=5$	-188.94***	-123.22***	-258.74***	-391.78***	485.29***	102.55***
$h=10$	-263.93***	-104.41***	-227.79***	-417.14***	794.93***	90.13***
$h=20$	-234.27***	-125.93***	-101.58***	-446.55***	329.88***	51.58***
$h=30$	-118.98***	-140.09***	-60.05***	-273.43***	201.10***	24.73***

Note: This table reports the estimated Diebold and Mariano (1995) test statistics that compare the predictive power of the GARCH-MIDAS-GFCy model (as the benchmark) against the GARCH-MIDAS-GECON (Panel A) and GARCH-MIDAS-PCA (Panel B) variations. January 2008 is used as the cutoff point for the pre- and post-GFC samples. A significantly negative value in each cell implies that the GARCH-MIDAS-GFCy specification is preferred over the GARCH-MIDAS (GECON or PCA factor) model, while positive and statistically significant Diebold and Mariano (1995) test statistics indicate preference for the latter specification. *** denotes statistical significance at 1% level.

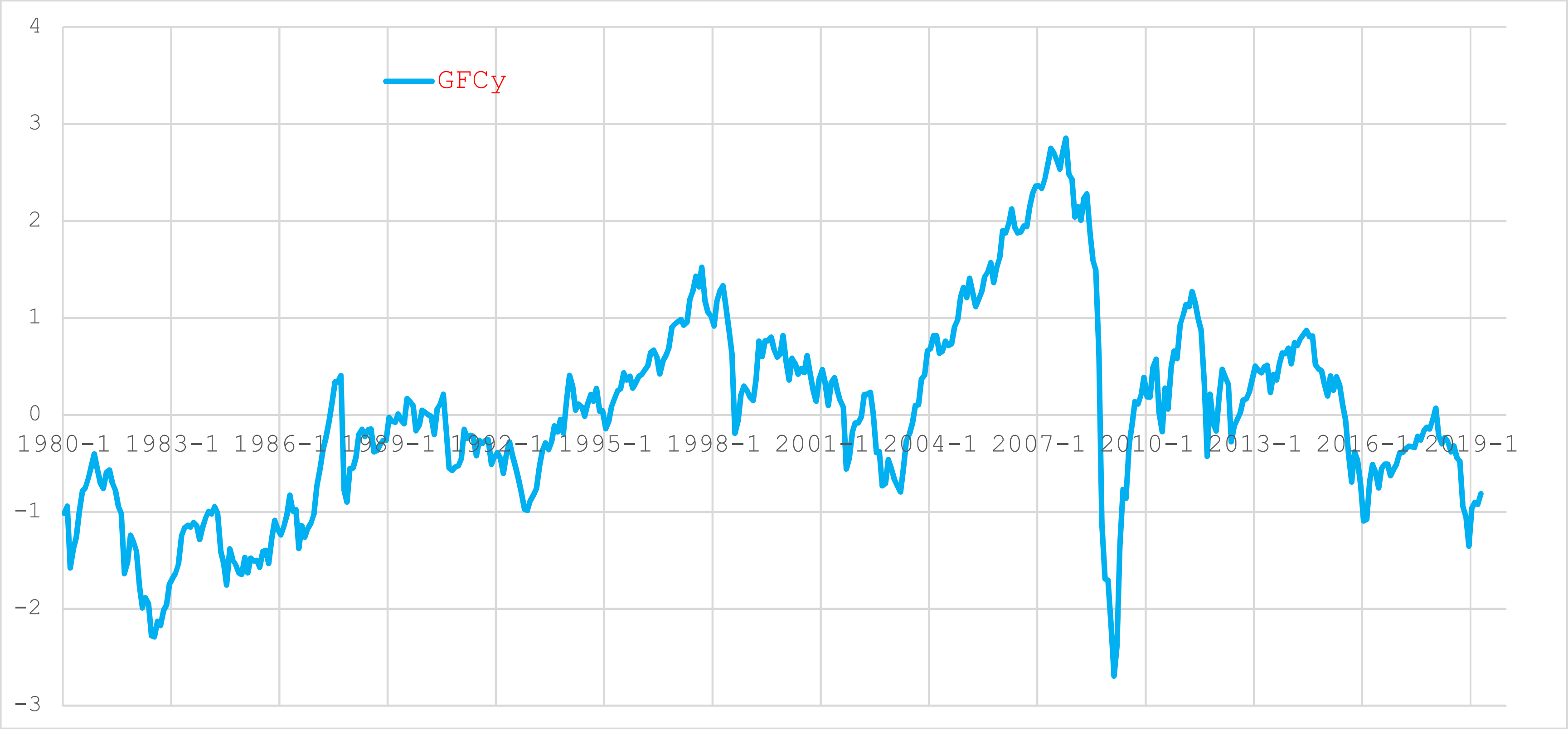
Table 4. Economic significance of incorporating the global finance cycle in the forecasting model.

	Full sample				Pre-GFC				Post-GFC			
	Returns	**Volatility**	**CER**	**SP**	**Returns**	**Volatility**	**CER**	**SP**	**Returns**	**Volatility**	**CER**	**SP**
$\gamma = 3$ *and* $\lambda = 6$												
WTI												
RV	19.336	0.013	19.336	150.396	108.399	0.380	108.395	168.762	19.334	0.013	19.334	150.620
GFCy	19.235	0.013	19.235	148.498	107.099	0.145	107.095	**269.962**	19.226	0.013	19.226	147.518
Brent												
RV	19.287	0.025	19.287	105.888	109.280	0.283	109.277	197.048	19.299	0.025	19.299	107.103
GFCy	19.138	0.024	19.137	**107.130**	108.689	0.277	108.685	**198.377**	19.232	0.025	19.232	106.753
$\gamma = 3$ *and* $\lambda = 8$												
WTI												
RV	26.109	0.022	26.109	157.956	149.971	0.675	149.968	177.251	26.106	0.022	26.106	158.191
GFCy	25.973	0.023	25.973	156.004	148.892	0.623	148.888	**183.175**	25.962	0.023	25.962	154.979
Brent												
RV	26.042	0.045	26.042	111.217	151.255	0.504	151.251	206.945	26.058	0.044	26.058	112.489
GFCy	25.843	0.043	25.843	**112.566**	150.467	0.491	150.463	**208.409**	25.969	0.044	25.969	112.141

Note: This table presents the economic gains from incorporating the GFCy index as a predictor in the GARCH-MIDAS model over the alternative specification that excludes GFCy as a predictor, along the lines of Liu et al. (2019). January 2008 is used as the cutoff point for the pre- and post-GFC samples.

APPENDIX:

Figure A1. Plot of monthly Global Financial Cycle (GFCy) index values.



Note: This figure presents the plot of monthly GFCy index values for the period 1980:01 to 2019:04.

Table A1. Out-of-Sample Forecast Evaluation of Gold Market Volatility using Diebold and Mariano (1995) Test (GARCH-MIDAS-GFCy).

Forecast Horizon	**Full**	**Pre-GFC**	**Post-GFC**
$h = 5$	-126.908***	-160.205***	-215.200***
$h = 10$	-164.926***	-186.706***	-244.462***
$h = 20$	-246.582***	-235.604***	-163.244***
$h = 30$	-192.648***	-281.957***	-89.321***

Note: See Notes to Table 2.