Modeling and forecasting commodity market volatility with long-term economic and financial variables

Nguyen, Duc Khuong and Walther, Thomas

IPAG Business School, Paris, France Indiana University, Bloomington, USA;, University of St. Gallen, St. Gallen, Switzerland Technische Universitat Dresden, Dresden, Germany

May 2017

Modeling and Forecasting Commodity Market Volatility with Long-term Economic and Financial Variables☆

Duc Khuong Nguyen[a,b], Thomas Walther[c,d,*]

[a] *IPAG Lab, IPAG Business School, 184 Boulevard Saint-Germain, 75006 Paris, France*
[b] *School of Public and Environmental Affairs, Indiana University, 107 S Indiana Ave, Bloomington, IN 47405, USA*
[c] *Institute for Operations Research and Computational Finance, University of St. Gallen, 9000 St. Gallen, Switzerland*
[d] *Faculty of Business and Economics, Technische Universität Dresden, 01062 Dresden, Germany*

Abstract

This paper investigates the time-varying volatility patterns of some major commodities as well as the potential factors that drive their long-term volatility component. For this purpose, we make use of a recently proposed GARCH-MIDAS approach which typically allows us to examine the role of economic and financial variables of different frequencies. Using commodity futures for Crude Oil (WTI and Brent), Gold, Silver and Platinum as well as a commodity index, our results show the necessity of disentangling the short-term and long-term components in modeling and forecasting commodity volatility. They also indicate that the long-term volatility of most commodity futures is significantly driven by the level of the global real economic activity as well as the changes in consumer sentiment, industrial production, and economic policy uncertainty. However, the forecasting results are not alike across commodity futures as no single model fits all commodities.

Keywords: Commodity futures, GARCH, Long-term volatility, Macroeconomic effects, Mixed data sampling.
JEL: C58, G17, Q02

☆This paper has been circulated with the title "Identifying the Long-term Volatility Drivers of Commodity Markets". We appreciate the comments of two anonymous reviewers and the special issue editor Hans-Jörg von Mettenheim which led to an significant improvement of a previous version of this paper. We thank Paul Bui Quang, Christian Conrad, Steffi Höse, Stefan Huschens, Lutz Kilian, Tony Klein, Christoph Koser, Robinson Kruse-Becher, Hermann Locarek-Junge, Marcel Prokopczuk, Anne Sumpf, and the participants of the 2nd Joint Seminar on Finance (2016, TU Dresden), HVB doctoral seminar (2017, FU Berlin), the 5th International Symposium on Environment and Energy Finance Issues (2017, Paris), the 6th International Ruhr Energy Conference (2017, Essen), the PhD in Finance Seminar (2018, University of St. Gallen), the Energy Finance Workshop (2018, Stolberg), the 16th INFINITI Conference on International Finance (2018, Poznan), and the 12th Risk Symposium (2018, Dresden) for advice, remarks, and hints. This publication is part of SCCER CREST (Swiss Competence Center for Energy Research), which is supported by Innosuisse (Swiss Innovation Agency). Thomas Walther is grateful for the funding received for conducting this research.

*Mail: thomas.walther@unisg.ch, Phone: +41 (0)71 224 2088.

1. Introduction

Earlier studies on commodity markets have shown that commodity futures can be a valuable source of diversification benefits for investors and portfolio managers, given their distinct risk-return characteristics as compared to traditional assets like bonds and stocks. Bodie & Rosansky (1980) note, for example, that their benchmark portfolio of commodity futures performs as well as the portfolio of common stocks in terms of average returns over the period 1950-1976. More importantly, a diversified portfolio of 60% stocks and 40% commodity futures leads to a return variability reduction of about one-third relative to the 100% stock portfolio, while having the same level of return. The hedging ability against inflation is another interesting feature of commodity futures (Lucey et al., 2017). Similarly, Lintner (1983) finds that the variability of portfolios of stocks and bonds is consistently lower when they are combined with managed commodity futures. More recent studies such as Gorton & Rouwenhorst (2006), Arouri et al. (2011), Narayan et al. (2013), and Klein (2017) also find evidence to confirm this diversifying potential of commodity futures through the use of various datasets and evaluation methods. The specific drivers of commodity returns as well as their low correlations with stocks and bonds can thus be viewed as the key factors that explain the increasing role of commodity futures in portfolio investments and diversification strategies (Domanski & Heath, 2007, Dwyer et al., 2011, Bekiros et al., 2017).

With the intensification of their financialization since 2004, commodity markets are exposed to some structural changes in the distributional characteristics of returns and dependence with other asset classes. Commodity futures returns now behave more like stock returns, and their correlation with stocks has become positive and increased in recent years, particularly after the collapse of Lehman Brothers (Büyükşahin & Robe, 2011, Daskalaki & Skiadopoulos, 2011, Tang & Xiong, 2012, Büyükşahin & Robe, 2014, Adams & Glück, 2015). As a result of this increasing equity-like behavior, researchers find evidence of lower diversification benefits associated with the inclusion of commodity futures in diversified portfolios and a higher level of their shock transmission and volatility spillovers with stocks (Baur & McDermott, 2010, Filis et al., 2011, Narayan & Sharma, 2011, Daskalaki & Skiadopoulos, 2011, Silvennoinen & Thorp, 2013).

The large fluctuations of commodity prices over recent years have also generated concerns for macroeconomic stability and overall economic performance. The standard deviation of the IMF all commodity price index over the 2005M1-2017M6 is 36.45%. The same price index also reached the highest value of 220.03 index points in July 2008 (base index of 100 points in 2005), or an increase of 120%. Since the information about volatility is a critical input for portfolio design, risk management and policy decisions (i.e., the volatility directly affects the cross-asset correlation and portfolio's risk level), an important strand of the commodity finance literature has devoted attention to commodity volatility modeling and the identification of its determinants. A general consensus from the majority of past studies is that main volatility drivers tend to differ across different classes of commodities.

For instance, Daskalaki et al. (2014) attempt to identify common factors for the pricing of commodities. They conclude that neither macroeconomic, equity-related, nor commodity-specific factors can explain the pricing over all commodity classes. Batten et al. (2010) analyze the macroeconomic drivers of monthly precious metal volatility and document that monetary (e.g., inflation) and financial (e.g., S&P 500 returns) variables can explain the volatility block wise, but their results do not hold for Silver. Moreover, the drivers of volatility within the group of precious metals are not alike. Silvennoinen & Thorp (2013) analyze the correlation of commodities and find lagged VIX to have positive impact on weekly energy volatility, but no impact on precious metals.

Regarding the energy market volatility, Pindyck (2004) document that macroeconomic variables such as treasury bill yields or effective exchange-weighted dollar rate do not affect oil price volatility using weekly data. Kilian & Vega (2011) find evidence that WTI oil price returns are not sensitive to macroeconomic news. Karali & Ramirez (2014) use macroeconomic variables, political and weather events to identify drivers of crude oil, heating oil, and natural gas futures volatility. Their results indicate that only crude oil's volatility increases following political, financial, and natural events, whereas macroeconomic variables have no significant impact on oil price volatility. A recent study by Yin (2016) shows that economic policy uncertainty spills over to oil price spot and futures volatility.

Nevertheless, several studies empirically uncover common volatility links among commodity classes. The work of Verma (2012) shows, for example, negative influence of sentiment on the volatility of energy and precious metal futures. Considering a sample of agricultural, energy, and metal commodities, Karali & Power (2013) find evidence of significant influences of inflation and industrial production on commodity markets long-term volatility. Smales (2017) documents that the volatility of commodity markets, represented by the Commodity Research Bureau Index and the S&P Goldman Sachs Commodity Index, react to both the U.S. and Chinese macroeconomic news including the U.S. employment and economic output as well as the purchasing intentions of Chinese manufacturers. Lastly, Prokopczuk et al. (2017) investigate the co-movement of commodity market volatility and economic uncertainty via regression with realized volatility and find that certain macroeconomic and financial variables (i.e., the inflation volatility, the VIX, the default return spread and the TED spread) drive the monthly commodity volatility. The authors suggest to scrutinize the issue further through the framework proposed by Engle et al. (2013) which combines Generalized Autoregressive Heteroskedasticity (GARCH, Engle, 1982, Bollerslev, 1986) models with the Mixed Data Sampling (MIDAS, Ghysels et al., 2004, 2007) technique. This combination particularly allows one to use macroeconomic variables, usually available at monthly or quarterly frequency, as explanatory variables of daily volatility.

The GARCH-MIDAS model has been mostly used to examine the macroeconomic effects of equity (Asgharian et al., 2013, Conrad & Loch, 2015, Opschoor et al., 2014) and bond markets (Nieto et al., 2015). Some studies have also employed this methodology to examine the volatility in commodity markets. Dönmez & Magrini (2013) investigate possible drivers of long-term volatility of agricultural commodities (wheat, corn, and soybean). For oil prices, Yin & Zhou (2016) and Pan et al. (2017) use GARCH-MIDAS with demand and supply shocks as explanatory variables for the volatility. Conrad et al. (2014) use macroeconomic variables to explain the dynamic correlations of stock markets and oil prices. Regarding commodities, Wei et al. (2017) and Fang et al. (2018) show that the economic policy uncertainty is positively associated with WTI spot returns and Gold futures variance and improves forecasts. Moreover, Liu et al. (2018) use news implied volatility indices to explain the long-term volatility of commodities. The authors present evidence that stock market related news affect energy and non-energy commodities. However, news on financial intermediaries are only associated with non-energy commodities.

Our paper contributes to the literature on modeling and forecasting the volatility of commodity markets for portfolio and risk management purposes to the extent that investors and portfolio managers would need accurate volatility to construct diversified portfolio including commodity assets. Going a step further, we particularly focus on the modeling and predictive ability of the GARCH-MIDAS model, while taking into account the potential macro-economic drivers of commodity volatility.

Using data of four economically-important commodity futures (Crude Oil, Gold, Silver, and Platinum) as well as a rich set of economic and financial variables (e.g., industrial production, consumer sentiment, economic uncertainty, implied volatility, and global real economic activity), we find that the growth rate of industrial production and consumer sentiment decreases volatility of commodity futures. Moreover, our analysis suggests that rising economic policy uncertainty and global real economic activity increase the long-term commodity volatility. When examining the usefulness of GARCH-MIDAS to forecast the volatility of commodity futures, we reveal that the inclusion of macroeconomic and financial variables in the volatility models improve the volatility forecast, especially on longer time horizons such as 5- or 20-days ahead prediction. However, no single model appears to be the best-suited specification for all commodity futures we consider. Hence, in the light of our empirical findings, investors would have to pay a close watch on the trends in industrial production, consumer sentiment, economic policy uncertainty, and global economic activities before making any tactical portfolio rebalancing related to commodity futures.

The remainder of the paper is structured as follows. In Section 2, we introduce our econometric framework. Section 3 presents our dataset. Section 4 reports and discusses the empirical results. Section 5 concludes the paper.

2. Methodology

2.1. Spline-GARCH

The Spline-GARCH by Engle & Rangel (2008) is a multiplicative alternative to the additive Component GARCH (Engle & Lee, 1999). The model allows one to disentangle the high and low frequency parts of conditional volatility. The long-term volatility $\sqrt{\tau_t}$ is described by a non-parametric spline. Engle & Rangel (2008) suggest to divide the sample in equidistant knots k. The Spline-GARCH can be formulated as follows:

$$r_t = \mu + z_t\sqrt{\tau_t g_t} \quad \text{with } z_t \sim t_\nu(0,1) \text{ i.i.d.}, \tag{1}$$

$$g_t = (1-\alpha-\beta) + \alpha\left(\frac{\varepsilon_{t-1}^2}{\tau_{t-1}}\right) + \beta g_{t-1}, \tag{2}$$

$$\tau_t = c\exp\left(\omega_0\frac{t}{T} + \sum_{i=1}^{k}\omega_i \max\left(\frac{t-t_i}{T},0\right)^2\right), \tag{3}$$

where $\mathbb{V}[r_t|\Omega_{t-1}] = \tau_t g_t$ with Ω_{t-1} as the information set at time $t-1$ containing all past returns r_t and residuals $\varepsilon_t = (r_t - \mu)$. The innovation z_t is an i.i.d. random variable from a Student's t distribution with ν degrees of freedom. The parameter μ describes the unconditional mean of the return series. The process $\sqrt{g_t}$ describes the high frequency part of the conditional volatility with the well known GARCH dynamics. To maintain non-negativity and weakly stationarity $\alpha, \beta \geq 0$ and $\alpha + \beta < 1$. Engle & Rangel (2008) suggest to identify the optimal choice of knots by using an information criterion such as Bayesian Information Criterion (BIC). However, we follow the approach of Walther et al. (2017), who choose the number and positions of knots by means of the Iterative Cumulative Sums of Squares (ICSS) variant of Sansó et al. (2004).

2.2. GARCH-MIDAS

Based on the Spline-GARCH, the GARCH-MIDAS model is introduced by Engle et al. (2013). It incorporates a long-term volatility component τ_q to a simple GARCH model (Bollerslev, 1986). Thus, the conditional volatility of r_t partly depends on a macroeconomic variable X with K lags.

$$r_{t,q} = \mu + z_{t,q}\sqrt{\tau_q g_{t,q}} \quad \text{with } z_{t,q} \sim t_\nu(0,1) \text{ i.i.d.}, \tag{4}$$

$$g_{t,q} = (1-\alpha-\beta) + \alpha\left(\frac{\varepsilon_{t-1,q}^2}{\tau_q}\right) + \beta g_{t-1,q}, \tag{5}$$

$$\tau_q = \exp\left(m + \theta\sum_{k=1}^{K}\varphi_k(\omega_1,\omega_2)X_{q-k}\right), \tag{6}$$

$$\varphi_k(\omega_1,\omega_2) = \frac{(k/(K+1))^{\omega_1-1}(1-k/(K+1))^{\omega_2-1}}{\sum_{j=1}^{K}(j/(K+1))^{\omega_1-1}(1-j/(K+1))^{\omega_2-1}}. \tag{7}$$

The constraints $\alpha, \beta \geq 0$ and $\alpha + \beta < 1$ have to hold in order to maintain the non-negativity and stationarity of the high-frequency part g_t. For a further discussion on stationarity and ergodicity, see Wang & Ghysels (2015). The Beta-weighting scheme $\varphi_k(\omega_1, \omega_2)$ is introduced to MIDAS by Ghysels et al. (2007). Dependent on the parameters $\omega_1, \omega_2 > 1$, the Beta scheme can depict increasing, decreasing, or hump-shaped weights, which sum up to unity.[1] Engle et al. (2013) also offer the possibility to use an exponential scheme, which is not as flexible as the Beta-function based scheme. Furthermore, Baumeister et al. (2014) consider unrestricted and equally-weighted schemes. Due to the exponential character of the low-frequency part τ_q, no additional restrictions for non-negativity are required. In our specification, τ_q stays constant for a quarter of a year q, which is associated with time t. Note that if we do not include a macroeconomic variable X, the long-term variance is $\tau_q = \exp(m)$ and the model degenerates to a simple GARCH representation.

For the $T+1$ prediction of GARCH-MIDAS, we estimate the parameters from the in-sample period up to T and the last quarter Q and calculate the forecast as follows:

$$\hat{h}_{T+1} = \mathbb{E}[\tau_Q g_{T+1,Q} | \Omega_T] = \tau_Q \mathbb{E}[g_{T+1,Q} | \Omega_T] \tag{8}$$

$$= \tau_Q \left((1 - \alpha - \beta) + \alpha \left(\frac{\varepsilon_{T,Q}^2}{\tau_Q} \right) + \beta g_{T,Q} \right). \tag{9}$$

The multi-step prediction $T+h$ is conducted by recursively substituting the unknown variance forecast until time T:

$$\hat{h}_{T+h} = \tau_Q \left((1 - \alpha - \beta) \sum_{i=0}^{h} (\alpha + \beta)^i + (\alpha + \beta)^h g_{T,Q} \right). \tag{10}$$

This technique of recursive substitution is criticized by Ederington & Guan (2010) for keeping the same weights for all forecast horizons. Admittedly, the short-term component of the GARCH-MIDAS model is prone to this critique. However, the long-term component is the estimate for longer horizons. Thus, the dissipating weights of the short-term component can be neglected for longer horizons. Another possible critique may that we apply quarterly macroeconomic variables for short-term forecast of 1-day or 5-days ahead. Nonetheless, the latest observation of a macroeconomic variable will influence the overall volatility level and thus also affect near-term forecasts.

At the empirical level, we first estimate the three baseline models (i.e., the simple GARCH, the Spline-GARCH, and the GARCH-MIDAS accommodating each of the financial and macroeconomic variables) over different sub-samples corresponding to different dynamics of commodity prices. We then compare the forecasting performance of these models over an out-of-sample

[1] Here, we use the scheme presented in Conrad & Loch (2015).

period.[2]

3. Data

We consider, in this paper, the most important commodity futures in the real economy, which are traded in the New York Mercantile Exchange (NYMEX) and the Commodity Exchange (COMEX) and are commonly investigated in commodity finance literature. We include the WTI crude oil index (RCLC1)[3], the Brent crude oil index (LLCCS00), Gold (NGCCS00), Silver (NSLCS00), and Platinum (NPDCS00).[4] In addition, we take the S&P Goldman Sachs Commodity Index (GSCI) into consideration, which collected from Datastream as well. For all price and index series we use the daily prices over the period from 1 January 1996 to 31 December 2015, and calculate the daily logarithmic returns as $r_t = 100 \cdot (\log(P_t/P_{t-1}))$.

For the set of macroeconomic variables which will be used as potential drivers of the long-term commodity volatility, we consider the Product Price Index (*PPI*), the Industrial Production (*IP*), the University of Michigan Consumer Sentiment (*SENTI*), the overall Economic Policy Uncertainty Index (*EPUI*)[5], the Effective Exchange Rate for the United States (*EERUS*) from the Bank of International Settlement, the bond market volatility index (*MOVE*), the S&P500 volatility index (*VIX*), the 3-month Treasury Bill rate (*TB3M*), the TED spread (*TED*), and the global real economic activity (*GREA*) from Kilian (2009)[6]. The latter is constructed by adjusting the prices of dry bulk cargo rates for various commodities. Given the data availability from 1 January 1992 to 1 October 2015, we calculate 95 quarterly growth rates as $X_q^M = 100 \cdot (P_q/P_{q-1} - 1)$ for each series, except the *GREA*, for Apr 1st 1992-Oct 1st 2015.[7] For the *GREA*, we choose to use the variable in levels, since it is already deflated and linearly detrended by construction. We subdivided the full sample into three periods: (I) 1996-2005, (II) 2006-2015, and the full sample (III) 1996-2015. Table 1 reports the descriptive statistics and some preliminary tests on all time series.

[include Table 1 about here]

[2] All calculations are exercised in MatLab R2017b. In addition, we are thankful to Kevin Sheppard for providing his MFE MatLab toolbox from which we used some functions including the Model Confidence Set. The toolbox is available from `https://www.kevinsheppard.com/MFE_Toolbox`.

[3] The price series is retrieved from `https://www.eia.gov/dnav/pet/pet_pri_fut_s1_d.htm`.

[4] Except for WTI, all price series are retrieved from Thompson Reuters Datastream. The price series are continuous futures series which roll over to the nearest contract at the first day of the month (Roll method Type 0).

[5] The data is obtained from `http://www.policyuncertainty.com/`.

[6] We are grateful to Lutz Kilian for kindly providing the data for the global real economic activity with recent updates on his personal webpage `http://www-personal.umich.edu/~lkilian/paperlinks.html`.

[7] We choose this time window, because the VIX is only available starting 1990. Choosing 1992 as a starting year allows us 1) have the necessary $K = 16$ quarters lag, i.e. four years, for the GARCH-MIDAS model and 2) to calculate proxies for the variance of all macroeconomic variables which includes a year of time lag.

We find that all time series are stationary, given the results of the Augmented Dickey-Fuller (ADF) test. Only for *GREA* in the first sample, the ADF test does not reject the hypothesis of a unit root in the sample. Moreover, the daily log-returns of the commodities exhibit high auto-correlation of squared returns at 12 lags (ARCH test), which suggests the use of GARCH models.

In addition to the growth rates of the macroeconomic variables, we also include the quarterly realized variance of the commodities, defined as

$$X_q^{RV} = \sum_{i=1}^{66} r_{t-i,q}^2. \tag{11}$$

Moreover, we use the quarterly variance of the growth rates of the macroeconomic variables X_q^{MV} as explanatory variable for the long-term volatility. We estimate the variance of the quarterly macroeconomic variables in a similar fashion as in Schwert (1989). In a first step, we filter the quarterly growth rates with a fourth-order Auto-Regressive model and four quarterly dummy variables to account for seasonal effects of the growth series:

$$X_q^M = \sum_{i=1}^{4} \phi_i X_{q-i}^M + \sum_{i=1}^{4} \eta_i D_i + \varepsilon_q. \tag{12}$$

In a second step, the filtered quarterly observations, ε_q, are squared and used as an estimator for the quarterly variance of the macroeconomic variables:

$$X_q^{MV} = \varepsilon_q^2. \tag{13}$$

4. Results and Discussions

We now turn to our results. We divide this section into three parts. In the first subsection, we estimate three GARCH models: the simple GARCH, the Spline-GARCH, and the GARCH-MIDAS-RV to examine whether including a time-varying long-term component can better explain the commodity volatility.

In the subsequent subsection, we estimate a total of 20 different models for each commodity, i.e. we use separately the quarterly growth rates and the quarterly variances of all explanatory macroeconomic and financial variables in our sample in combination with GARCH-MIDAS. Focusing on a single variable in the GARCH-MIDAS model allows us to conclude significance and direction of impact of the explanatory variables.

Lastly, we employ the GARCH-MIDAS models with quarterly growth rates of the macroeconomic and financial drivers, the simple GARCH model, as well as the GARCH-MIDAS-RV and the Spline-GARCH to forecast the volatility of our five commodities under investigation. Thus, a total of 13 models is incorporated to predict the 1-day, 1-week, and 1-month ahead volatility.

4.1. Long-term Volatility Patterns

We start our analysis by examining the parameter estimations of the simple GARCH, the Spline-GARCH, and the GARCH-MIDAS-*RV* models with Student's *t* distribution for the period from 2 January 1996 to 31 December 2015. The estimation of these models allows to straightforwardly assess whether it is economically meaningful to decompose the commodity return volatility into high and low frequencies. Note that the GARCH-MIDAS-*RV* has the quarterly realized variance of each commodity return as an explanatory variable of its long-term volatility.

[include Table 2 about here]

The estimation results are given in Tab. 2. As expected, the GARCH-MIDAS-*RV* model, which incorporates the quarterly realized variance of commodity returns, yields the best goodness-of-fit (i.e., lowest BIC) for all commodities under consideration, except for Platinum where the Spline-GARCH is the best-suited model. In all cases, the simple GARCH model has the worst fit, given its low Log-Likelihood (LL). For the Spline-GARCH model, the knots are identified by means of the ICSS approach and the results show five structural breakpoints for WTI and Brent oil indices, six for Gold, Silver and GSCI, and only one breakpoint for Platinum.

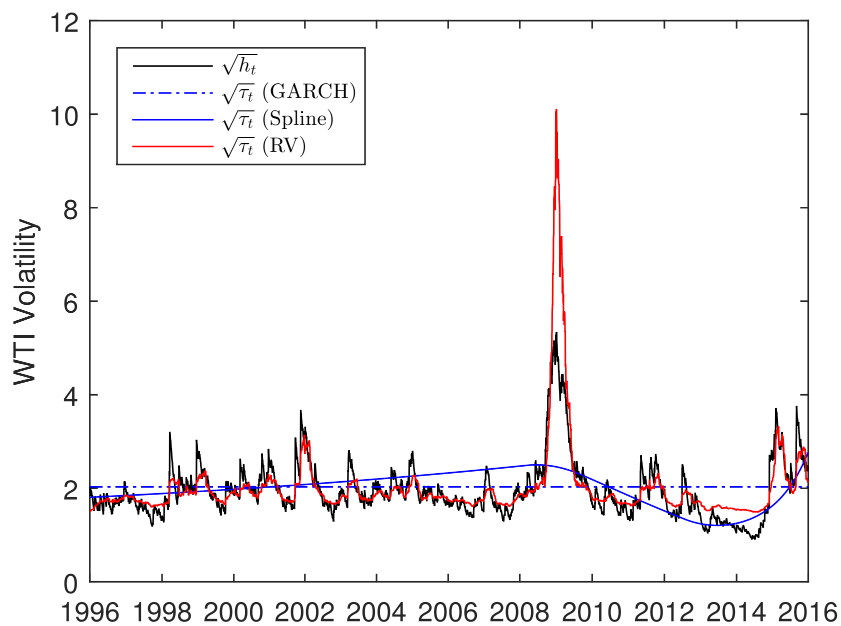

Figure 1: Volatility ($\sqrt{h_t}$) and long-term volatility ($\sqrt{\tau_t}$) of WTI oil price returns with GARCH, Spline-GARCH, and GARCH-MIDAS-*RV* for the period 1996-2015.

Tab. 2 also indicates that the short-term dynamics (i.e. α and β) of the three models are highly significant and very similar with relatively close values. This finding thus suggests that the differences in statistical fit (LL) and goodness-of-fit (BIC) rather arise from the long-term volatility component. Engle et al. (2013) use a variance ratio to determine the explanatory value of the long-term volatility. The measure $\text{VR} = \frac{\mathbb{V}(\log \tau_t)}{\mathbb{V}(\log h_t)}$ describes the proportion of variance of the logarithmic long-term volatility and the variance of the logarithmic conditional volatility. For each GARCH-based specification, we use the estimated conditional variance $\widehat{h}_t$ of the simple GARCH model as base.[8] For the remaining models, we see that the long-term component of the Spline-GARCH and the GARCH-MIDAS-*RV* explains the fluctuation of the variance in a range between 21% and 96%. As an illustration, we depict, in Fig. 1, the long-term components of each model for the WTI crude oil volatility. The long-term volatility pattern provided by the GARCH-MIDAS-*RV* follows closely the conditional volatility dynamics.

4.2. Drivers of Long-term Volatility

We now turn to present and discuss the results from the GARCH-MIDAS regressions over the three different sample periods for each commodity, whereby the long-term volatility component is modeled as a function of each of the financial and macroeconomic variables.

Before we present the regression analysis, we further test the legitimacy of a time-varying long-term component by means of a recently proposed regression-based misspecification test. To test the null hypothesis of a constant long-term component (simple GARCH), Conrad & Schienle (2018) suggest to run the following linear regression model:

$$\log RV_q = a_0 + a_1 X_{q-1} + \rho \log RV_{q-1} + \xi_q, \tag{14}$$

where RV_q is the quarterly realized variance based on the daily, standardized residuals from the simple GARCH model. X_{q-1} is the lagged, quarterly macroeconomic variable. The idea behind the test is that the realized variance should not be predictable. Hence, if a_1 is statistically different from zero, we can reject the null hypothesis of a constant long-term component. Our results show, that for all five commodities at least two variables are able to predict the realized variance. Thus, some variables might not be appropriate to predict RV, but it appears the simple GARCH model with constant long-term component is not correctly specified.[9]

Since a time-varying long-term component seems reasonable, we procede with the GARCH-MIDAS insample regression. This analysis allows us to identify the drivers of shocks or swings in the long-term volatility component. Without loss of generality, we solely concentrate on the

[8] Note that the simple GARCH has an VR of zero. Since its long-term component is constant over time, the variance of the constant logarithmic long-term component is zero.

[9] The complete regression results are given in the Appendix in Table 6.

interpretation of the MIDAS parameters θ, ω_1, and ω_2. The results are given in Tab. 3, where we summarize the sign of the statistically significant parameter θ.[10]

[include Table 3 about here]

The results for the WTI crude oil indicate that the quarterly growth rates of all macroeconomic variables have significant effects on the WTI long-term volatility in at least one out of the three periods we consider, except *PPI* and *TB3M*. In particular, the consumer sentiment (*SENTI*) consistently has a negative and significant impact in all three periods. Hence, when consumer sentiment rises the oil price volatility tends to decrease, which may suggest that the economy is in its stable state. As expected, the economic policy uncertainty (*EPUI*), the effective exchange rate for the United States (*EERUS*), and the global real economic activity (*GREA*) drive up the long-term oil price volatility. The effect of the quarterly variance of the growth rates of macroeconomic variables is however not exactly similar as the *PPI* and *TB3M* variables have now significant impacts. Also, the impact of the variance of the *SENTI* variable on long-term oil price volatility over the full period is positive. A close look at the *SENTI* variable shows that for the full period, we estimate the parameters $\widehat{\theta} = -0.2359$, $\widehat{\omega_1} = 1.7843$, and $\widehat{\omega_2} = 2.8450$. Hence, for a 1% increase of *SENTI* one quarter before, the long-term WTI volatility decreases by $\exp(-0.2359 \cdot 0.0549) - 1 = -0.0129$ or -1.29%. The highest impact is due to changes in the consumer sentiment five quarters before, i.e. a 1% increase in consumer sentiment decreases the long-term volatility in five quarters by $\exp(-0.2359 \cdot 0.1094) - 1 = -0.0258$ or -2.58%. Figure 2 shows the full lag structure for all three sample periods and how it changed from the first to the second decade of the whole sample. In the second sample period, the impact of *SENTI* is even bigger than for the full sample. As to the variance of the 3-month treasury bill rate, it negatively influences the long-term WTI volatility for all three sample periods. Thus, the U.S. oil price volatility decreases due to interest rate variability. This finding complements the observations of Barsky & Kilian (2002), who document that oil price increases (decreases) were preceded by low (high) interest rates.

The European Brent oil volatility shows similar patterns like its U.S. counterpart. Especially for the second period and the full sample, we observe that the *GREA* level is positively associated with the long-term oil price volatility. Hence, positive values in the global real economic activity index lead to higher oil price fluctuations. Kilian (2009) builds the index based on dry bulk ship cargo rates. These rates increase in times of high economic activity due to the fact that high demand meets an relatively inelastic supply curve. Thus, a positive index points towards a demand shock and an increased trading volume of commodities in general, which leads to their higher volatility. Analogously, if the *GREA* has a negative index, the markets cool down given the lower demand,

[10] The complete regression results are given in the Appendix in Tables 7-24.

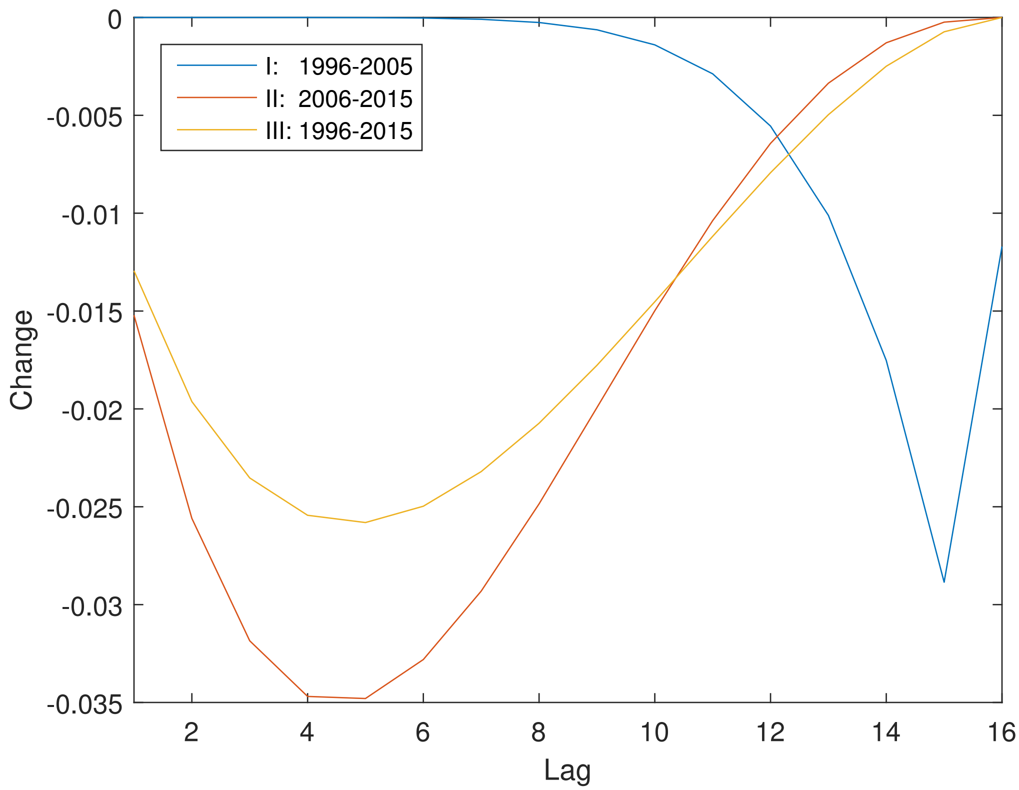

Figure 2: Change of the conditional variance of WTI due to the impact of consumer sentiment (*SENTI*) for quarterly lags up to $K = 16$.

and oil prices stabilize (less volatility). We find the *GREA* to be significant for all commodities in the second sub-sample. Figure 3 shows the effects of the lagged *GREA* levels on the long-term volatility of the two oil indices and the three metals. While the long-term volatility of the WTI and Brent is influenced by the *GREA* index from its first lag onwards, the metal volatility only reacts five quarters after and their highest reaction is observed at the seventh lag. Interestingly, we find that Brent reacts one quarter quicker to demand shocks than WTI, which could be explained by the fact that the Brent oil price is used as the benchmark for two-thirds of the world's oil trades.

For the long-term volatility of Gold and Silver, we find a negative effect of the *IP* variable. Industrial production generally reflects the state of the U.S. economy. Thus, an increase in the *IP* growth rates will decrease the long-term metal volatility. This is because Gold and Silver are often used for hedge and/or safe-haven purposes during turbulent periods (Baur & Lucey, 2010) and are not invested extensively when the economy performs well. We also find that the *EPUI* growth rates positively affect Gold's and Platinum's volatility whatever the sub-samples, but it is not the case for Silver. This finding suggests that increases in the economic policy uncertainty leads to different expectations by investors. Hence, we can support the results of Fang et al. (2018) and Wei et al.

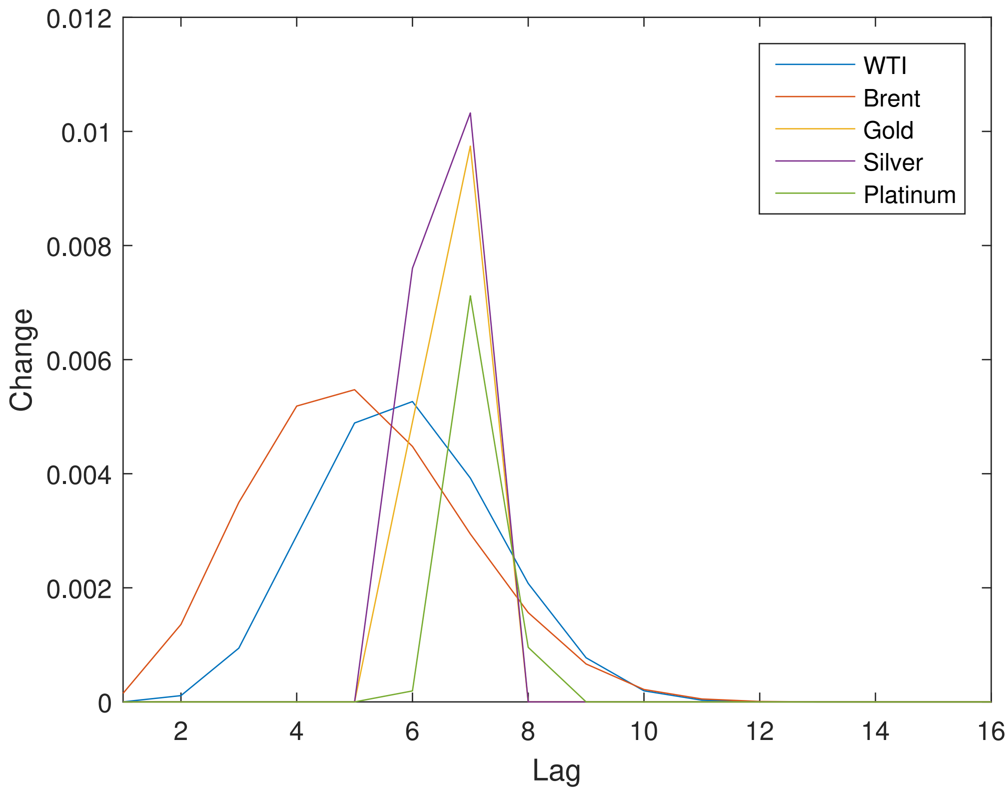

Figure 3: Change of the long-term conditional volatility of WTI, Brent, Gold, Silver, and Platinum due to the impact of global real economic activity (*GREA*) index for quarterly lags up to $K = 16$. The period spans from 2006-2015.

(2017), which show the importance of EPUI for Gold and WTI, respectively.

To summarize, our findings show that the growth rates of the industrial production (*IP*) and consumer sentiment (*SENTI*) negatively influence the long-term commodity volatility regardless of subsample periods and commodities, whenever the associated coefficients are statistically significant. The same result is reported in Karali & Power (2013) where changes in the industrial production are negatively associated with crude oil and Gold. There is also a positive link between the growth rate of *EPUI* and the level of *GREA* with the long-term commodity volatility. Except for *EPUI*, we can confirm these results for the GSCI. The impact of the variance of macroeconomic variables, albeit significant, is however not consistent across commodities or subsamples. We only find the variance of *SENTI* $(+)$ and *PPI* $(+)$ to be consistent with only one exception each. Both variables confirm the assumption, that uncertainty about sentiment and inflation impacts prices, which is the idea behind the standard ARCH model (Engle, 1982).

4.3. Forecasting Commodity Volatility

Whether the GARCH-MIDAS specifications with financial and macroeconomic variables are helpful for forecasting commodity volatility is of great interest to investors and portfolio managers. This subsection compares their predictive ability with the one of the simple GARCH, the Spline-GARCH, and the GARCH-MIDAS-*RV* models.[11] We choose an out-of-sample period of four years from 3 January 2012 to 30 December 2015 (i.e. $M = 1005$ observations), with an expanding training window starting from 2 January 1996. Three loss functions are used to compare the forecasting performance of the different models and model specifications. They are described as follows:

$$\text{RMSE} = \frac{1}{M}\sqrt{\sum_{i=1}^{M}\left(\hat{h}_i - (r_i - \hat{\mu}_i)^2\right)},$$

$$\text{MAE} = \frac{1}{M}\sum_{i=1}^{M}\left|\hat{h}_i - (r_i - \hat{\mu}_i)^2\right|,$$

$$\text{QLIKE} = \frac{1}{M}\sum_{i=1}^{M}\left(\log\hat{h}_i + \frac{(r_i - \hat{\mu}_i)^2}{\hat{h}_i}\right),$$

where $\hat{h}_i$ is the forecasted conditional variance and the squared residual $(r_i - \hat{\mu}_i)^2$ is the proxy for the actual variance at time i in the out-of-sample set $i = 1, \ldots, M$.

Moreover, following Hansen et al. (2011), we employ the Model Confidence Set (MCS) with 10% level of significance to identify the best forecasting models and to avoid the problem of data snooping.

[include Table 4 about here]

The results of the variance forecast are given in Tab. 4. For oil price returns (WTI and Brent), the Spline-GARCH yields the best variance prediction performance and is present in the MCS of almost all loss functions over all horizons. All GARCH-MIDAS models with macroeconomic and financial variables have relatively equal performance in forecasting the oil price volatility with respect to the RMSE criterion over 1- or 5-days ahead. For the other loss functions, only the GARCH-MIDAS-*GREA* model joins the Spline-GARCH in the MCS, while the GARCH-MIDAS-*VIX* model for the Brent oil is also included in the MCS with respect to the QLIKE. Putting together with the findings in subsection 4.2, the *GREA* is not only suitable for explaining the in-sample volatility, but also a promising candidate to conduct forecasts of long-term oil price volatility.

[11] Due to the fact that we do not find consistent patterns for the variance of these variables, we use the growth rates of the macroeconomic and financial variables only.

The results for Gold show that all competing models belong to the set of equally well-performing models at the 1-day ahead forecast horizon with respect to the RMSE and at the 5- and 20-days ahead forecast horizon with respect to QLIKE. Only the GARCH-MIDAS-*TB3M* model is present in all MCS regardless of time horizons and loss functions. This is a little bit surprising in our study, because (a) it is not significant in all in-sample estimations and (b) the direction of effects is not consistent. Its predictive power seems to suggest that it contains information about the long-term volatility which is used as a tendency for the short-term forecasts. For instance, a rising tendency in the *TB3M* could signal stock market booms and thus more stable Gold prices in the long-run because Gold will be less used in hedging and diversification strategies.

For Silver, the RMSE and QLIKE loss functions indicate that almost all GARCH-MIDAS models with financial and macroeconomic variables, the GARCH, and the GARCH-MIDAS-*RV* have equal performance at the three forecasting horizons under consideration. The MAE, on the other hand, only identifies four out of 13 models with superior performance. The inclusion of *SENTI*, *EPUI*, and *MOVE* variables into the GARCH-MIDAS models results in lower MAE for 5- and 20-days than the other specifications. Having realized volatility as explanatory variable for the long-term volatility shows better performance for 1- and 5-days ahead forecasts.

The long-term volatility of Platinum appears to be harder to predict. We find the same macroeconomic variables as for Silver to be included in the MCS. While the GARCH-MIDAS-*SENTI* and GARCH-MIDAS-*MOVE* models (also simple GARCH) show good performance for 5- and 20-days horizons, the GARCH-MIDAS-*EPUI* and GARCH-MIDAS-*RV* belong to the MCS for 1-day ahead prediction.

The variance of the commodity index GSCI is relatively well predicted by all explanatory variables. Only the MAE indicates that the Spline-GARCH maybe favourable.

The results from the variance forecasting show that no single GARCH-MIDAS specification is able to predict the volatility better than the others, and this result holds across all commodities. Especially, the use of the *TED* to predict commodity volatility is not recommended. From 54 tests (three horizons, three loss functions, and six commodities), it is only included in 15 MCS. On the contrary, the GARCH-MIDAS model using the *GREA* level appears to have 29 inclusions.

In addition to the volatility forecast, we evaluate the Value-at-Risk (VaR) forecast performance of the models. For this purpose, we use the multivariate unconditional coverage test of Pérignon & Smith (2008) to jointly test the coverage of $p = 95\%$, 97.5%, and 99% VaRs. The idea of the test is based on the hit ratio test of Kupiec (1995), which compares the empirically observed VaR exceedance with the theoretical one. Since the test by Kupiec (1995) only compares one coverage ratio at a time, the extension of Pérignon & Smith (2008) allows us to scrutinize the performance of a specific VaR forecast at three different coverage ratios jointly. We define the coverage as the ratio of VaR violations to the number of out-of-sample observations. The backtest compares this number to the theoretical coverage, e.g. for a 95% VaR the theoretical coverage is 5%.

Based on the GARCH models, we estimate the VaR as follows:

$$\widehat{\text{VaR}}_{t,p} = \hat{\mu}_t + \sqrt{\hat{h}_t} F^{-1}_{1-p}(\hat{\nu}), \tag{15}$$

where $F^{-1}_{1-p}(\nu)$ is the $(1-p)$-quantile function of the Student-t distribution with ν degrees of freedom.[12]

[include Table 5 about here]

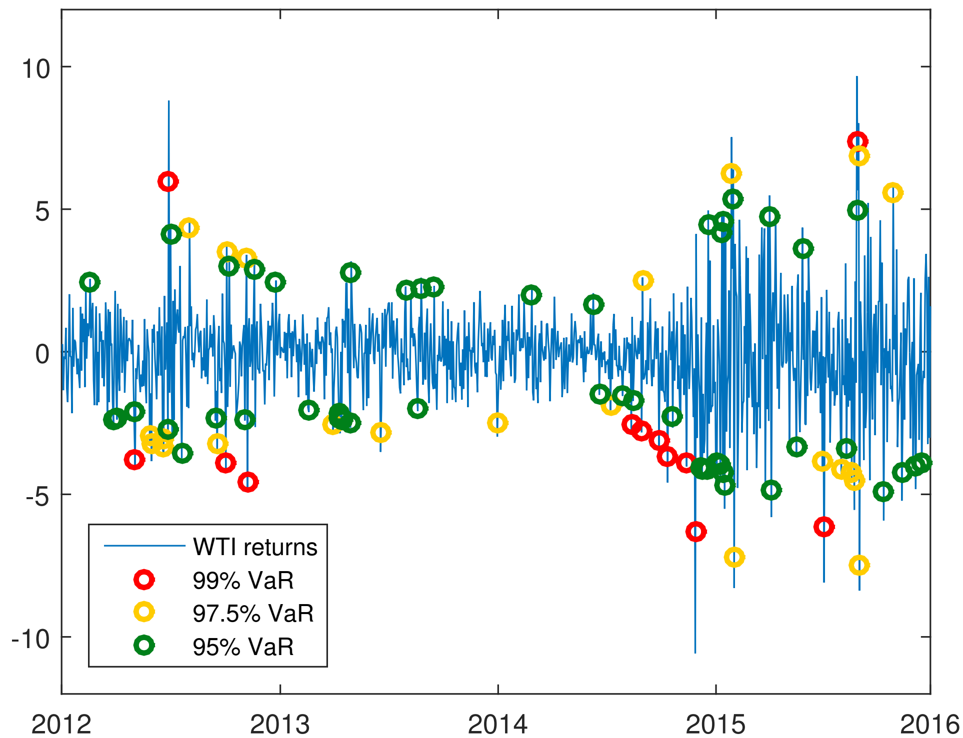

Figure 4: Value-at-Risk forecast for WTI 2012-2015 with GARCH-MIDAS-*SENTI*.

The results of the VaR backtest in Table 5 can be summarized as follows. First, for the WTI and Brent crude oil as well as for GSCI, almost all models pass the VaR test from a long trading

[12] In addition, we calculate the Expected Shortfall (ES) for our commodities. The ES is the expected value of the returns which are lower than the estimated VaR. We use the ES backtest by Acerbi & Szekely (2014), which evaluates the number and the size of exceedances jointly. We incorporate a level of confidence of 97.5%, which is the usual level under the Basel requirements Basel Committee on Banking Supervision (2016). For the sake of brevity, our results are presented in the Appendix Tab. 25. Basically, the ES results confirm the impression of the VaR backtest.

position, but fail when the short trading perspective is evaluated. For the GSCI, the result may partly be explained due to the fact that a large share of the index includes crude oil. Second, the test rejects more models on the long trading positions for Gold and Silver. Finally, except for some models at 5-days ahead VaR forecast for long trading positions, all forecasting models for Platinum fail to obtain satisfactory results. Figure 4 demonstrates the VaR forecast for WTI with GARCH-MIDAS-*SENTI*, which has the least rejections over all VaR tests conducted (17 out of 36). On the short trading positions, i.e. traders being susceptible to earn positive returns, the GARCH-MIDAS model with the sentiment index as an explanatory variable is rejected by the backtest due to the fact that the predictions are too conservative. For example, the 95% VaR forecast which is supposed to have a coverage of 5% only yields 2.69% (27 exceptions). The 97.5% VaR only has 0.90% (9 exceptions) and the 99% VaR only has a coverage of 0.02% (2 exceptions), where 2.5% and 1% are required, respectively.[13] Since the model fails to provide a sufficient estimate of the VaR at any quantile, it is rejected by the Pérignon & Smith (2008) test. Models that yield too conservative VaR estimates are costly in terms of capital requirements of banks or VaR-limits of traders. However, as mentioned above, the VaR estimates for the long trading position pass the test. Here, the coverage of the 95% VaR is 5.57% (56 exceptions).

In order to check for robustness of our in-sample and out-of-sample results, we check for several different settings of our models. First, we change the number of lags K, i.e. how many past quarters information of macroeconomic variables are used. Second, we use logarithmic differences of the macroeconomic variables instead of growth rates. Third, we attempt to incorporate the first principal component of all macroeconomic and financial variables. Fourth, instead of using the Student-*t* distribution for the innovations z_t, we evaluated our results assuming a Normal distribution. Finally, we change the frequency of our explanatory variable, which we use at a quarterly rate, to monthly growth rates to explain the long-term volatility of daily commodity returns. For all mentioned robustness checks, the results remain qualitatively intact.

5. Conclusion

The motivation of this paper was to identify the potential drivers of the long-term volatility of commodity prices through the GARCH-MIDAS class model, at both modeling and forecasting levels. We conduct our empirical investigation in three steps including the in-sample estimation, the identification of the long-term commodity volatility drivers, and the out-of-sample volatility forecasting. In the first step, we show that disentangling long-term and short-term volatility of

[13]The exceptions can be counted by the dots in Fig. 4. For the 95% VaR the sum of all yellow, green, and red dots is the number of exceptions for each trading position. For the 97.5% VaR, one has to sum the yellow and the red dots. For the 99% VaR, the number of exceptions is given by the sum of the red dots only.

commodity futures leads to a better in-sample fit by means of the Spline-GARCH and the GARCH-MIDAS models with commodity's realized volatility.

In the second step, we employ the GARCH-MIDAS framework to examine whether each of the financial and macroeconomic variables in our study matters for the long-term commodity volatility. We find that the long-term commodity volatility is negatively influenced by the growth rates of the consumer sentiment and the industrial production, but positively by the growth rate of the economic policy uncertainty and the level of the general real economic activity. We also investigate whether the variance of these financial and macroeconomic variables inhibits any information for the long-term commodity volatility, but we do not find any consistent results across commodity futures.

The last part of the paper uses the GARCH-MIDAS with financial and macroeconomic variables to forecast the volatility of commodities over the 1-, 5-, and 20-days ahead horizons. It is important to stress that the consistent results for in-sample estimations are not translated into forecasting performance. Thus, we find different best-suited models for each commodity. For example, the oil price volatility is best predicted with either Spline-GARCH or the GARCH-MIDAS-*GREA*. For Gold, the GARCH-MIDAS-*TB3M* is recommended for forecasting the volatility at the 1-, 5-, and 20-days ahead forecasts. For Silver and Platinum, we find the GARCH-MIDAS-*SENTI*, the GARCH-MIDAS-*EPUI*, the GARCH-MIDAS-*MOVE*, and the GARCH-MIDAS-*RV* to have equally well results. At the same time, our forecasting results show, from a risk management perspective, that the inclusion of financial and macroeconomic variables in the volatility models does not lead to better Value-at-Risk predictions than the simple GARCH model.

The findings of our paper can be improved by potentially considering the asymmetric effects of financial and macroeconomic variables. For instance, Verma (2012) and Bahloul & Bouri (2016) report volatility asymmetric responses in times of bullish and bearish markets. Moreover, the forecastability of GARCH-MIDAS models might be improved by model averaging.

References

Acerbi, C., & Szekely, B. (2014). Backtesting Expected Shortfall. *Risk Magazine*, (pp. 76–81).

Adams, Z., & Glück, T. (2015). Financialization in commodity markets: A passing trend or the new normal? *Journal of Banking & Finance*, *60*, 93–111. doi:10.1016/j.jbankfin.2015.07.008.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance*, *30*, 1387–1405. doi:10.1016/j.jimonfin.2011.07.008.

Asgharian, H., Hou, A. J., & Javed, F. (2013). The importance of the macroeconomic variables in forecasting stock return variance: A GARCH-MIDAS approach. *Journal of Forecasting*, *32*, 600–612. doi:10.1002/for.2256.

Bahloul, W., & Bouri, A. (2016). The impact of investor sentiment on returns and conditional volatility in U.S. futures markets. *Journal of Multinational Financial Management*, *36*, 89–102. doi:10.1016/j.mulfin.2016.07.003.

Barsky, R., & Kilian, L. (2002). Do We Really Know that Oil Caused the Great Stagflation? A Monetary Alternative. In B. S. Bernake, & K. S. Rogoff (Eds.), *NBER Macroeconomics Annual 2001* (pp. 137–183). volume 16.

Basel Committee on Banking Supervision (2016). *Minimum capital requirements for market risk*. Technical Report January 2016. URL: www.bis.org/bcbs/publ/d352.pdf.

Batten, J. A., Ciner, C., & Lucey, B. M. (2010). The macroeconomic determinants of volatility in precious metals markets. *Resources Policy*, *35*, 65–71. doi:10.1016/j.resourpol.2009.12.002.

Baumeister, C., Guérin, P., & Kilian, L. (2014). Do high-frequency financial data help forecast oil prices? The MIDAS touch at work. *International Journal of Forecasting*, *31*, 238–252. doi:10.1016/j.ijforecast.2014.06.005.

Baur, D. G., & Lucey, B. M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *Financial Review*, *45*, 217–229. doi:10.1111/j.1540-6288.2010.00244.x.

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, *34*, 1886–1898. doi:10.1016/j.jbankfin.2009.12.008.

Bekiros, S., Nguyen, D. K., Sandoval Junior, L., & Uddin, G. S. (2017). Information diffusion, cluster formation and entropy-based network dynamics in equity and commodity markets. *European Journal of Operational Research*, *256*, 945–961. doi:10.1016/j.ejor.2016.06.052.

Bodie, Z., & Rosansky, V. I. (1980). Risk and Return in Commodity Futures. *Financial Analysts Journal*, *36*, 27–39. doi:10.2469/faj.v36.n3.27.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*, 307–327. doi:10.1016/0304-4076(86)90063-1.

Büyükşahin, B., & Robe, M. A. (2011). Does 'Paper Oil' Matter? Energy Markets' Financialization and Equity-Commodity Co-Movements. URL: http://www.ssrn.com/abstract=1855264.

Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. *Journal of International Money and Finance*, *42*, 38–70. doi:10.1016/j.jimonfin.2013.08.004.

Conrad, C., & Loch, K. (2015). Anticipating Long-Term Stock Market Volatility. *Journal of Applied Econometrics*, *30*, 1090–1114. doi:10.1002/jae.2404.

Conrad, C., Loch, K., & Rittler, D. (2014). On the macroeconomic determinants of long-term volatilities and correlations in U.S. stock and crude oil markets. *Journal of Empirical Finance*, *29*, 26–40. doi:10.1016/j.jempfin.2014.03.009.

Conrad, C., & Schienle, M. (2018). Testing for an Omitted Multiplicative Long-Term Component in GARCH Models. *Journal of Business & Economic Statistics*, *0015*, 1–14. doi:10.1080/07350015.2018.1482759.

Daskalaki, C., Kostakis, A., & Skiadopoulos, G. (2014). Are there common factors in individual commodity futures returns? *Journal of Banking and Finance*, *40*, 346–363. doi:10.1016/j.jbankfin.2013.11.034.

Daskalaki, C., & Skiadopoulos, G. (2011). Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking and Finance*, *35*, 2606–2626. doi:10.1016/j.jbankfin.2011.02.022.

Domanski, D., & Heath, A. (2007). Financial investors and commodity markets. *BIS Quarterly Review*, (pp. 53–67).

Dönmez, A., & Magrini, E. (2013). *Agricultural Commodity Price Volatility and Its Macroeconomic Determinants*. Technical Report EUR 26183 EN Joint Research Centre Luxembourg. doi:10.2791/23669.

Dwyer, A., Gardner, G., & Williams, T. (2011). Global Commodity Markets – Price Volatility and Financialisation. *Bulletin*, (pp. 49–58).

Ederington, L. H., & Guan, W. (2010). Longer-term time-series volatility forecasts. *Journal of Financial and Quantitative Analysis*, *45*, 1055–1076. doi:10.1017/S0022109010000372.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*, 987–1007. doi:10.2307/1912773.

Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock Market Volatility and Macroeconomic Fundamentals. *Review of Economics and Statistics*, *95*, 776–797.

Engle, R. F., & Lee, G. (1999). A long-run and short-run component model of stock return volatility. In R. Engle, & H. White (Eds.), *Cointegration, Causality, and Forecasting: A Festschrift in Honour of Clive W.J. Granger* (pp. 475–497). Oxford: Oxford University Press.

Engle, R. F., & Rangel, J. G. (2008). The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies*, *21*, 1187–1222. doi:10.1093/rfs/hhn004.

Fang, L., Chen, B., Yu, H., & Qian, Y. (2018). The importance of global economic policy uncertainty in predicting gold futures market volatility: A GARCH-MIDAS approach. *Journal of Futures Markets*, *38*, 413–422. doi:10.1002/fut.21897.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, *20*, 152–164. doi:10.1016/j.irfa.2011.02.014.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). The MIDAS Touch: Mixed Data Sampling Regression Models. *CIRANO Working Papers*, *20*, 1–33.

Ghysels, E., Sinko, A., & Valkanov, R. (2007). MIDAS Regressions: Further Results and New Directions. *Econometric Reviews*, *26*, 53–90. doi:10.1080/07474930600972467.

Gorton, G., & Rouwenhorst, K. G. (2006). Facts and Fantasies about Commodity Futures. *Financial Analysts Journal*, *62*, 47–68. doi:10.3386/w10595.

Hansen, P. R., Lunde, A., & Nason, J. M. (2011). The Model Confidence Set. *Econometrica*, *79*, 453–497. doi:10.3982/ECTA5771.

Karali, B., & Power, G. J. (2013). Short- and long-run determinants of commodity price volatility. *American Journal of Agricultural Economics*, *95*, 724–738. doi:10.1093/ajae/aas122.

Karali, B., & Ramirez, O. A. (2014). Macro determinants of volatility and volatility spillover in energy markets. *Energy Economics*, *46*, 413–421. doi:10.1016/j.eneco.2014.06.004.

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review*, *99*, 1053–1069. doi:10.1257/aer.99.3.1053.

Kilian, L., & Vega, C. (2011). Do Energy Prices Respond to U.S. Macroeconomic News? A Test of the Hypothesis of Predetermined Energy Prices. *Review of Economics and Statistics*, *93*, 660–671. doi:10.1162/REST{_}a{_}00086.

Klein, T. (2017). Dynamic Correlation of Precious Metals and Flight-to-Quality in Developed Markets. *Finance Research Letters*, *23*, 283–290. doi:10.1016/j.frl.2017.05.002.

Kupiec, P. H. (1995). Techniques for Verifying the Accuracy of Risk Measurement Models. *The Journal of Derivatives*, *3*, 73–84. doi:10.3905/jod.1995.407942.

Lintner, J. V. (1983). *The potential role of managed commodity-financial futures accounts (and/or funds) in portfolios of stocks and bonds*. Division of Research, Graduate School of Business Administration, Harvard University.

Liu, Y., Han, L., & Yin, L. (2018). Does news uncertainty matter for commodity futures markets? Heterogeneity in energy and non-energy sectors. *Journal of Futures Markets*, *38*, 1246–1261. doi:10.1002/fut.21916.

Lucey, B. M., Sharma, S. S., & Vigne, S. A. (2017). Gold and inflation(s) – A time-varying relationship. *Economic Modelling*, *67*, 88–101. doi:10.1016/j.econmod.2016.10.008.

Narayan, P. K., Narayan, S., & Sharma, S. S. (2013). An analysis of commodity markets: What gain for investors? *Journal of Banking & Finance*, *37*, 3878–3889. doi:10.1016/j.jbankfin.2013.07.009.

Narayan, P. K., & Sharma, S. S. (2011). New evidence on oil price and firm returns. *Journal of Banking and Finance*, *35*, 3253–3262. doi:10.1016/j.jbankfin.2011.05.010.

Nieto, B., Novales, A., & Rubio, G. (2015). Macroeconomic and Financial Determinants of the Volatility of Corporate Bond Returns. *Quarterly Journal of Finance*, *05*, 1550021. doi:10.1142/S2010139215500214.

Opschoor, A., van Dijk, D., & van der Wel, M. (2014). Predicting volatility and correlations with Financial Conditions Indexes. *Journal of Empirical Finance*, *29*, 435–447. doi:10.1016/j.jempfin.2014.10.003.

Pan, Z., Wang, Y., Wu, C., & Yin, L. (2017). Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model. *Journal of Empirical Finance*, *43*, 130–142. doi:10.1016/j.jempfin.2017.06.005.

Pérignon, C., & Smith, D. R. (2008). A New Approach to Comparing VaR Estimation Methods. *The Journal of Derivatives*, *16*, 54–66. doi:10.3905/JOD.2008.16.2.054.

Pindyck, R. S. (2004). Volatility and commodity price dynamics. *Journal of Futures Markets*, *24*, 1029–1047. doi:10.1002/fut.20120.

Prokopczuk, M., Stancu, A., & Symeonidis, L. (2017). The economic drivers of time-varying commodity market volatility. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2678883.

Sansó, A., Aragó, V., & Carrion, J. (2004). Testing for changes in the unconditional variance of financial time series. *Revista de Economía financiera*, *4*, 32–53.

Schwert, G. W. (1989). Why Does Stock Market Volatility Change Over Time? *The Journal of Finance*, *44*, 1115–1153. doi:10.1111/j.1540-6261.1989.tb02647.x.

Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money*, *24*, 42–65. doi:10.1016/j.intfin.2012.11.007.

Smales, L. A. (2017). Commodity market volatility in the presence of U.S. and Chinese macroeconomic news. *Journal of Commodity Markets*, *7*, 15–27. doi:10.1016/j.jcomm.2017.06.002.

Tang, K., & Xiong, W. (2012). Index Investment and the Financialization of Commodities. *Financial Analysts Journal*, *68*, 54–74. doi:10.2469/faj.v68.n6.5.

Verma, R. (2012). Behavioral Finance and Pricing of Derivatives: Implications for Dodd-Frank Act. *Review of Futures Markets*, *20*, 21–67.

Walther, T., Klein, T., Pham Thu, H., & Piontek, K. (2017). True or spurious long memory in European Non-EMU currencies. *Research in International Business and Finance*, *40C*, 217–230. doi:10.1016/j.ribaf.2017.01.003.

Wang, F., & Ghysels, E. (2015). Econometric Analysis of Volatility Component Models. *Econometric Theory*, *31*, 362–393. doi:10.1017/S0266466614000334.

Wei, Y., Liu, J., Lai, X., & Hu, Y. (2017). Which determinant is the most informative in forecasting crude oil market volatility: Fundamental, speculation, or uncertainty? *Energy Economics*, *68*, 141–150. URL: https://doi.org/10.1016/j.eneco.2017.09.016. doi:10.1016/j.eneco.2017.09.016.

Yin, L. (2016). Does oil price respond to macroeconomic uncertainty? New evidence. *Empirical Economics*, *51*, 921–938. doi:10.1007/s00181-015-1027-7.

Yin, L., & Zhou, Y. (2016). What Drives Long-term Oil Market Volatility? Fundamentals versus Speculation. *Economics: The Open-Access, Open-Assessment E-Journal*, *10*, 1–26. doi:10.5018/economics-ejournal.ja.2016-20.

	T	Mean	Min.	Max.	Stand.Dev.	Skewness	Kurtosis	LB(12)	ARCH(12)	ADF
Commodities (daily returns) Jan 1st 1996-Dec 30th 2005										
WTI	2501	0.0492	-12.1607	11.6594	1.9820	-0.2029	5.2754	15.7446	64.4502***	-49.6648***
Brent	2610	0.0448	-14.4372	12.8982	2.2517	-0.2308	5.4517	9.7797	50.7701***	-52.9709***
Gold	2610	0.0110	-5.1049	8.8872	0.8800	0.6539	12.7778	17.1831	112.6825***	-51.0886***
Silver	2610	0.0205	-11.8323	7.6612	1.4473	-0.4294	8.3490	23.0132**	175.5339***	-51.0985***
Platinum	2610	0.0342	-14.4173	18.6781	1.3806	1.1136	30.8952	30.6490***	12.0356	-52.0306***
GSCI	2610	0.0350	-9.1695	6.5670	1.3058	-0.1160	4.8398	9.4775	67.5175***	-51.7882***
Jan 2nd 2006-Dec 31st 2015										
WTI	2514	-0.0199	-10.5782	12.1150	2.1369	-0.1592	6.2928	21.3814**	452.5556***	-53.5608***
Brent	2609	-0.0176	-10.9455	12.7066	2.0985	-0.0683	6.8232	51.0998***	592.7609***	-54.3737***
Gold	2609	0.0275	-9.8206	8.6250	1.2635	-0.3727	8.0461	27.4426***	130.4636***	-51.0980***
Silver	2609	0.0171	-19.5185	12.3585	2.2741	-0.8740	9.2652	14.8882	141.0550***	-52.5413***
Platinum	2609	-0.0033	-9.6033	16.0210	1.5176	-0.0922	11.2790	15.7196	164.1283***	-48.1499***
GSCI	2609	-0.0428	-8.6486	7.2159	1.4950	-0.3046	6.3860	20.0830*	477.3502***	-53.0929***
Jan 1st 1996-Dec 31st 2015										
WTI	5015	0.0146	-12.1607	12.1150	2.0612	-0.1826	5.8927	17.6758	527.7097***	-73.1878***
Brent	5219	0.0136	-14.4372	12.8982	2.1765	-0.1553	6.0644	32.4483***	535.3568***	-75.8587***
Gold	5219	0.0193	-9.8206	8.8872	1.0887	-0.1107	10.0088	33.3773***	269.7001***	-72.2897***
Silver	5219	0.0188	-19.5185	12.3585	1.9058	-0.8372	10.7768	17.0178	341.2088***	-73.7414***
Platinum	5219	0.0154	-14.4173	18.6781	1.4507	0.4234	19.4480	19.3300*	84.9298***	-70.5618***
GSCI	5219	-0.0039	-9.1695	7.2159	1.4040	-0.2416	5.9329	16.2624	655.5203***	-74.3136***
Macroeconomic Variables (monthly growth rates) Apr 1st 1992-Oct 1st 2005										
PPI	55	0.6694	-0.3376	2.0451	0.4754	0.6912	3.7751	318.2274***	50.1899***	-3.6043***
IP	55	0.8200	-1.8292	2.8383	0.9645	-0.3809	3.1006	35.2119***	14.3579	-3.2424***
SENTI	55	0.4590	-23.1088	21.8281	7.6340	0.0805	4.2131	41.7492***	32.1541***	-9.3907***
EPUI	55	1.7363	-38.8710	69.5293	22.3375	0.4208	3.1595	39.2926***	17.0294	-11.0963***
EERUS	55	0.0478	-6.9507	6.1370	3.0024	-0.2221	2.6952	21.6967**	17.2949	-7.0971***
MOVE	55	1.3843	-29.3532	63.6364	18.5001	1.0442	4.1247	21.9241**	9.1196	-10.0174***
VIX	55	2.3680	-40.3663	107.7626	28.2879	1.5510	5.8957	35.4489***	11.1852	-10.2729***
TB3M	55	1.0094	-38.4615	41.4894	14.5236	0.1139	4.0666	87.7110***	33.2890***	-3.5105***
TED	55	6.2467	-60.2941	86.1111	34.0892	0.4774	2.6466	31.6456***	33.4887***	-8.9898***
GREA	55	-0.4675	-31.9724	50.0013	20.8700	0.8223	3.0898	164.7693***	48.2137***	-1.4067
Apr 1st 2002-Oct 1st 2015										
PPI	55	0.5419	-2.5072	2.3931	0.9436	-0.5981	4.1356	40.2087***	15.1128	-5.9474***
IP	55	0.2587	-6.3991	2.2055	1.4753	-2.5494	11.3393	45.8746***	32.7200***	-3.2404***
SENTI	55	0.3614	-23.1088	23.3553	9.2580	0.1338	3.3880	33.7638***	5.9681	-10.0613***
EPUI	55	2.6112	-45.3283	81.8613	25.4964	1.0549	4.3691	18.0936	11.2170	-9.1542***
EERUS	55	-0.2340	-7.9567	7.5602	3.5305	0.1185	2.6679	34.7111***	17.9774	-5.5318***
MOVE	55	0.8816	-38.2632	74.1710	20.6668	1.4848	5.8719	8.3091	11.6003	-8.3127***
VIX	55	4.4193	-45.5307	160.0484	34.2312	2.1021	9.7139	30.7492***	8.4924	-8.8370***
TB3M	55	0.8119	-80.5970	166.6667	43.9323	1.7308	8.3431	12.7389	18.4377	-6.4236***
TED	55	10.6581	-63.4146	246.1538	52.2457	2.2308	10.1778	18.6416*	13.1449	-8.8564***
GREA	55	14.6714	-52.8075	64.3385	30.4095	-0.3424	2.1175	155.1052***	49.8877***	-2.1508**
Apr 1st 1992-Oct 1st 2015										
PPI	95	0.5767	-2.5072	2.3931	0.7532	-0.7862	6.0136	70.8559***	28.7945***	-6.8992***
IP	95	0.5351	-6.3991	2.8383	1.3503	-2.2119	11.4121	60.7998***	42.0781***	-4.2607***
SENTI	95	0.6426	-23.1088	23.3553	8.3201	0.2527	3.7418	38.7771***	8.6220	-12.9977***
EPUI	95	2.7076	-45.3283	81.8613	24.7079	0.8304	3.8843	25.0137**	12.1545	-13.2026***
EERUS	95	0.1405	-7.9567	7.5602	3.2155	-0.0054	2.7492	23.7173**	15.9138	-8.0968***
MOVE	95	1.8373	-38.2632	74.1710	20.5543	1.1986	4.7469	14.3955	9.1704	-12.0629***
VIX	95	4.2099	-45.5307	160.0484	32.1412	1.9710	8.8980	36.8007***	8.0812	-12.6911***
TB3M	95	-0.0771	-80.5970	166.6667	34.1781	2.1582	13.2354	18.4462	30.7764***	-8.4102***
TED	95	7.8327	-63.4146	246.1538	45.9179	2.0660	10.5898	28.4977***	19.9667*	-11.7807***
GREA	95	4.8672	-52.8075	64.3385	26.9702	0.3593	2.3448	309.0392***	81.8343***	-2.8191***

Table 1: Descriptive statistics of commodity returns and growth rates of macroeconomic variables.

Note: Rejection of the respective hypothesis at 1%, 5% and 10% is marked by ***, **, and *, respectively. LB(12) and ARCH(12) are the Ljung-Box and ARCH test at 12 lags auto-correlation of returns and squared returns. ADF is the Augmented Dickey-Fuller test for stationarity.

Commodity	Model	knots	μ	α	β	ν	LL	BIC	VR
WTI	GARCH	–	0.0439	0.0396***	0.9559***	8.2406***	-10251	20545	–
	Spline	5	0.0455	0.0398***	0.9478***	8.0593***	-10240	20573	0.4983
	RV	–	0.0434***	0.0414***	0.9338***	8.9963***	-10222	**20513**	0.7782
Brent	GARCH	–	0.0391*	0.0413***	0.9560***	7.0635***	-10893	21828	–
	Spline	5	0.0409	0.0432***	0.9424***	6.9465***	-10878	21851	0.5524
	RV	–	0.0398*	0.0425***	0.9437***	7.3761***	-10869	**21806**	0.6319
Gold	GARCH	–	0.0111	0.0399***	0.9578***	4.5391***	-7000	14043	–
	Spline	6	0.0092	0.0469***	0.9459***	3.9893***	-6980	14063	0.7281
	RV	–	0.0126*	0.0467***	0.9443***	4.2017***	-6973	**14015**	0.7653
Silver	GARCH	–	0.0437***	0.0320***	0.9651***	4.0933***	-9822	19686	–
	Spline	6	0.0400*	0.0349***	0.9595***	3.7689***	-9806	19716	0.9574
	RV	–	0.0458***	0.0408***	0.9397***	3.8973***	-9798	**19665**	0.8059
Platinum	GARCH	–	0.0330**	0.0518***	0.9388***	4.7068***	-8460	16962	–
	Spline	1	0.0307**	0.0535***	0.9344***	4.5654***	-8450	**16960**	0.2618
	RV	–	0.0309**	0.0560***	0.9311***	4.6732***	-8453	16975	0.2055
GSCI	GARCH	–	0.0138	0.0355***	0.9388***	7.9946***	-8633	17309	–
	Spline	6	0.0141	0.0351***	0.9542***	7.8838***	-8621	17345	0.6525
	RV	–	0.0138	0.0321**	0.9612***	8.3741***	-8616	**17301**	0.4904

Table 2: Parameter estimation results of the GARCH, Spline-GARCH, and GARCH-MIDAS-*RV*: 2 January 1996 - 31 December 2015.

Note: The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. LL is the Log-Likelihood and the BIC is the Bayesian Information Criterion. Numbers in bold face indicate the model with the best goodness-of-fit (lowest BIC). The variance ratio VR represents the proportion of long-term variance to total variance.

Commodity	WTI			Brent			Gold			Silver			Platinum			GSCI		
Period	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III	I	II	III
quarterly growth rates																		
PPI						$-$	$-$	$+$	$-$	$-$			$-$		$-$	$+$		$+$
IP		$-$			$-$		$-$	$-$	$-$	$-$	$-$	$-$		$-$	$-$	$-$		
SENTI	$-$	$-$	$-$	$-$	$-$	$-$	$-$	$-$			$-$		$-$	$-$		$-$	$-$	$-$
EPUI		$+$		$+$		$+$	$+$	$+$	$+$			$+$	$+$	$+$	$+$			
EERUS	$-$	$+$		$+$						$-$	$-$		$+$		$+$	$-$		
MOVE			$+$	$+$		$+$	$-$			$-$		$-$	$+$			$+$		$+$
VIX		$-$	$-$										$+$		$+$	$-$		
TB3M		$-$		$+$		$-$	$-$	$+$			$+$	$-$	$-$			$-$		$-$
TED	$-$		$-$	$+$	$+$	$-$	$-$			$-$	$+$		$-$	$+$				
GREA		$+$	$+$		$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$	$+$
quarterly variance																		
PPI	$+$	$+$		$+$	$+$		$+$	$+$	$+$	$+$	$+$	$+$	$-$			$+$	$+$	
IP	$-$	$+$		$+$				$+$	$+$		$+$					$-$		
SENTI	$-$	$+$					$+$	$+$	$+$		$+$	$+$	$+$	$+$				$+$
EPUI				$+$		$-$		$+$		$+$	$-$	$+$	$+$		$+$	$+$	$+$	
EERUS		$+$				$-$		$+$	$+$		$+$	$+$	$-$	$-$	$+$			$+$
MOVE	$-$		$-$				$-$			$-$	$-$		$-$		$+$			
VIX		$-$	$-$	$+$	$-$	$-$		$+$		$+$	$-$			$-$	$-$		$-$	$-$
TB3M	$-$	$-$	$-$	$+$	$-$	$-$	$-$	$-$	$+$		$-$		$+$		$+$	$+$	$-$	$-$
TED	$+$					$-$	$-$	$+$	$+$	$-$	$+$		$+$		$+$	$+$	$-$	
GREA				$+$						$+$					$+$			

Table 3: Regression results for GARCH-MIDAS model using macroeconomic and financial variables.

Note: The sign ($+$ or $-$) is given if the parameter θ is statistically significant, i.e. p-value $< 10\%$. Otherwise the field is left blank. The periods span from (I) 1996-2005, (II) 2006-2015, and (III) 1996-2015.

		PPI	*IP*	*SENTI*	*EPUI*	*EERUS*	*MOVE*	*VIX*	*TB3M*	*TED*	*GREA*	GARCH	*RV*	Spline
WTI														
RMSE	1-day	**3.4620**	**3.4717**	**3.4609**	**3.4717**	**3.4561**	**3.4647**	**3.4679**	**3.4636**	**3.4588**	**3.4633**	**3.4587**	**3.4366**	**3.4466**
	5-days	**3.6689**	3.6779	**3.6705**	**3.6582**	**3.6638**	**3.6692**	**3.6651**	**3.6967**	**3.6679**	**3.6604**	**3.6661**	3.7518	**3.6738**
	20-days	3.7608	3.7893	**3.7525**	**3.7457**	3.7605	3.7603	**3.7426**	3.8008	3.7671	**3.7372**	3.7550	3.9878	3.7846
MAE	1-day	0.7105	0.7173	0.6833	0.7054	0.7044	0.7090	0.7011	0.7157	0.7190	0.6906	0.7067	0.7220	**0.6738**
	5-days	0.7670	0.7844	0.7410	0.7554	0.7631	0.7680	0.7546	0.7789	0.7789	0.7420	0.7628	0.8526	**0.7293**
	20-days	0.8466	0.8864	0.8217	0.8271	0.8489	0.8539	0.8251	0.8629	0.8673	**0.8093**	0.8405	1.0394	**0.7966**
QLIKE	1-day	0.8807	0.8864	0.8304	0.8725	0.8753	0.8763	0.8637	0.8938	0.8943	0.8457	0.8745	0.9077	**0.8461**
	5-days	0.9300	0.9475	0.8830	0.9165	0.9267	0.9294	**0.9090**	0.9465	0.9470	**0.8894**	0.9229	1.0410	**0.8985**
	20-days	1.0081	1.0532	0.9651	0.9838	1.0099	1.0159	**0.9793**	1.0258	1.0353	**0.9554**	0.9988	1.2578	**0.9600**
Brent														
RMSE	1-day	**3.0136**	**3.0106**	**3.0028**	**3.0022**	**3.0052**	**3.0112**	**3.0068**	**2.9924**	**2.9959**	**3.0038**	**3.0008**	**2.9952**	**3.0020**
	5-days	**3.2042**	**3.2030**	**3.1999**	**3.1934**	**3.1989**	**3.2002**	**3.2020**	**3.2011**	**3.1962**	**3.1834**	**3.1963**	3.2741	**3.2395**
	20-days	3.3086	3.3167	3.3050	3.2908	3.3114	3.3040	3.3033	3.3126	3.3044	**3.2665**	3.3017	3.5075	3.4219
MAE	1-day	0.6585	0.6670	0.6525	0.6620	0.6656	0.6656	0.6631	0.6599	0.6667	**0.6430**	0.6606	0.6830	**0.6461**
	5-days	0.7072	0.7198	0.7036	0.7109	0.7182	0.7167	0.7150	0.7158	0.7210	**0.6866**	0.7115	0.7837	0.7043
	20-days	0.7733	0.7960	0.7759	0.7751	0.7936	0.7852	0.7845	0.7886	0.7927	**0.7442**	0.7812	0.9387	0.7830
QLIKE	1-day	0.8238	0.8408	0.8134	0.8335	0.8417	0.8392	0.8340	0.8415	0.8484	0.8007	0.8330	0.8747	**0.8492**
	5-days	0.8637	0.8842	0.8558	0.8721	0.8851	0.8795	0.8760	0.8865	0.8914	**0.8362**	0.8739	0.9720	**0.9067**
	20-days	0.9217	0.9535	0.9200	0.9272	0.9534	0.9406	0.9386	0.9494	0.9578	0.8862	0.9356	1.1416	**0.9776**
Gold														
RMSE	1-day	**1.6349**	**1.6345**	**1.6286**	**1.6315**	**1.6332**	**1.6363**	**1.6335**	**1.6324**	**1.6350**	**1.6340**	**1.6359**	**1.6154**	**1.6206**
	5-days	1.7210	1.7189	1.7202	1.7187	1.7180	1.7207	1.7162	**1.7149**	1.7219	1.7183	1.7192	1.7351	1.7229
	20-days	1.7288	1.7304	1.7294	1.7274	**1.7252**	1.7284	**1.7219**	**1.7236**	1.7300	1.7271	1.7266	1.7618	1.7384
MAE	1-day	0.2628	0.2593	0.2557	0.2566	0.2560	0.2597	0.2568	**0.2519**	0.2559	0.2576	0.2590	0.2640	0.2617
	5-days	0.2775	0.2743	0.2702	0.2716	0.2693	0.2737	0.2701	**0.2654**	0.2712	0.2717	0.2725	0.2889	0.2837
	20-days	0.2902	0.2907	0.2824	0.2851	0.2810	0.2850	0.2816	**0.2769**	0.2829	0.2840	0.2834	0.3249	0.3110
QLIKE	1-day	0.4122	0.4108	0.4093	0.4098	0.4087	0.4127	0.4061	**0.4060**	0.4105	0.4111	0.4113	**0.4143**	0.4079
	5-days	**0.4667**	**0.4639**	**0.4625**	**0.4628**	**0.4629**	**0.4680**	**0.4584**	**0.4598**	**0.4650**	**0.4661**	**0.4652**	**0.4719**	**0.4611**
	20-days	**0.4756**	**0.4787**	**0.4745**	**0.4712**	**0.4694**	**0.4759**	**0.4612**	**0.4727**	**0.4760**	**0.4767**	**0.4744**	**0.4948**	**0.4754**
Silver														
RMSE	1-day	**3.4798**	**3.4808**	**3.4786**	**3.4844**	**3.4695**	**3.4722**	**3.4790**	**3.4746**	**3.4827**	**3.4593**	**3.4787**	**3.4671**	**3.4754**
	5-days	**3.6118**	**3.6079**	**3.5963**	**3.6027**	**3.6112**	**3.6053**	**3.6117**	**3.6080**	3.6355	**3.5970**	**3.6056**	**3.6028**	3.6394
	20-days	**3.6370**	3.6847	**3.6231**	**3.6284**	**3.6349**	**3.6294**	**3.6414**	**3.6361**	3.6705	**3.6447**	**3.6312**	3.6480	3.7435
MAE	1-day	0.7748	0.7733	0.7640	0.7675	0.7710	0.7672	0.7721	0.7704	0.7822	0.7656	0.7724	**0.7571**	0.8025
	5-days	0.8113	0.8145	**0.7972**	**0.8008**	0.8134	**0.8022**	0.8091	0.8064	0.8205	0.8117	0.8068	**0.7988**	0.8636
	20-days	0.8472	0.8769	**0.8324**	**0.8327**	0.8544	**0.8369**	0.8449	0.8437	0.8618	0.8800	0.8413	0.8531	0.9605
QLIKE	1-day	0.8651	**0.8624**	**0.8474**	**0.8546**	**0.8627**	**0.8543**	**0.8629**	**0.8610**	**0.8812**	**0.8547**	0.8615	**0.8418**	0.9129
	5-days	**0.9121**	**0.9178**	**0.8902**	**0.8987**	**0.9137**	**0.9027**	**0.9086**	**0.9074**	**0.9290**	**0.9135**	**0.9071**	**0.8942**	**0.9852**
	20-days	**0.9499**	0.9984	**0.9299**	**0.9340**	**0.9569**	**0.9387**	**0.9469**	**0.9463**	0.9720	**0.9970**	**0.9461**	**0.9597**	1.1089
Platinum														
RMSE	1-day	0.9786	0.9725	0.9751	**0.9532**	0.9836	0.9814	0.9907	0.9811	0.9838	0.9798	0.9822	**0.9505**	0.9954
	5-days	1.0680	1.0511	**1.0461**	1.0604	1.0520	**1.0451**	1.0671	1.0523	1.0509	**1.0484**	**1.0457**	1.0609	1.0931
	20-days	1.1481	1.0992	1.0862	1.1429	1.0803	**1.0706**	1.1447	1.0889	1.0791	1.0842	**1.0709**	1.1617	1.2173
MAE	1-day	0.2944	0.2810	0.2740	**0.2718**	0.2861	0.2814	0.2906	0.2803	0.2836	0.2796	0.2816	**0.2712**	0.3101
	5-days	0.3368	0.3162	**0.3048**	0.3225	0.3154	0.3078	0.3273	0.3112	0.3115	0.3094	0.3084	0.3285	0.3582
	20-days	0.3976	0.3603	**0.3394**	0.3846	0.3482	**0.3359**	0.3828	0.3441	0.3412	0.3440	**0.3373**	0.4025	0.4368
QLIKE	1-day	0.4903	0.4751	0.4683	**0.4679**	0.4791	0.4760	0.4876	0.4753	0.4776	0.4760	0.4754	**0.4663**	0.5087
	5-days	0.5327	**0.5110**	**0.5013**	0.5192	0.5098	**0.5043**	0.5264	0.5075	0.5070	**0.5081**	**0.5038**	0.5237	0.5564
	20-days	0.6020	0.5583	**0.5389**	0.5906	0.5428	**0.5317**	0.5878	0.5422	0.5359	0.5433	**0.5317**	0.6092	0.6466
GSCI														
RMSE	1-day	**1.1906**	**1.1889**	**1.1854**	**1.1918**	**1.1892**	**1.1878**	**1.1857**	**1.1867**	**1.1898**	**1.1863**	**1.1877**	**1.1871**	**1.1876**
	5-days	**1.2466**	**1.2481**	**1.2458**	**1.2478**	**1.2469**	**1.2466**	**1.2453**	**1.2512**	**1.2483**	**1.2430**	**1.2467**	1.2619	**1.2520**
	20-days	**1.2660**	1.2749	**1.2673**	**1.2655**	1.2714	**1.2640**	**1.2635**	1.2725	**1.2680**	**1.2606**	**1.2652**	1.3184	1.2765
MAE	1-day	0.2536	0.2578	0.2499	0.2565	0.2558	0.2560	0.2569	0.2592	0.2575	0.2505	0.2558	0.2593	**0.2412**
	5-days	0.2695	0.2774	0.2680	0.2717	0.2742	0.2726	0.2741	0.2779	0.2737	0.2677	0.2724	0.2929	**0.2606**
	20-days	0.2926	0.3085	0.2974	0.2932	0.3031	0.2958	0.2976	0.3025	0.2965	0.2951	0.2953	0.3513	**0.2841**
QLIKE	1-day	0.4201	0.4253	0.4158	0.4263	0.4215	0.4250	0.4242	0.4288	0.4260	0.4148	0.4240	0.4249	**0.4277**
	5-days	**0.4452**	**0.4525**	**0.4423**	**0.4508**	**0.4480**	**0.4504**	**0.4492**	**0.4562**	**0.4509**	**0.4398**	**0.4492**	0.4634	**0.4602**
	20-days	**0.4601**	0.4754	0.4602	**0.4647**	0.4684	**0.4650**	**0.4643**	**0.4729**	**0.4659**	**0.4553**	**0.4638**	0.5147	**0.4740**

Table 4: Out-of-sample forecasting results tested with loss functions.

Note: We report RMSE, MAE, and QLIKE results from out-of-sample variance forecasting with 1-day, 5-day, and 20-days ahead horizons. Bold face values indicate models which are included in the Model Confidence Set $M_{90\%}$ with 10% level of significance. The Model Confidence Set is constructed with 1 000 bootstraps with block length 2.

		PPI	*IP*	*SENTI*	*EPUI*	*EERUS*	*MOVE*	*VIX*	*TB3M*	*TED*	*GREA*	GARCH	*RV*	Spline
							WTI							
long	1-day	1.3291	1.1545	0.7991	0.0892	1.6975	1.0796	2.8591	0.7387	3.8566	0.6516	1.3291	6.1798	14.5278***
	5-days	2.4676	0.7679	3.4783	1.6457	3.5441	1.6851	1.2782	1.0554	2.0651	1.0521	0.8176	2.9684	10.3501**
	20-days	0.6864	4.8842	1.4394	0.8465	0.5415	0.5240	1.8007	1.5031	1.1241	3.9504	1.5194	7.3225*	3.9551
short	1-day	20.9990***	22.2830***	17.8585***	19.5237***	22.2830***	20.5433***	17.8585***	25.5188***	22.2830***	16.1967***	22.2830***	26.8411***	11.8460***
	5-days	19.7260***	19.7260***	16.2864***	17.9250***	19.7260***	22.6564***	15.2284***	18.2351***	20.5608***	14.4342***	19.7260***	24.5973***	3.8532
	20-days	21.8583***	23.4792***	16.3097***	16.6369***	20.9999***	17.9309***	16.6369***	25.2843***	24.8083***	15.4233***	23.4792***	37.0052***	9.5762**
							Brent							
long	1-day	1.3212	1.9542	3.2275	2.5316	3.4419	3.0767	3.4419	3.4419	3.4872	2.5772	2.9013	3.8418	13.2270***
	5-days	0.5081	0.1887	0.8625	2.0491	2.3435	0.5373	0.1447	1.1387	0.3684	1.3616	0.4033	2.4273	6.9526*
	20-days	0.1827	2.8120	0.2733	0.2733	2.4930	0.0777	1.5195	1.4823	0.7019	1.7862	1.9348	8.5164**	13.6750***
short	1-day	14.9398***	13.2542***	16.7118***	17.4813***	18.0098***	13.8808***	20.0969***	13.0955***	17.2960***	12.8030***	17.4813***	22.6950***	8.4746**
	5-days	7.7895*	8.5757**	8.3241**	7.0146*	9.6155**	11.1006**	9.5324**	9.7748**	11.5543***	6.9029*	8.5757**	18.7983***	7.5898*
	20-days	7.0655*	11.8865***	8.3241**	9.5324**	10.5743**	13.1998***	8.7765**	11.8865***	14.7199***	7.0091*	11.8865***	23.9646***	8.1956**
							Gold							
long	1-day	5.4212	7.4347*	6.5363*	12.8347***	5.8312	4.8550	7.1804*	8.5736**	5.1490	5.9782	5.8508	7.6761*	7.6761*
	5-days	7.4729*	6.6538*	12.2202***	9.5941**	10.9482**	8.2508**	8.8531**	16.0478***	8.8893**	8.6701**	10.0241**	2.9920	4.2414
	20-days	3.1121	7.2493*	5.7318	5.9918	6.6734*	5.7318	3.4979	8.8540**	7.2806*	6.6082*	7.0935*	2.4357	4.6911
short	1-day	5.6325	6.8793*	7.8011*	8.3499**	9.0662**	8.2540**	7.6206*	9.0571**	8.5955**	8.2408**	9.1922**	5.8510	6.1055
	5-days	5.1960	6.4311*	4.0094	2.3093	3.8040	2.3093	3.8040	3.2804	3.2821	1.8667	3.0748	9.4037**	9.1922**
	20-days	1.6759	2.6478	2.9517	2.2724	4.6223	4.7104	4.8257	4.0689	2.6671	4.2187	4.4200	4.1172	1.8214
							Silver							
long	1-day	8.3506**	8.3717**	3.4444	9.6970**	11.9246***	6.6478*	5.3758	6.8155*	4.2605	7.0210*	5.6580	3.3027	10.0485**
	5-days	10.1703**	8.8807**	5.8659	12.0897***	8.9491**	7.2200*	10.7235**	9.1486**	12.0458***	10.3623**	7.8693**	3.9186	7.7240*
	20-days	8.9082**	3.4429	7.7535*	7.0703*	8.3852**	6.7105*	8.4334**	7.2591*	6.3901*	5.8254	7.7535*	5.5627	4.4962
short	1-day	6.0082	6.5606*	3.8869	5.1025	6.0082	4.7434	3.1086	6.4065*	4.9452	5.5046	4.4973	5.2996	5.2704
	5-days	3.4635	3.5168	2.1808	3.2898	2.4989	3.6571	3.4419	3.8246	3.4766	2.2704	2.6531	2.5205	2.3807
	20-days	2.2842	2.5435	3.4147	0.8214	1.1282	2.3183	1.8214	1.8214	2.7952	2.9651	1.8214	5.4773	5.9199
							Platinum							
long	1-day	19.9014***	19.6155***	21.0900***	27.8269***	19.6155***	13.9264***	8.5953**	15.5119***	14.8219***	13.3196***	16.6391***	24.4327***	15.3000***
	5-days	3.8151	3.4504	6.7372*	1.9001	2.8531	4.7311	1.1156	8.4307**	6.0150	5.5998	5.0833	1.8731	7.4687*
	20-days	17.8293***	8.0833**	5.7995	9.2022**	6.6313*	5.7705	10.1528**	6.5700*	5.5198	4.3314	5.8722	13.4484***	17.2960***
short	1-day	27.8042***	23.5669***	13.9304***	22.6623***	17.2199***	15.1807***	11.6623***	17.5100***	15.1069***	16.7712***	17.0085***	24.5270***	27.0605***
	5-days	14.0903***	12.4601***	5.5615	7.2440*	15.3856***	9.5994**	8.5491**	10.6561**	11.1458**	8.2407**	9.5994**	12.4414***	17.8791***
	20-days	31.9399***	20.8183***	13.9301***	22.3735***	16.7704***	15.5485***	25.0142***	17.5100***	15.1058***	15.1807***	17.8012***	34.1885***	37.8763***
							GSCI							
long	1-day	1.4158	0.8195	2.6487	1.3086	0.2419	0.6172	2.0186	0.9560	0.7246	5.5553	1.6527	0.4558	2.6326
	5-day	3.2518	1.9640	2.8505	3.1964	1.0931	4.8702	3.7042	4.7722	3.4969	2.1090	3.7949	1.1036	9.7574**
	20-day	2.1576	6.8216*	4.8381	4.2624	6.3728*	5.9076	2.7729	5.8866	4.2624	3.9438	5.4887	8.4895**	4.0112
short	1-day	15.3333***	17.7034***	12.3636***	15.3333***	15.4901***	16.9663***	18.2407***	17.7034***	16.9663***	13.0210***	17.7034***	21.5876***	9.5326**
	5-day	12.5020***	15.5200***	12.5020***	12.8814***	15.2607***	15.7697***	17.0451***	15.6749***	14.2475***	10.7001**	15.7697***	21.1838***	6.4446*
	20-day	17.0474***	20.1984***	17.0474***	14.1518***	17.5953***	18.3818***	20.5667***	20.5407***	17.5953***	14.7650***	17.3125***	34.4316***	8.9230**

Table 5: Results for the Value-at-Risk with multivariate unconditional coverage test at 0.95%, 0.975%, and 0.99% confidence.

Appendix A Misspecification Test Results

Commodity	WTI	Brent	Gold	Silver	Platinum	GSCI
PPI	**0.0005**	**0.0233**	0.9075	**0.0925**	0.9656	**0.0602**
IP	**0.0166**	**0.0283**	0.2160	0.5425	0.1646	**0.0116**
SENTI	0.8144	0.3272	0.0732	0.1922	**0.0862**	0.1005
EPUI	**0.0114**	**0.0370**	0.6813	0.5567	0.7283	**0.0056**
EERUS	0.1311	**0.0958**	0.5110	0.7992	0.6556	0.4134
MOVE	0.1499	0.4188	**0.0222**	**0.0092**	0.1139	**0.0905**
VIX	**0.0055**	**0.0543**	**0.0011**	**0.0004**	**0.0544**	**0.0010**
TB3M	**0.0316**	**0.0683**	0.3664	0.3079	0.2420	**0.0704**
TED	0.5037	0.5975	0.0632	**0.0131**	**0.0213**	0.4535
GREA	0.9110	0.5901	0.5594	0.2826	0.6389	0.6366

Table 6: Test results from the regression-based misspecification test of Conrad & Schienle (2018). The values presented are p-values for the coefficient a_1 in the regression Eq. 14. Bold faced figures are indicating p-values of 10% or less.

Appendix B Estimation Results

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0662*	0.0235***	0.9610***	1.3442***				7.3371***	-5173.52	10386.16	–
GARCH-*RV*	0.0598**	0.0194	0.8188***	0.5098***	0.0030***	1.0081	84.7548***	8.5403***	-5146.45	10355.50	2.0557
					quarterly growth rates						
PPI	0.0656	0.0209	0.9639***	1.8656	-0.8437	35.3324	6.7549	7.2906***	-5170.66	10403.91	0.3950
IP	0.0648	0.0217***	0.9635***	1.4700	-0.1454	8.5688	1.0000**	7.2451***	-5172.31	10407.21	0.2212
SENTI	0.0688*	0.0217***	0.9591***	1.3908***	-0.0790*	8.6486	1.0420***	7.3093***	-5168.06	10398.71	0.6124
EPUI	0.0661	0.0195***	0.9684***	1.3156***	0.0095	3.5530	29.4196	7.3811***	-5172.11	10406.81	0.1431
EERUS	0.0664*	0.0240***	0.9582***	1.3543***	-0.0399*	29.8139	179.9190	7.3247***	-5171.58	10405.76	0.1895
MOVE	0.0676*	0.0237***	0.9608***	1.3562***	-0.0131	17.9453*	50.4967*	7.3290***	-5171.77	10406.14	0.1723
VIX	0.0670*	0.0245***	0.9608***	1.3342***	0.0042	177.3029***	1.3560***	7.3441***	-5172.47	10407.54	0.0851
TB3M	0.0680*	0.0235***	0.9620***	1.3472***	0.0059	275.1401*	869.3456**	7.2795***	-5172.39	10407.38	0.1360
TED	0.0662*	0.0229***	0.9627***	1.3544***	-0.0024*	1.1083***	109.8121	7.3234***	-5171.84	10406.27	0.1213
GREA	0.0662*	0.0234***	0.9607***	1.3619***	0.0020	81.9892***	1.6231	7.3467***	-5173.46	10409.51	0.0103
					quarterly variances						
PPI	0.0628*	0.0205***	0.9648***	0.9814***	1.9056**	3.1102	1.0974***	7.1587***	-5169.76	10402.11	0.6266
IP	0.0672*	0.0223***	0.9633***	1.4308***	-0.1676*	45.9446	139.8659	7.4050***	-5171.01	10404.62	0.2246
SENTI	0.0668*	0.0235***	0.9605***	1.3846***	-0.0986*	299.9747***	15.4201*	7.4282***	-5172.26	10407.12	0.1032
EPUI	0.0675**	0.0234***	0.9615***	1.4068***	-0.0744	425.8406	44.6619	7.3785***	-5172.55	10407.70	0.0974
EERUS	0.0655*	0.0216***	0.9647***	1.4587***	-0.1252	3.8376	34.3449	7.2796***	-5172.33	10407.25	0.1277
MOVE	0.0684*	0.0212***	0.9629***	1.4320***	-0.1210**	141.2469**	488.3996**	7.3892***	-5169.77	10402.14	0.3607
VIX	0.0702**	0.0251***	0.9579***	1.4392***	-0.1219	79.4647	11.1845	7.5197***	-5169.94	10402.47	0.3623
TB3M	0.0685**	0.0220***	0.9635***	1.4031***	-1.2953**	159.0463	2.6100	7.4197***	-5171.10	10404.79	0.2092
TED	0.0657*	0.0226***	0.9635***	1.2421***	0.1478*	340.8063***	35.5891***	7.2947***	-5171.88	10406.36	0.2044
GREA	0.0655	0.0236***	0.9587***	1.0938***	0.8111	4.8713	2.4795	7.2785***	-5172.75	10408.09	0.1398

Table 7: GARCH-MIDAS estimation results for WTI log returns 02 Jan 1996-30 Dec 2005 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Appendix C Expected Shortfall Results

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0439*	0.0396***	0.9559***	1.4152***				8.2405***	-10251.29	20545.18	–
GARCH-*RV*	0.0434*	0.0414***	0.9339***	0.7312***	0.0021***	1.0090**	83.9421***	8.9921***	-10222.39	20512.94	0.7781
					quarterly growth rates						
PPI	0.0437*	0.0389***	0.9569***	1.8931***	-0.7933	9.6178	4.9566	8.3242***	-10250.16	20568.48	0.0776
IP	0.0435**	0.0375***	0.9579***	1.4301***	-0.0708	4.1419	171.0336***	8.2199***	-10250.13	20568.42	0.0317
SENTI	0.0442**	0.0401***	0.9516***	1.4563***	-0.2358***	1.7845***	2.8456	8.0824***	-10246.60	20561.37	0.3746
EPUI	0.0435	0.0364***	0.9586***	1.2572***	0.0487	1.4480	3.1990	8.2006***	-10248.33	20564.82	0.1442
EERUS	0.0447	0.0390***	0.9556***	1.4134***	0.2066	5.7845	1.8151	8.3647***	-10247.79	20563.74	0.1930
MOVE	0.0444*	0.0383***	0.9560***	1.3136***	0.0671**	1.2579***	2.1798***	8.2353***	-10247.82	20563.80	0.2052
VIX	0.0467**	0.0375***	0.9572***	1.4137***	-0.0086*	65.2652*	28.8864*	8.2042***	-10246.86	20561.89	0.0553
TB3M	0.0438*	0.0393***	0.9559***	1.4062***	0.0031	76.0193	15.7319	8.2363***	-10250.24	20568.64	0.0190
TED	0.0456*	0.0395***	0.9551***	1.6324***	-0.0265***	6.5371***	4.4292***	8.3307***	-10247.50	20563.16	0.2421
GREA	0.0437	0.0379***	0.9559***	1.2659***	0.0143***	9.9051***	22.3021***	8.0910***	-10246.79	20561.74	0.3782
					quarterly variances						
PPI	0.0451*	0.0394***	0.9560***	1.4468***	-0.0543	431.0154***	472.4755***	8.2833***	-10249.59	20567.33	0.0389
IP	0.0440	0.0396***	0.9560***	1.4106***	0.0071	93.1714	1.4359	8.2432***	-10251.24	20570.64	0.0007
SENTI	0.0445**	0.0393***	0.9549***	1.7079***	-0.3954	4.5379*	5.3025*	8.3932***	-10249.30	20566.77	0.1721
EPUI	0.0443**	0.0396***	0.9559***	1.3686***	0.0418	335.7813***	87.5495***	8.2424***	-10249.84	20567.85	0.0147
EERUS	0.0443	0.0414***	0.9523***	1.1746***	0.1875	2.5551	10.9575**	8.2579***	-10250.37	20568.90	0.0660
MOVE	0.0452**	0.0393***	0.9544***	1.6285***	-0.2314***	7.5151***	22.3919***	8.2475***	-10246.80	20561.77	0.1758
VIX	0.0462**	0.0401***	0.9459***	1.7531***	-0.3881***	10.6926	5.6186*	8.3157***	-10239.45	20547.06	0.3613
TB3M	0.0458**	0.0392***	0.9487***	1.6150***	-1.3559***	18.0971***	15.2119***	8.3524***	-10240.50	20549.16	0.4255
TED	0.0444**	0.0394***	0.9564***	1.4066***	0.0099	182.2665	1.8471	8.2752***	-10250.62	20569.40	0.0050
GREA	0.0455**	0.0395***	0.9556***	1.4450***	-0.0413	312.8666***	371.7751***	8.3227***	-10248.85	20565.86	0.0532

Table 8: GARCH-MIDAS estimation results for WTI log returns 02 Jan 1996-30 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0286	0.0546***	0.9411***	1.4195***				10.0821***	-5066.68	10172.52	–
GARCH-*RV*	0.0279	0.0638***	0.9143***	0.7061***	0.0020***	1.0091	83.7974**	11.1036***	-5053.22	10169.08	0.7126
					quarterly growth rates						
PPI	0.0286	0.0533***	0.9429***	2.0460	-1.0944	8.8428	4.9528	10.4109***	-5065.72	10194.09	0.1252
IP	0.0286	0.0504***	0.9456***	1.4944***	-0.1145*	1.6841	163.7524	10.0182***	-5065.10	10192.84	0.0642
SENTI	0.0297	0.0585***	0.9293***	1.4222***	-0.2857***	2.0030***	3.5371**	9.6653***	-5063.88	10190.40	0.5146
EPUI	0.0314	0.0532***	0.9410***	1.3063***	0.0544***	9.8069***	19.1486***	10.0040***	-5062.43	10187.51	0.2908
EERUS	0.0316	0.0490***	0.9506***	3.0846***	0.8373*	3.2174***	1.6692***	9.5562***	-5061.31	10185.25	0.7858
MOVE	0.0289	0.0537***	0.9417***	1.4559***	0.0775	1.1604**	1.9372**	9.7172***	-5063.93	10190.49	0.2319
VIX	0.0333	0.0537***	0.9403***	1.3486***	-0.0064**	406.7213***	163.0740***	10.1173***	-5063.52	10189.68	0.0457
TB3M	0.0294	0.0572***	0.9374***	1.5504***	-0.0247*	2.6795*	3.3784***	9.9203***	-5065.39	10193.42	0.1533
TED	0.0287	0.0549***	0.9381***	1.1643***	0.0204	2.0699**	5.9154**	10.1046***	-5065.11	10192.86	0.1243
GREA	0.0297	0.0558***	0.9307***	0.8570***	0.0211***	8.9299**	15.3925**	9.9207***	-5061.06	10184.76	0.4400
					quarterly variances						
PPI	0.0289	0.0550***	0.9387***	0.8066*	0.4461***	1.0000	1.4579	9.8409***	-5063.89	10190.42	0.2504
IP	0.0289	0.0553***	0.9393***	1.0785***	0.3594*	1.0000	1.4348	9.9637***	-5065.05	10192.73	0.1742
SENTI	0.0298	0.0510***	0.9437***	0.8463*	0.5304*	8.6925	2.1792	10.3900***	-5062.38	10187.39	0.2961
EPUI	0.0302	0.0555***	0.9400***	1.0562***	0.3597	2.9625	1.0426***	10.1742***	-5064.87	10192.38	0.1219
EERUS	0.0290	0.0582***	0.9338***	0.9664***	0.3078**	1.8273	9.1927	10.0634***	-5064.50	10191.63	0.1569
MOVE	0.0296	0.0565***	0.9401***	1.1125**	0.3966	3.2913	1.4248	10.1875***	-5065.27	10193.18	0.1710
VIX	0.0317	0.0532***	0.9293***	1.8201***	-0.4233***	14.3902**	7.4703***	9.9043***	-5057.03	10176.69	0.4439
TB3M	0.0303	0.0526***	0.9347***	1.8269***	-1.5398***	17.9972***	15.1325***	9.9078***	-5059.93	10182.49	0.3916
TED	0.0294	0.0537***	0.9423***	1.3991***	0.0116	235.1124	2.1210**	10.2009***	-5065.93	10194.50	0.0072
GREA	0.0309	0.0539***	0.9417***	1.4647	-0.0422	143.9873	193.0913	10.2171***	-5065.09	10192.81	0.0539

Table 9: GARCH-MIDAS estimation results for WTI log returns 03 Jan 2006-30 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0794*	0.0290***	0.9547***	1.6412***				5.8893***	-5704.53	11448.40	–
GARCH-*RV*	0.0764*	0.0257**	0.8389***	0.7362***	0.0024***	1.0081**	84.8301***	6.7592***	-5678.03	11418.99	1.6833
quarterly growth rates											
PPI	0.0823**	0.0291***	0.9544***	1.5410***	0.1488	1.0865	111.0648	5.8706***	-5703.08	11469.10	0.0821
IP	0.0789*	0.0287***	0.9538***	1.5615***	0.0899	431.7507**	290.0333**	5.9048***	-5703.75	11470.44	0.0950
SENTI	0.0776*	0.0264***	0.9567***	1.6328***	-0.0472*	5.7097	33.4820	5.8805***	-5702.44	11467.83	0.2150
EPUI	0.0793*	0.0250***	0.9577***	1.5930***	0.0169**	4.1082***	26.8004**	5.8842***	-5702.42	11467.77	0.2226
EERUS	0.0769*	0.0275***	0.9495***	1.5939***	0.1017*	30.8319	13.5147	5.9490***	-5702.11	11467.15	0.3033
MOVE	0.0787*	0.0277***	0.9544***	1.6232***	0.0180**	1.0000	6.2839	5.9642***	-5702.91	11468.76	0.1469
VIX	0.0816**	0.0295***	0.9550***	1.6334***	0.0034	172.9569**	1.3710***	5.9087***	-5703.49	11469.91	0.0642
TB3M	0.0830***	0.0290***	0.9556***	1.6500***	0.0082***	326.7210	1001.1585	5.8352***	-5702.49	11467.92	0.1980
TED	0.0823**	0.0250***	0.9632***	1.5989***	0.0056**	232.8204***	23.4961***	5.8945***	-5701.97	11466.87	0.2099
GREA	0.0805**	0.0291***	0.9526***	1.7050***	0.0076	820.4496	125.4143	5.9403***	-5703.69	11470.33	0.1165
quarterly variances											
PPI	0.0788**	0.0272***	0.9573***	1.4739***	0.8336**	365.3434***	137.8913***	5.9284***	-5701.29	11465.53	0.3273
IP	0.0798**	0.0283***	0.9519***	1.2452***	0.7040*	13.6770	13.4601	5.8683***	-5701.06	11465.05	0.4925
SENTI	0.0793**	0.0281***	0.9568***	1.6112***	0.0658	566.1770	70.7841	5.9051***	-5704.07	11471.08	0.0335
EPUI	0.0765*	0.0262***	0.9624***	1.5014***	0.1761**	92.4390	170.0783	5.9102***	-5700.65	11464.23	0.3451
EERUS	0.0810**	0.0285***	0.9519***	1.4590***	0.2068	20.9637	4.3382	5.9553***	-5703.78	11470.50	0.1097
MOVE	0.0793	0.0286**	0.9541***	1.5589***	0.1054	5.4162	45.0300	5.9520***	-5703.67	11470.28	0.1062
VIX	0.0782**	0.0269***	0.9579***	1.4869***	0.1929**	4.3678**	31.0806***	5.8870***	-5702.22	11467.38	0.2513
TB3M	0.0782**	0.0258***	0.9581***	1.4978***	1.9915***	35.2943	349.7361	5.9021***	-5701.68	11466.30	0.2321
TED	0.0786*	0.0264***	0.9576***	1.5356***	0.1668	7.5629	42.6644	5.8816***	-5703.43	11469.80	0.1495
GREA	0.0788**	0.0268***	0.9583***	1.5421***	0.3049*	358.6663	95.7315	5.8934***	-5702.12	11467.18	0.1758

Table 10: GARCH-MIDAS estimation results for Brent log returns 01 Jan 1996-30 Dec 2005 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0391**	0.0413***	0.9560***	1.7228***				7.0635***	-10892.81	21828.42	–
GARCH-*RV*	0.0398*	0.0422***	0.9442***	0.9011***	0.0019***	1.0092***	83.7747**	7.3900***	-10868.94	21806.36	0.6140
quarterly growth rates											
PPI	0.0395*	0.0404***	0.9573***	1.9064***	-0.2977**	52.6614***	37.3540***	7.0876***	-10890.58	21849.64	0.0330
IP	0.0387	0.0400***	0.9573***	1.7284***	-0.0501	1.0091	83.7762	7.0442***	-10892.28	21853.04	0.0128
SENTI	0.0397	0.0417***	0.9533***	1.7244***	-0.2193***	1.9143***	3.1494**	6.8354***	-10890.06	21848.60	0.2764
EPUI	0.0386	0.0397***	0.9581***	1.7547***	0.0037***	429.8582	87.3651	7.0649***	-10889.90	21848.28	0.0173
EERUS	0.0389	0.0397***	0.9574***	1.6975***	0.3520	4.3312	1.7986	7.2184***	-10888.67	21845.82	0.3629
MOVE	0.0387*	0.0391***	0.9577***	1.5995***	0.0728*	1.2266***	2.4010***	7.0733***	-10887.77	21844.02	0.2203
VIX	0.0393	0.0415***	0.9552***	1.8809***	-0.0479	4.1850	2.9425	6.9516***	-10890.68	21849.83	0.1487
TB3M	0.0403	0.0431***	0.9531***	1.7405***	-0.0222***	4.6519***	5.1642***	6.9698***	-10890.11	21848.70	0.1616
TED	0.0412*	0.0416***	0.9551***	1.9759***	-0.0322**	4.9531***	3.4181***	7.0685***	-10889.68	21847.85	0.2324
GREA	0.0411	0.0392***	0.9569***	1.4976***	0.0137***	157.1200	423.7567*	7.0023***	-10885.44	21839.36	0.3445
quarterly variances											
PPI	0.0395*	0.0412***	0.9561***	1.7307***	-0.0228	363.0267**	69.0795**	7.0754***	-10892.54	21853.56	0.0048
IP	0.0394	0.0406***	0.9567***	1.7362***	-0.0389	812.3569**	100.9616	7.0706***	-10891.40	21851.28	0.0165
SENTI	0.0399	0.0414***	0.9543***	2.0201***	-0.4870	5.2990	7.2992	7.1336***	-10890.13	21848.73	0.2428
EPUI	0.0396	0.0399***	0.9567***	1.7612***	-0.1075***	20.7665*	101.2644	7.0357***	-10889.05	21846.59	0.0603
EERUS	0.0406*	0.0407***	0.9551***	1.9450***	-0.2535*	18.4517	2.4228	6.9597***	-10887.78	21844.03	0.1249
MOVE	0.0391*	0.0410***	0.9552***	1.9455***	-0.2472	6.9609	22.4703	6.9623***	-10888.27	21845.01	0.1640
VIX	0.0404	0.0430***	0.9440***	2.1546***	-0.6247***	4.2526	2.6998	6.9803***	-10878.25	21824.98	0.5306
TB3M	0.0411	0.0415***	0.9456***	1.8457***	-1.7622***	14.5751**	14.3853*	7.0559***	-10878.23	21824.94	0.5652
TED	0.0401*	0.0408***	0.9564***	1.7235***	-0.0136*	465.3439	64.3570	7.0830***	-10891.79	21852.05	0.0075
GREA	0.0386	0.0401***	0.9566***	1.8793***	-0.2427	1.6053	4.0392	7.1536***	-10890.22	21848.93	0.3248

Table 11: GARCH-MIDAS estimation results for Brent log returns 01 Jan 1996-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0198	0.0546***	0.9423***	1.5212***				9.1887***	-5174.70	10388.74	–
GARCH-*RV*	0.0201	0.0623***	0.9248***	0.8574***	0.0017***	1.0093	83.6529	9.4896***	-5166.06	10395.05	0.5619
					quarterly growth rates						
PPI	0.0192	0.0512***	0.9450***	0.9825	0.7115	3.5710	9.0788	9.2305***	-5174.03	10411.00	0.0629
IP	0.0190	0.0505***	0.9468***	1.6518***	-0.1430**	1.1327	198.1292	9.0883***	-5172.36	10407.65	0.0941
SENTI	0.0210	0.0573***	0.9335***	1.4652***	-0.2954***	1.9374***	3.1332*	8.7528***	-5172.81	10408.55	0.4663
EPUI	0.0203	0.0549***	0.9409***	1.3770***	0.0793	2.0858	5.1262	8.9194***	-5172.10	10407.14	0.3045
EERUS	0.0191	0.0515***	0.9446***	1.3705***	-0.2905	3.3980	6.9437	9.2703***	-5173.41	10409.75	0.1316
MOVE	0.0189	0.0521**	0.9451***	1.6082**	0.0644	1.0493	2.0981	9.0048***	-5171.81	10406.56	0.1738
VIX	0.0203	0.0553***	0.9415***	1.5149***	0.0085	15.7627	48.6047	9.2185***	-5173.43	10409.80	0.0290
TB3M	0.0211	0.0568***	0.9396***	1.7014***	-0.0229	4.6825	5.2851	8.9775***	-5172.97	10408.88	0.1771
TED	0.0194	0.0529***	0.9438***	1.0947***	0.0404*	1.0000***	1.1141***	9.0427***	-5171.64	10406.22	0.1233
GREA	0.0202	0.0542***	0.9340***	0.7799***	0.0256***	5.1782	11.0962	8.8998***	-5168.27	10399.47	0.5997
					quarterly variances						
PPI	0.0200	0.0549***	0.9406***	0.9413*	0.4341**	1.0000	1.7103	8.9181***	-5172.44	10407.81	0.2427
IP	0.0202	0.0550***	0.9412***	1.2135**	0.3413	1.0000	1.7941	9.0087***	-5173.49	10409.91	0.1689
SENTI	0.0221	0.0497***	0.9478***	0.8688	0.7251	7.0203	2.3635	8.9869***	-5169.90	10402.73	0.3667
EPUI	0.0208	0.0534***	0.9444***	1.0401*	0.5672	1.0000	1.0475***	9.1331***	-5173.50	10409.93	0.1255
EERUS	0.0203	0.0559***	0.9395***	1.2204***	0.2169	1.0000	8.5541	9.1091***	-5172.53	10407.99	0.0938
MOVE	0.0209	0.0562***	0.9417***	1.2691***	0.4303	3.3155**	1.3649	9.1800***	-5173.51	10409.95	0.1914
VIX	0.0210	0.0534***	0.9289***	1.9656***	-0.5538***	9.0335*	5.6418**	8.9773***	-5163.95	10390.83	0.5804
TB3M	0.0225	0.0540***	0.9341***	1.9235***	-1.7958***	13.9763***	14.1407**	8.9573***	-5167.32	10397.57	0.4755
TED	0.0189	0.0492***	0.9479***	1.3852***	0.1183	1.6790	9.9834	9.0410***	-5171.31	10405.56	0.1476
GREA	0.0189	0.0509***	0.9462***	1.6695***	-0.1678	1.7362	5.1397	9.3411***	-5173.42	10409.78	0.1679

Table 12: GARCH-MIDAS estimation results for Brent log returns 02 Jan 2006-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	-0.0063	0.0480***	0.9486***	-0.0736				4.1517***	-2986.31	6011.96	–
GARCH-*RV*	-0.0053	0.0642***	0.9257***	-0.7402	0.0212***	1.0000	8.4528	3.7816***	-2974.39	6011.72	0.6597
					quarterly growth rates						
PPI	-0.0068	0.0565***	0.9392***	4.4361**	-6.5927**	1.3087***	1.0258***	3.9631***	-2982.97	6028.88	0.2795
IP	-0.0067	0.0546***	0.9370***	0.6681	-0.6291***	50.8573	52.7204	3.7538***	-2978.69	6020.31	0.6819
SENTI	-0.0068	0.0555***	0.9277***	0.1701	-0.4198***	4.1774***	2.0004***	3.6899***	-2975.79	6014.51	0.7431
EPUI	-0.0061	0.0544***	0.9265***	-0.4683	0.1487***	7.4260	2.7882	3.7882***	-2975.39	6013.72	0.7058
EERUS	-0.0077	0.0512*	0.9421***	-0.0965	-0.2263	7.6506	28.8344	4.0438***	-2984.45	6031.83	0.3597
MOVE	-0.0066	0.0467***	0.9488***	0.3805	-0.2624**	1.8033***	2.1635*	3.9729***	-2979.51	6021.95	0.5505
VIX	-0.0072	0.0495	0.9466***	0.1976	-0.0295	16.5236	11.2721	4.0616*	-2985.31	6033.56	0.0778
TB3M	-0.0076	0.0553***	0.9279***	-0.1367	-0.0786***	7.4019**	6.4276*	3.7012***	-2972.67	6008.27	0.7652
TED	-0.0066	0.0507***	0.9279***	0.2775	-0.0911***	5.0520***	3.6726***	3.7270***	-2970.56	6004.06	0.8130
GREA	-0.0063	0.0489***	0.9459***	-0.0779	0.0212***	1.2564	226.1724	4.0405***	-2982.11	6027.15	0.5670
					quarterly variances						
PPI	-0.0076	0.0520***	0.9359***	-1.3397***	7.0229***	2.4532***	3.1795***	3.6833***	-2973.82	6010.57	0.9732
IP	-0.0071	0.0496***	0.9442***	0.3769	-0.8283	2.5334	14.4310	4.0336***	-2983.98	6030.90	0.2037
SENTI	-0.0063	0.0536***	0.9390***	-0.7613*	1.9547***	2.4203***	5.0475***	3.8622***	-2981.53	6025.99	0.5366
EPUI	-0.0061	0.0471***	0.9497***	0.0317	-0.1113	157.9278	1.3253	4.1866***	-2985.62	6034.18	0.0269
EERUS	-0.0073	0.0505***	0.9448***	0.2044	-0.2320	348.2565	35.3930	4.0838***	-2985.14	6033.23	0.0482
MOVE	-0.0053	0.0558***	0.9280***	1.0713**	-1.4279***	2.1832*	4.7614	3.7343***	-2975.47	6013.87	0.8051
VIX	-0.0079	0.0562**	0.9371***	0.6181	-0.5239	17.7737	12.3365	3.9006***	-2983.67	6030.27	0.1892
TB3M	-0.0055	0.0406***	0.9561***	-0.1366	-3.7329**	144.1225	509.3292	4.3050***	-2982.12	6027.18	0.1558
TED	-0.0080	0.0380***	0.9607***	0.5356	-2.6951**	1.2195**	2.0021**	4.3669***	-2981.92	6026.78	2.3908
GREA	-0.0071	0.0460***	0.9501***	-1.2550	3.9935	2.2698*	2.7228***	3.9230***	-2977.82	6018.58	0.7409

Table 13: GARCH-MIDAS estimation results for Gold log returns 01 Jan 1996-30 Dec 2005 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0111	0.0399***	0.9578***	-0.0064**				4.5391***	-6999.85	14042.51	–
GARCH-*RV*	0.0126	0.0467***	0.9443***	-0.4543**	0.0107***	1.0000	15.4420	4.2019***	-6973.45	14015.37	0.7652
					quarterly growth rates						
PPI	0.0101	0.0415***	0.9563***	2.6572***	-4.1571***	3.1520***	2.4573***	4.4335***	-6994.06	14056.59	0.6663
IP	0.0106	0.0437***	0.9518***	0.7593***	-0.8213***	1.1768	1.1548***	4.2259***	-6992.84	14054.17	0.5417
SENTI	0.0107	0.0427***	0.9537***	0.4770*	-0.2690	2.4985	1.5160***	4.2807***	-6994.70	14057.88	0.2907
EPUI	0.0109	0.0405***	0.9559***	-0.1940	0.1306***	1.3286***	1.0161***	4.4043***	-6992.65	14053.79	0.3743
EERUS	0.0112	0.0398***	0.9577***	-0.0078	-0.0146	298.5877	30.6834	4.5356***	-6999.66	14067.81	0.0025
MOVE	0.0111	0.0397***	0.9582***	-0.0023	0.0039	11.8956	81.3825	4.5484***	-6998.95	14066.38	0.0064
VIX	0.0112	0.0395***	0.9578***	-0.0079	0.0203	13.3564	18.9974	4.4888***	-6997.82	14064.12	0.0601
TB3M	0.0111	0.0399*	0.9578***	-0.0048	0.0002	81.8171	10.6749	4.5381***	-6999.85	14068.18	0.0000
TED	0.0108	0.0397***	0.9572***	0.4695	-0.0318	13.4047	10.1279	4.3877***	-6991.57	14051.62	0.3690
GREA	0.0092	0.0404***	0.9571***	0.0906	0.0390**	2.3630	1.0000***	4.3121***	-6987.87	14044.23	1.2407
					quarterly variances						
PPI	0.0102	0.0420***	0.9545***	-0.1863	0.6714***	1.0295***	1.1398***	4.2715***	-6989.63	14047.73	0.6539
IP	0.0099	0.0403***	0.9574***	-0.2014	0.5305***	4.6840	2.3209	4.4440***	-6993.48	14055.45	0.4093
SENTI	0.0117	0.0415***	0.9530***	-0.9896***	1.5606***	1.1595***	1.3229***	4.2007***	-6987.97	14044.43	1.0896
EPUI	0.0110	0.0398***	0.9578***	-0.0140	0.0485	37.6192	346.9290	4.5362***	-6998.29	14065.06	0.0132
EERUS	0.0097	0.0397***	0.9574***	-0.5081**	0.6944***	16.8067**	7.9749***	4.4111***	-6989.58	14047.64	0.5018
MOVE	0.0116	0.0406***	0.9566***	0.2243	-0.1517	9.3847	25.8016	4.5069***	-6998.76	14066.00	0.0488
VIX	0.0108	0.0403***	0.9572***	-0.0269	0.0663	76.8542*	102.4869*	4.5406***	-6997.60	14063.69	0.0261
TB3M	0.0104	0.0417***	0.9555***	-0.1229	1.8944***	9.5790***	16.9602***	4.3972***	-6994.09	14056.65	0.4953
TED	0.0114	0.0391***	0.9585***	-0.0285	0.0331*	31.1878	290.8318	4.5425***	-6997.10	14062.69	0.0197
GREA	0.0100	0.0401***	0.9574***	-0.1692	0.2863	6.6844	3.6795	4.4617***	-6993.68	14055.84	0.4009

Table 14: GARCH-MIDAS estimation results for Gold log returns 01 Jan 1996-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0533***	0.0378***	0.9586***	0.9930**				4.3351***	-3998.31	8035.95	–
GARCH-*RV*	0.0561***	0.0307***	0.9215***	-0.3495***	0.0066***	1.0092*	83.7635*	4.8198***	-3978.81	8020.56	1.0031
					quarterly growth rates						
PPI	0.0527***	0.0321***	0.9650***	0.8799*	0.1722**	89.4027***	436.1480**	4.4236***	-3993.15	8049.24	0.1009
IP	0.0537***	0.0357***	0.9604***	1.0935	-0.1511***	1.3349	179.6378	4.1842***	-3994.74	8052.42	0.2178
SENTI	0.0522***	0.0292***	0.9564***	0.5629***	-0.1873***	2.2877***	7.0555**	4.4506***	-3989.78	8042.49	0.8206
EPUI	0.0536***	0.0370***	0.9588***	0.8557	0.0597**	2.1970***	6.4966***	4.1478***	-3994.89	8052.71	0.4198
EERUS	0.0507**	0.0337***	0.9592***	0.5893	-0.3873	2.4038	3.8472***	4.4914***	-3996.03	8054.99	0.3168
MOVE	0.0534***	0.0374***	0.9578***	0.8820	0.0190	4.0866	25.3003	4.2914***	-3995.45	8053.83	0.1418
VIX	0.0528***	0.0381***	0.9581***	0.9821**	0.0030	14.2641*	78.7089	4.3137***	-3997.75	8058.43	0.0136
TB3M	0.0531***	0.0374***	0.9594***	1.0675**	0.0039**	465.8977***	89.4272***	4.3558***	-3995.46	8053.85	0.0870
TED	0.0518***	0.0373***	0.9587***	0.7173	0.0257	1.3768***	1.2248**	4.2911***	-3997.00	8056.93	0.0863
GREA	0.0513***	0.0342***	0.9583***	0.3619	0.0146***	347.4642**	501.3855**	4.3382***	-3991.69	8046.31	0.5259
					quarterly variances						
PPI	0.0539***	0.0361***	0.9589***	0.7325	0.0679**	33.8917***	332.4765***	4.3598***	-3996.31	8055.55	0.0970
IP	0.0546**	0.0348***	0.9600***	0.7194	0.0910**	33.6692	332.2703	4.3355***	-3994.91	8052.75	0.1492
SENTI	0.0537***	0.0351***	0.9542***	-1.0135	1.2936***	1.0558***	1.0443***	4.3795***	-3994.91	8052.75	0.4641
EPUI	0.0534***	0.0371***	0.9592***	0.9208	0.0735*	36.8038*	354.9241*	4.3153***	-3996.44	8055.81	0.0621
EERUS	0.0501***	0.0332***	0.9642***	0.6495	0.2513**	74.4816**	27.6554**	4.3852***	-3993.72	8050.38	0.2685
MOVE	0.0540***	0.0377***	0.9585***	0.9247	0.0567	7.6241	53.8093	4.3105***	-3997.41	8057.75	0.0301
VIX	0.0519***	0.0372***	0.9594***	0.9492**	0.0627***	308.5964	357.9909	4.3818***	-3995.93	8054.79	0.0862
TB3M	0.0518***	0.0344***	0.9576***	1.0640***	-1.2912***	13.9594**	9.5808*	4.4049***	-3994.24	8051.41	0.5110
TED	0.0537***	0.0348***	0.9617***	0.9349*	0.0442***	15.9730***	142.1546***	4.3178***	-3994.20	8051.33	0.1027
GREA	0.0536***	0.0378***	0.9585***	0.9805**	0.0095	1.2144	195.9439	4.3257***	-3998.13	8059.19	0.0063

Table 15: GARCH-MIDAS estimation results for Gold log returns 02 Jan 2006-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0256	0.0267***	0.9693***	0.8990***				4.0100***	-4328.07	8695.48	–
GARCH-*RV*	0.0293	0.0260***	0.9350***	-0.0256	0.0052***	1.0096	83.3781**	4.0128***	-4311.63	8686.19	1.0460
quarterly growth rates											
PPI	0.0265	0.0236***	0.9718***	1.9031***	-1.5942*	2.5646*	8.8017	3.9515***	-4325.63	8714.19	0.1959
IP	0.0235	0.0217***	0.9726***	1.2240***	-0.4997*	26.3244	8.3590	4.0081***	-4323.26	8709.46	0.5734
SENTI	0.0248	0.0250***	0.9709***	1.0632***	-0.1306	8.0119	2.3737*	3.8982***	-4326.37	8715.68	0.1898
EPUI	0.0258	0.0255***	0.9711***	0.8139**	0.0440	1.8150	1.5926	4.0071***	-4327.73	8718.40	0.0458
EERUS	0.0243	0.0251***	0.9703***	0.8453***	-0.1283*	71.0667	31.5628	4.0634***	-4323.69	8710.31	0.1850
MOVE	0.0248	0.0277***	0.9665***	1.1603***	-0.1078***	5.2926**	6.0696***	3.8375***	-4323.78	8710.50	0.3425
VIX	0.0251	0.0260***	0.9701***	0.9104***	-0.0027	1.1029	103.0630	4.0076***	-4326.71	8716.35	0.0243
TB3M	0.0255	0.0271***	0.9688***	0.9103***	0.0023	1.0091	83.7994	4.0003***	-4327.98	8718.90	0.0047
TED	0.0260	0.0210***	0.9750***	1.1719***	-0.0577**	7.3549	3.2300**	3.9547***	-4323.09	8709.13	0.7070
GREA	0.0258	0.0265***	0.9659***	1.3515***	0.0653***	2.5013***	1.0000***	3.9074***	-4323.11	8709.15	0.5908
quarterly variances											
PPI	0.0255	0.0250***	0.9709***	0.5932*	2.0331**	23.6553	22.3869	3.9071***	-4324.55	8712.04	0.3095
IP	0.0243	0.0248***	0.9698***	1.1851***	-0.7281	9.5033	9.2858	4.0277***	-4326.21	8715.36	0.1139
SENTI	0.0232	0.0252***	0.9707***	0.4672	0.9662	1.8210	3.6961	3.9573***	-4325.41	8713.75	0.2096
EPUI	0.0243	0.0237***	0.9711***	0.3670	0.5371*	11.3211	4.7761	4.0525***	-4325.75	8714.43	0.3068
EERUS	0.0249	0.0251***	0.9672***	0.1209	0.6854	1.9638	7.5044	4.0094***	-4324.44	8711.81	0.2996
MOVE	0.0236	0.0248***	0.9699***	1.5228***	-0.7865***	6.0742**	7.3216**	3.8945***	-4323.23	8709.39	0.4685
VIX	0.0256	0.0276***	0.9680***	0.6562**	0.4084**	4.0166**	16.2990*	3.9070***	-4324.78	8712.50	0.1503
TB3M	0.0257	0.0266***	0.9695***	0.8351***	1.0013	10.3411	76.6569	4.0069***	-4327.47	8717.88	0.0169
TED	0.0259	0.0252***	0.9690***	1.0498***	-0.4232**	2.3613	18.6653	4.0432***	-4323.46	8709.85	0.2514
GREA	0.0250	0.0261***	0.9680***	0.2193	2.0565***	1.4045***	2.4596***	3.8446***	-4323.41	8709.76	0.4006

Table 16: GARCH-MIDAS estimation results for Silver log returns 01 Jan 1996-30 Dec 2005 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0437**	0.0320***	0.9651***	1.3212***				4.0933***	-9821.85	19686.50	–
GARCH-*RV*	0.0465***	0.0443**	0.9381***	0.7810**	0.0024***	1.0099	83.0789*	3.9107***	-9807.06	19682.60	0.6349
quarterly growth rates											
PPI	0.0438**	0.0313***	0.9661***	1.8006**	-0.8058	3.8597	3.5828	4.1071***	-9821.54	19711.56	0.0328
IP	0.0413**	0.0313***	0.9638***	1.6979***	-0.5755***	7.9290**	3.2556**	3.9458***	-9810.22	19688.91	0.5929
SENTI	0.0432**	0.0310***	0.9660***	1.4688***	-0.1096	6.3735	1.9238	4.0162***	-9818.16	19704.79	0.1200
EPUI	0.0432***	0.0304***	0.9670***	1.0527***	0.1041***	1.3912***	1.0160***	4.0715***	-9817.14	19702.77	0.2633
EERUS	0.0433***	0.0332***	0.9633***	1.3684***	-0.1165	10.6712	6.3816	4.0422***	-9820.93	19710.34	0.0468
MOVE	0.0424**	0.0330***	0.9640***	1.5793***	-0.0989***	4.8681***	6.2699***	4.0090***	-9815.79	19700.06	0.5141
VIX	0.0432**	0.0323***	0.9648***	1.3804***	-0.0177	1.0000	1.5541	4.1158***	-9821.13	19710.75	0.0127
TB3M	0.0437**	0.0319***	0.9652***	1.3197***	-0.0002***	1.0091*	83.8038***	4.0940***	-9821.83	19712.15	0.0001
TED	0.0436***	0.0324***	0.9645***	1.1627***	0.0187	2.8007	1.0278***	4.0941***	-9820.27	19709.03	0.0555
GREA	0.0409**	0.0343***	0.9585***	1.2123***	0.0303***	1.7438***	1.0000***	3.8106***	-9805.35	19679.18	0.7758
quarterly variances											
PPI	0.0423***	0.0328***	0.9624***	1.0157***	0.5806***	3.8481	2.0668**	3.8862***	-9809.51	19687.49	0.6934
IP	0.0431	0.0310***	0.9663***	1.1171*	0.4158	11.7699	5.1126	4.0287***	-9814.09	19696.67	0.4184
SENTI	0.0429***	0.0324***	0.9621***	0.5284*	1.0944***	1.1030***	1.1206***	3.9014***	-9812.88	19694.23	0.5758
EPUI	0.0425***	0.0331***	0.9624***	0.8464***	0.5059***	7.7741***	2.3468***	4.0287***	-9815.66	19699.80	0.3144
EERUS	0.0430**	0.0348***	0.9588***	0.0987	1.1393***	1.0000***	1.0035***	3.9217***	-9812.08	19692.65	0.5212
MOVE	0.0440**	0.0315***	0.9654***	1.2063***	0.0900	2.8670**	17.8667***	4.0923***	-9820.99	19710.47	0.0207
VIX	0.0438**	0.0330***	0.9637***	1.1519***	0.2404	3.3450***	7.9462*	4.0268***	-9820.63	19709.73	0.0866
TB3M	0.0438	0.0335***	0.9629***	1.1401***	1.5771	1.9279	4.7203	3.9665***	-9817.53	19703.54	0.3332
TED	0.0426**	0.0318***	0.9648***	1.0386**	0.3296	9.2090	3.9062	3.9782***	-9812.80	19694.08	0.5940
GREA	0.0429*	0.0328***	0.9634***	1.1146*	0.3024	6.6235	3.9496	3.9844***	-9814.33	19697.14	0.4840

Table 17: GARCH-MIDAS estimation results for Silver log returns 01 Jan 1996-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0907***	0.0375***	0.9587***	2.1132***				3.8691***	-5483.77	11006.88	–
GARCH-*RV*	0.0993***	0.0548***	0.8743***	0.9295***	0.0019***	1.0095**	83.4410***	4.1106***	-5468.47	10999.88	0.9018
					quarterly growth rates						
PPI	0.0913***	0.0348***	0.9621***	2.4923***	-0.6830	9.8578	5.0049	3.9153***	-5483.29	11029.52	0.0970
IP	0.0878***	0.0364***	0.9587***	2.1420***	-0.2459***	179.9227	82.6539	3.8218***	-5476.51	11015.96	0.4993
SENTI	0.0897**	0.0417***	0.9431***	1.9118***	-0.2218*	1.9385	3.9716	3.7376***	-5477.23	11017.40	0.6529
EPUI	0.0902***	0.0374***	0.9587***	2.0856***	0.0012	81.9244	1.6282	3.8775***	-5483.64	11030.21	0.0026
EERUS	0.0874***	0.0348***	0.9585***	1.8484***	-0.4669**	1.8373*	3.5444***	3.8450***	-5478.97	11020.87	0.5169
MOVE	0.0888***	0.0369***	0.9600***	2.2329***	0.0205	48.2304	17.1513	3.8579***	-5481.21	11025.35	0.1320
VIX	0.0909***	0.0373***	0.9588***	2.0690***	0.0020	145.5044	1.3124***	3.8846***	-5483.30	11029.53	0.0094
TB3M	0.0876**	0.0306***	0.9659***	1.8408***	0.0100*	22.8378	38.3590	4.0344***	-5479.86	11022.65	0.2495
TED	0.0859***	0.0447***	0.9420***	1.1699***	0.0665***	1.4902***	1.6795***	3.6900***	-5477.28	11017.50	0.5806
GREA	0.0856***	0.0394***	0.9461***	1.4230***	0.0179***	287.3127***	416.9896***	3.7682***	-5472.45	11007.82	0.7409
					quarterly variances						
PPI	0.0849***	0.0359***	0.9614***	1.9179***	0.4612*	5.4713	2.5666	3.6182***	-5475.67	11014.28	0.9643
IP	0.0871***	0.0345***	0.9613***	1.8278***	0.3100**	13.8031	5.9790	3.7692***	-5476.30	11015.54	0.6944
SENTI	0.0921***	0.0377***	0.9583***	1.8458***	0.3124*	14.0765	3.1050*	3.8052***	-5481.10	11025.14	0.2584
EPUI	0.0907***	0.0337***	0.9630***	2.1305***	-0.0776*	362.5067***	406.4929***	3.9312***	-5482.07	11027.06	0.0681
EERUS	0.0845***	0.0380***	0.9561***	0.9829**	0.7489***	1.8372	1.9628**	3.7743***	-5478.60	11020.14	0.6017
MOVE	0.0904***	0.0346***	0.9620***	2.1397***	-0.0851*	326.3961**	367.8816**	3.9291***	-5481.69	11026.31	0.0811
VIX	0.0881***	0.0368***	0.9550***	2.1525***	-0.1949*	20.5215	9.7711	3.8327***	-5480.11	11023.15	0.2124
TB3M	0.0856**	0.0403***	0.9513***	2.2544***	-1.0564**	13.2454	5.1491	3.8439***	-5480.91	11024.75	0.3405
TED	0.0903***	0.0375***	0.9586***	2.0368***	0.0866**	17.1358	30.7011	3.7756***	-5481.07	11025.08	0.1611
GREA	0.0887***	0.0353***	0.9615***	1.9409***	0.1567	16.5214	9.0003	3.8249***	-5479.60	11022.12	0.4984

Table 18: GARCH-MIDAS estimation results for Silver log returns 02 Jan 2006-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0339*	0.1586	0.8150***	1.2934**				3.4664***	-4013.71	8066.76	–
GARCH-*RV*	0.0323*	0.0791	0.8947***	0.3364	0.0035***	1.0090	83.9702	3.8138***	-4002.70	8068.34	0.4224
					quarterly growth rates						
PPI	0.0333*	0.2578**	0.6848***	3.2823***	-3.1115***	2.5128***	12.1340***	3.2540***	-3992.55	8048.03	0.7136
IP	0.0342*	0.1589	0.8132***	1.2390	0.0286	81.9483	1.6262	3.4693***	-4013.66	8090.25	0.0021
SENTI	0.0304*	0.2158	0.7206**	1.2214**	-0.2600***	3.7847	1.5212**	3.3790***	-4000.42	8063.77	0.3361
EPUI	0.0341*	0.2128	0.6749	0.6886**	0.0631***	15.6968**	4.1246***	3.4973***	-4004.72	8072.38	0.2287
EERUS	0.0341*	0.2151	0.7316***	1.2224	0.2138***	35.3422	55.6114	3.3163***	-4000.45	8063.83	0.3790
MOVE	0.0277	0.2776***	0.6991***	1.6964**	0.1594***	11.8624***	3.0591***	3.1712***	-3994.52	8051.98	1.0162
VIX	0.0381**	0.2031**	0.6526***	0.5193**	0.0535***	12.4498**	17.1932***	3.5645***	-3999.16	8061.26	0.3510
TB3M	0.0343**	0.2459*	0.6558***	0.9231**	-0.0630***	1.2903***	1.8357***	3.4004***	-3999.79	8062.52	0.3113
TED	0.0311*	0.2491	0.6734**	1.4745**	-0.0810***	2.4157***	2.1967***	3.3456***	-3996.69	8056.32	0.3832
GREA	0.0353**	0.1719*	0.7982***	1.4817**	0.0183**	82.0635***	1.6174	3.4072***	-4010.61	8084.17	0.1210
					quarterly variances						
PPI	0.0380*	0.2257	0.7067**	1.5199***	-2.1606**	55.1574	13.8272	3.3845***	-4005.06	8073.06	0.3001
IP	0.0356	0.1887	0.7544	0.7661	0.6056	85.9877	26.9975	3.4357***	-4006.44	8075.82	0.2591
SENTI	0.0312*	0.2359*	0.7218***	0.8482	1.3691***	7.9020***	28.7594**	3.3212***	-3997.67	8058.28	0.5587
EPUI	0.0331*	0.1728	0.7969***	1.1877**	0.1453*	149.8911**	523.9091**	3.4414***	-4011.60	8086.13	0.0530
EERUS	0.0404**	0.2106***	0.5791***	1.3501***	-0.7587***	20.7528***	31.0566***	3.6414***	-3996.97	8056.88	0.3435
MOVE	0.0021	0.3876***	0.6095***	5.9311***	-3.0950**	21.0106***	21.3607***	3.3348***	-3986.76	8036.47	9.9683
VIX	0.0233	0.2835***	0.7061***	4.9491*	-2.7049	5.1241	4.8063	3.1888***	-3989.07	8041.07	1.1482
TB3M	0.0302*	0.1901*	0.7805***	0.9941	7.1550***	20.5930	28.3359	3.4395***	-4006.26	8075.47	0.2142
TED	0.0386**	0.2278	0.6869	0.8365	0.3116**	1.0746	47.3333	3.4125***	-4009.09	8081.11	0.1941
GREA	0.0293	0.3390*	0.6287***	2.5732	-1.9193	110.8338	13.6325	3.2338***	-4002.47	8067.88	1.1297

Table 19: GARCH-MIDAS estimation results for Platinum log returns 01 Jan 1996-30 Dec 2005 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0330^{**}	0.0518^{***}	0.9388^{***}	0.7359^{***}				4.7068^{***}	-8459.52	16961.84	–
GARCH-*RV*	0.0335^{**}	0.0700^{***}	0.8912^{***}	0.1348	0.0036^{***}	1.0094^{***}	83.5819^{***}	4.9570^{***}	-8432.08	16932.63	0.6199
quarterly growth rates											
PPI	0.0335^{**}	0.0553^{***}	0.9326^{***}	1.4729^{***}	-1.3339^{***}	2.5123^{***}	7.4165^{**}	4.5780^{***}	-8453.98	16976.44	0.2098
IP	0.0316^{**}	0.0581^{***}	0.9267^{***}	0.9541^{***}	-0.4889^{***}	1.0000	2.0819	4.5984^{***}	-8452.55	16973.58	0.3059
SENTI	0.0331^{**}	0.0507^{***}	0.9386^{***}	0.7362^{***}	-0.0631	21.1998	21.8385	4.6768^{***}	-8456.72	16981.91	0.0820
EPUI	0.0340^{**}	0.0651^{*}	0.9111^{***}	0.4465^{***}	0.0820^{***}	1.8464^{**}	4.2458	4.6069^{***}	-8452.31	16973.11	0.3451
EERUS	0.0335^{**}	0.0503^{***}	0.9407^{***}	0.7561^{***}	0.2414^{***}	5.9780^{**}	9.7761^{**}	4.6249^{***}	-8453.59	16975.67	0.2373
MOVE	0.0317^{**}	0.0522^{***}	0.9396^{***}	0.8088^{***}	-0.0473	2.8624	4.6507	4.6995^{***}	-8458.52	16985.52	0.1128
VIX	0.0345^{**}	0.0492^{***}	0.9348^{***}	0.4568^{**}	0.0461^{*}	8.3231	11.4871	4.6300^{***}	-8450.06	16968.60	0.2675
TB3M	0.0334^{**}	0.0524^{***}	0.9376^{***}	0.7355^{***}	0.0026	78.4182^{*}	8.0393	4.6778^{***}	-8458.93	16986.35	0.0128
TED	0.0335^{**}	0.0491^{***}	0.9428^{***}	0.8346^{***}	-0.0160	1.0000	1.7985^{**}	4.7439^{***}	-8458.59	16985.67	0.0399
GREA	0.0315^{**}	0.0535^{***}	0.9358^{***}	0.6453^{***}	0.0128^{***}	6.1040	3.0419	4.6273^{***}	-8454.99	16978.47	0.1994
quarterly variances											
PPI	0.0322^{**}	0.0567^{***}	0.9279^{***}	0.4254^{**}	0.3385	1.0000	2.7265	4.5680^{***}	-8451.67	16971.83	0.2871
IP	0.0326^{*}	0.0543^{***}	0.9335^{***}	0.4305	0.3813	1.0000	1.0077^{***}	4.6311^{***}	-8455.44	16979.35	0.1471
SENTI	0.0333	0.0484^{***}	0.9379^{***}	0.3791	0.3483	8.8676	42.0634	4.6234^{***}	-8445.72	16959.92	0.3033
EPUI	0.0334^{*}	0.0545^{***}	0.9343^{***}	0.2920	0.4199^{**}	1.9911	2.7254	4.6435^{***}	-8456.91	16982.31	0.1540
EERUS	0.0342^{**}	0.0472^{***}	0.9425^{***}	0.4624^{**}	0.1590^{***}	134.5047^{***}	476.9330^{***}	4.7343^{***}	-8455.09	16978.65	0.0767
MOVE	0.0328^{**}	0.0530^{***}	0.9364^{***}	0.5011^{**}	0.2338^{**}	24.9823	7.5259	4.6662^{***}	-8456.59	16981.67	0.1004
VIX	0.0321^{**}	0.0502^{***}	0.9398^{***}	0.9216^{***}	-0.1957^{*}	23.5924^{***}	13.9511^{***}	4.7352^{***}	-8456.27	16981.02	0.1133
TB3M	0.0329^{**}	0.0514^{***}	0.9383^{***}	0.4731^{**}	1.1478^{***}	8.7651^{***}	17.6852^{***}	4.6256^{***}	-8452.49	16973.46	0.2356
TED	0.0329^{**}	0.0534^{***}	0.9344^{***}	0.5419^{***}	0.1390^{***}	7.9833	15.0613^{*}	4.6330^{***}	-8454.88	16978.23	0.1449
GREA	0.0331^{**}	0.0538^{***}	0.9342^{***}	0.5439^{**}	0.1548^{**}	2.4824	6.7928	4.6040^{***}	-8454.58	16977.64	0.1589

Table 20: GARCH-MIDAS estimation results for Platinum log returns 01 Jan 1996-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0300	0.0456^{***}	0.9447^{***}	0.7478^{***}				6.2938^{***}	-4425.83	8890.99	–
GARCH-*RV*	0.0311	0.0604^{***}	0.8774^{***}	0.0758	0.0037^{***}	24.3272	255.1780	6.9227^{***}	-4409.27	8881.47	0.8150
quarterly growth rates											
PPI	0.0306	0.0440^{***}	0.9437^{***}	1.0334	-0.5756	12.6634	3.4820	6.2714^{***}	-4424.10	8911.13	0.0877
IP	0.0315	0.0529^{***}	0.9253^{***}	0.7417^{***}	-0.2508^{**}	1.0000	5.7033	6.3182^{***}	-4424.12	8911.18	0.2267
SENTI	0.0287	0.0545^{***}	0.9139^{***}	0.7380^{***}	-0.1761^{***}	2.6163^{***}	5.7937^{***}	6.4853^{***}	-4422.37	8907.67	0.4884
EPUI	0.0340	0.0524^{***}	0.9225^{***}	0.5001^{***}	0.0528^{***}	6.4260^{*}	14.3876^{**}	6.2923^{***}	-4421.54	8906.01	0.3897
EERUS	0.0304	0.0424^{**}	0.9472^{***}	0.8112^{***}	0.1081	19.5980	4.4161	6.2459^{***}	-4423.75	8910.43	0.1019
MOVE	0.0311	0.0462^{***}	0.9418^{***}	0.7085^{***}	0.0293	6.5894	6.5141^{**}	6.2270^{***}	-4424.36	8911.65	0.1159
VIX	0.0317	0.0493^{**}	0.9348^{***}	0.5724^{**}	0.0362	3.9869	6.6769^{**}	6.2280^{***}	-4423.99	8910.92	0.1590
TB3M	0.0296	0.0448^{***}	0.9454^{***}	0.7415^{***}	0.0027	75.4897	16.0426	6.3418^{***}	-4425.07	8913.08	0.0260
TED	0.0303	0.0516^{***}	0.9211^{***}	0.4067^{**}	0.0243^{**}	3.8885	7.4124^{*}	6.4031^{***}	-4422.02	8906.97	0.2929
GREA	0.0294	0.0430^{***}	0.9419^{***}	0.5022^{***}	0.0083^{***}	157.0659^{**}	194.9784^{**}	6.4949^{***}	-4422.73	8908.39	0.1519
quarterly variances											
PPI	0.0301	0.0452^{***}	0.9437^{***}	0.6786^{***}	0.0372	1.2090	186.0719	6.3186^{***}	-4424.98	8912.88	0.0355
IP	0.0304	0.0429^{***}	0.9481^{***}	0.6976^{***}	0.0433	274.0033^{***}	507.6348^{***}	6.2969^{***}	-4424.74	8912.42	0.0342
SENTI	0.0301	0.0359^{**}	0.9527^{***}	0.3958^{**}	0.1810^{***}	65.6088^{***}	354.0111^{***}	6.4251^{***}	-4420.05	8903.03	0.2115
EPUI	0.0300	0.0454^{***}	0.9451^{***}	0.7255^{***}	0.0245	64.3915	14.7670	6.2937^{***}	-4425.72	8914.37	0.0036
EERUS	0.0312	0.0360^{**}	0.9562^{***}	0.8525^{***}	-0.1308^{*}	365.2327^{**}	418.5269^{**}	6.3115^{***}	-4423.51	8909.96	0.0866
MOVE	0.0304	0.0406^{***}	0.9511^{***}	0.7785^{***}	-0.0420	437.5169	471.1373	6.3628^{***}	-4424.19	8911.31	0.0353
VIX	0.0288	0.0458^{***}	0.9406^{***}	0.8521^{***}	-0.1153^{*}	28.6868	13.5037	6.4315^{***}	-4423.86	8910.66	0.0840
TB3M	0.0289	0.0455^{***}	0.9434^{***}	0.8256^{***}	-0.2740	14.2147	9.1240	6.3559^{***}	-4425.59	8914.12	0.0202
TED	0.0302	0.0431^{***}	0.9468^{***}	0.6224^{***}	0.0613	18.2489	31.1852	6.2360^{***}	-4424.42	8911.76	0.0746
GREA	0.0309	0.0428^{***}	0.9477^{***}	0.7735^{***}	-0.0245	292.0120	416.8249	6.3483^{***}	-4424.89	8912.72	0.0285

Table 21: GARCH-MIDAS estimation results for Platinum log returns 02 Jan 2006-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0337	0.0296***	0.9623***	0.5866***				7.7919***	-4296.02	8631.38	–
GARCH-*RV*	0.0413*	0.0273**	0.8740***	-0.3922***	0.0076***	1.0092*	83.7609	9.3249***	-4274.46	8611.86	1.2897
quarterly growth rates											
PPI	0.0351	0.0298***	0.9593***	0.0490	0.8052***	2.3534*	14.5811*	7.6468***	-4293.61	8650.16	0.2351
IP	0.0328	0.0265***	0.9642***	0.7595***	-0.2368**	69.8688	93.1873	7.7217***	-4292.31	8647.56	0.3913
SENTI	0.0373	0.0297***	0.9534***	0.6121***	-0.2158***	1.4336	1.0305***	8.1249***	-4292.43	8647.80	0.4481
EPUI	0.0350	0.0281***	0.9635***	0.5517***	0.0129	57.5813	15.4331	7.9140***	-4293.48	8649.90	0.1192
EERUS	0.0328	0.0294***	0.9547***	0.5349***	-0.1210**	8.8021	34.7204	7.8958***	-4293.11	8649.15	0.4082
MOVE	0.0335	0.0295***	0.9635***	0.5756***	0.0109**	165.2972	1.3426***	7.8307***	-4291.79	8646.52	0.1743
VIX	0.0341	0.0284***	0.9540***	0.6867***	-0.0442*	2.7346	6.3189	7.9551***	-4292.48	8647.91	0.5282
TB3M	0.0348	0.0302***	0.9467***	0.4599***	-0.0384***	3.7532	1.4671	8.1731***	-4292.12	8647.19	0.5351
TED	0.0326	0.0263***	0.9673***	0.5283***	0.0090	7.1072	45.6490	7.9765***	-4292.44	8647.83	0.1953
GREA	0.0351	0.0302***	0.9535***	0.5230***	0.0107***	1.0942***	215.7361	7.9720***	-4292.45	8647.83	0.5465
quarterly variances											
PPI	0.0307	0.0140	0.9814***	0.2032	1.7909**	16.4393	1.2627**	7.7372***	-4287.23	8637.40	0.7699
IP	0.0347	0.0298***	0.9589***	0.9351***	-0.7060*	8.2033*	19.8492**	7.8330***	-4293.06	8649.06	0.4240
SENTI	0.0346	0.0314***	0.9587***	0.5201***	0.1329	12.1836	73.1224	7.8001***	-4295.40	8653.74	0.0397
EPUI	0.0331	0.0267***	0.9650***	0.3415**	0.2801***	44.8413***	76.6800**	7.8621***	-4290.06	8643.06	0.4668
EERUS	0.0334	0.0295***	0.9631***	0.5552***	0.0500	539.9855	362.1371	7.7629***	-4295.79	8654.51	0.0112
MOVE	0.0356	0.0297***	0.9600***	0.6920***	-0.1632	30.3358	90.4268	7.8497***	-4293.46	8649.86	0.2200
VIX	0.0361	0.0308***	0.9607***	0.7287**	-0.1846	58.1115	10.6744	8.1741***	-4291.18	8645.29	0.2935
TB3M	0.0351	0.0247***	0.9644***	0.2718*	4.4812***	22.4442***	48.3471***	7.7858***	-4290.20	8643.34	0.4628
TED	0.0337	0.0290***	0.9585***	0.2638	0.4441**	10.6457	2.9070**	7.8732***	-4293.75	8650.43	0.4117
GREA	0.0337	0.0289***	0.9631***	0.5704***	0.0311	1.1348	163.7488	7.8064***	-4295.95	8654.83	0.0034

Table 22: GARCH-MIDAS estimation results for GSCI log returns 01 Jan 1996-30 Dec 2005 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	0.0138	0.0355***	0.9621***	0.7735***				7.9946***	-8633.33	17309.47	–
GARCH-*RV*	0.0138	0.0321**	0.9612***	0.1774	0.0036***	1.0093	83.6688	8.3741***	-8616.70	17301.88	0.4904
quarterly growth rates											
PPI	0.0140	0.0337***	0.9634***	0.1585	0.9523***	2.7977*	7.9148	7.9797***	-8631.41	17331.30	0.1195
IP	0.0138	0.0355***	0.9619***	0.8864*	-0.1665	1.0002	1.3451	7.9548***	-8633.16	17334.81	0.0329
SENTI	0.0145	0.0366***	0.9581***	0.8109***	-0.2637***	1.9431***	2.4398**	7.8219***	-8630.43	17329.34	0.3646
EPUI	0.0140	0.0339***	0.9635***	0.6465**	0.0433	1.3927**	2.4952**	7.9557***	-8631.76	17332.00	0.0846
EERUS	0.0133	0.0343***	0.9625***	0.6732	-0.1964	3.6775	6.7039	8.0688***	-8631.81	17332.11	0.1524
MOVE	0.0139	0.0350***	0.9617***	0.6130**	0.0801*	1.6295***	2.3221**	7.9797***	-8631.09	17330.67	0.2385
VIX	0.0140	0.0355***	0.9612***	0.9785***	-0.0643	2.7828	2.3999**	7.8885***	-8631.26	17330.99	0.2274
TB3M	0.0147	0.0373***	0.9589***	0.7852***	-0.0260**	3.9756*	4.3302***	7.9396***	-8630.82	17330.12	0.2172
TED	0.0139	0.0349***	0.9621***	0.6522**	0.0160	2.7806***	10.7078	8.0273***	-8629.56	17327.61	0.1362
GREA	0.0156	0.0338***	0.9616***	0.5567***	0.0133***	139.2172***	379.6359***	8.1156***	-8626.68	17321.84	0.3587
quarterly variances											
PPI	0.0137	0.0328***	0.9650***	0.7209***	0.0629	5.1439	57.4938	7.9586***	-8631.28	17331.04	0.0409
IP	0.0141	0.0357***	0.9616***	0.5661*	0.3206	1.0000	1.6954	7.9292***	-8631.93	17332.33	0.1472
SENTI	0.0142	0.0307***	0.9672***	0.5416	0.1484***	355.1335	98.6121	8.1465***	-8628.22	17324.93	0.0861
EPUI	0.0136	0.0350**	0.9625***	0.4693	0.2860	1.9733	1.0097***	8.0058***	-8632.48	17333.45	0.0634
EERUS	0.0145	0.0357***	0.9612***	0.5736***	0.1239**	117.4395	421.5937	8.0356***	-8630.49	17329.45	0.0517
MOVE	0.0146	0.0361***	0.9603***	0.9706***	-0.2153	5.4298	16.9621	7.9138***	-8630.69	17329.86	0.1218
VIX	0.0155	0.0367***	0.9545***	1.1878***	-0.5452**	4.1654	2.4004*	8.0417***	-8624.41	17317.29	0.4437
TB3M	0.0157	0.0343***	0.9602***	0.9128***	-1.3805***	15.0349**	14.8720*	8.0454***	-8626.68	17321.85	0.3833
TED	0.0145	0.0345***	0.9630***	0.7758***	-0.0229	156.1020*	26.7437*	8.0657***	-8631.77	17332.02	0.0142
GREA	0.0138	0.0355***	0.9621***	0.7736***	-0.0004	81.9808	3.7147	7.9945***	-8633.33	17335.15	0.0000

Table 23: GARCH-MIDAS estimation results for GSCI log returns 01 Jan 1996-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

	μ	α	β	m	θ	ω_1	ω_2	ν	LogL	BIC	VR
GARCH	-0.0013	0.0410***	0.9577***	0.9868***				8.2257***	-4332.77	8704.88	–
GARCH-*RV*	-0.0030	0.0366**	0.9611***	0.5325	0.0027***	1.0094	83.5544	8.4427***	-4325.33	8713.59	0.2929
quarterly growth rates											
PPI	-0.0012	0.0393***	0.9594***	0.9292***	0.0861	86.9516**	335.2204*	8.2212***	-4331.70	8726.34	0.0103
IP	-0.0013*	0.0421***	0.9561***	1.2429***	-0.5693	1.0000	1.2227	8.0693***	-4331.83	8726.60	0.1853
SENTI	-0.0010	0.0427***	0.9523***	0.9142**	-0.3322***	1.9839***	2.6837**	7.9402***	-4331.53	8726.00	0.5223
EPUI	-0.0012	0.0399***	0.9588***	1.0297**	0.0684	1.8943	3.9855	8.0367***	-4331.05	8725.03	0.2017
EERUS	-0.0014	0.0386***	0.9597***	0.8613**	-0.2350	3.0571**	6.6568**	8.2653***	-4331.82	8726.57	0.0911
MOVE	-0.0020	0.0388***	0.9601***	1.1720***	0.0586	1.1462***	1.9691***	8.0081***	-4330.91	8724.75	0.1293
VIX	-0.0011	0.0399***	0.9570***	0.7976***	-0.0417	5.2271	3.5473**	8.2804***	-4332.06	8727.04	0.1370
TB3M	-0.0003	0.0428***	0.9556***	1.2595**	-0.0267	3.6507	4.1815***	8.0109***	-4331.62	8726.17	0.2036
TED	-0.0010	0.0390***	0.9599***	1.2940***	-0.0295	4.3113***	3.6607**	8.2753***	-4331.58	8726.10	0.1438
GREA	-0.0011	0.0388***	0.9513***	0.0211**	0.0300***	4.1313	8.3313	8.2099***	-4326.54	8716.02	0.7998
quarterly variances											
PPI	-0.0014	0.0417***	0.9564***	0.4472	0.5034**	1.0000	1.3721	7.9760***	-4330.54	8724.01	0.2963
IP	-0.0011	0.0416	0.9566***	0.6878	0.3966	1.0000	1.4148	8.0926***	-4331.60	8726.13	0.2007
SENTI	-0.0002	0.0360***	0.9632***	0.5362	0.6649	6.3414	2.2041**	8.1227***	-4328.28	8719.49	0.2877
EPUI	-0.0006	0.0381***	0.9613***	0.4079	0.8519**	1.0423***	1.0280***	8.1019***	-4330.06	8723.05	0.2776
EERUS	-0.0015	0.0412***	0.9571***	0.8314	0.1266	1.0000	8.5213	8.1972***	-4331.88	8726.70	0.0324
MOVE	-0.0004	0.0407***	0.9580***	0.9732***	0.0363	299.1063	14.4674	8.2752***	-4332.16	8727.26	0.0073
VIX	0.0005	0.0401***	0.9437***	1.3351***	-0.5838***	8.4087*	4.9784**	8.2239***	-4323.59	8710.11	0.6389
TB3M	0.0009	0.0382***	0.9534***	1.3114***	-1.9862***	12.2317**	11.1743*	8.1446***	-4326.98	8716.90	0.5752
TED	-0.0004**	0.0383***	0.9604***	0.9876***	-0.0235*	264.0076**	45.8487*	8.3710***	-4331.07	8725.08	0.0181
GREA	-0.0011	0.0399***	0.9588***	0.9779**	0.0176	420.2258	44.6902	8.2203***	-4332.32	8727.58	0.0086

Table 24: GARCH-MIDAS estimation results for GSCI log returns 02 Jan 2006-31 Dec 2015 with $K = 16$ and Beta-weighting scheme. The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

		PPI	*IP*	*SENTI*	*EPUI*	*EERUS*	*MOVE*	*VIX*	*TB3M*	*TED*	*GREA*	GARCH	*RV*	Spline
							WTI							
long	1-day	0.0859	0.1252	-0.0288	0.0027	0.0831	0.1027	0.1562	0.0436	0.1305	-0.0141	0.0872	0.2118	-0.0200
	5-day	-0.1012	0.0129	-0.3228**	-0.1772	-0.1664	-0.1414	-0.0930	-0.1592	-0.0165	-0.2359*	-0.1640	0.1840	-0.4295***
	20-day	-0.0509	0.0829	-0.2178*	-0.1651	-0.1054	-0.0175	-0.0903	-0.2322*	0.0563	-0.1937*	-0.0478	0.3919	-0.4810***
short	1-day	0.7265	0.6922	0.6540	0.6570	0.6924	0.6556	0.6579	0.7235	0.6962	0.6580	0.6944	0.7655	0.5562
	5-day	0.4534	0.4544	0.3353	0.4432	0.4456	0.3812	0.4736	0.4735	0.4900	0.3479	0.4498	0.5660	0.2919
	20-day	0.4875	0.4907	0.4352	0.4431	0.4538	0.4583	0.4560	0.4750	0.4714	0.4488	0.4840	0.5864	0.2625
							Brent							
long	1-day	0.0654	0.1660	0.0943	0.0698	0.1687	0.0295	0.1743	0.1752	0.2402	0.0654	0.1951	0.2347	-0.2265*
	5-day	-0.1097	-0.0580	-0.1420	-0.1628	-0.1447	-0.1055	-0.0616	-0.1346	0.0177	-0.1968*	-0.0643	0.1129	-0.5346***
	20-day	0.0398	0.1704	-0.0115	-0.0206	0.1418	0.0376	0.1182	0.0384	0.1383	0.0211	0.1406	0.3841	-0.4741***
short	1-day	0.6285	0.6025	0.6611	0.6569	0.6632	0.5981	0.6920	0.5703	0.6673	0.5925	0.6619	0.6766	0.3696
	5-day	0.3581	0.3722	0.3930	0.3696	0.4032	0.3742	0.3724	0.3319	0.4788	0.3319	0.3717	0.4585	0.0876
	20-day	0.3242	0.3535	0.3676	0.3531	0.3885	0.3610	0.3902	0.3628	0.3826	0.3405	0.3511	0.5002	0.1905
							Gold							
long	1-day	-0.1284	-0.1815	-0.1602	-0.2137	-0.2586*	-0.1984	-0.1395	-0.2618*	-0.1809	-0.2284	-0.2269	0.0381	0.0430
	5-day	-0.6236***	-0.5865***	-0.7474***	-0.6876***	-0.7362***	-0.6510***	-0.6504***	-0.8511***	-0.6831***	-0.6795***	-0.7038***	-0.3897**	-0.4258**
	20-day	-0.4255**	-0.5302***	-0.5573***	-0.5335***	-0.5942***	-0.5651***	-0.4464**	-0.6777***	-0.5985***	-0.6004***	-0.5961***	-0.0772	-0.1800
short	1-day	0.3159	0.2041	0.1554	0.1397	0.0997	0.1320	0.1592	0.0944	0.1330	0.1322	0.1058	0.3179	0.4005
	5-day	0.0178	-0.0446	-0.0923	-0.0250	-0.0997	-0.0401	-0.0903	-0.1386	-0.0706	-0.0669	-0.0653	0.0539	0.0596
	20-day	0.0265	-0.0268	-0.0736	-0.0329	-0.1319	-0.1670	-0.1157	-0.1864	-0.1184	-0.1638	-0.1620	0.3050	0.3017
							Silver							
long	1-day	-0.3196**	-0.3449**	-0.2468*	-0.3913**	-0.3390**	-0.3222**	-0.2993*	-0.2965*	-0.2384*	-0.2949*	-0.2979**	-0.2468*	-0.1982
	5-day	-0.5890***	-0.5829***	-0.5185***	-0.6511***	-0.5774***	-0.5696***	-0.6128***	-0.5591***	-0.6490***	-0.5574***	-0.5547***	-0.4472**	-0.3961**
	20-day	-0.5108***	-0.3552**	-0.4743**	-0.4737***	-0.4504**	-0.4839***	-0.4864***	-0.4800***	-0.4486**	-0.2744*	-0.4748**	-0.4654**	-0.1380
short	1-day	0.2521	0.3223	0.2516	0.2447	0.2539	0.2280	0.2773	0.2808	0.3648	0.2045	0.2815	0.1565	0.3655
	5-day	0.1398	0.1322	0.1400	0.0746	0.1363	0.1120	0.1643	0.1667	0.1157	0.1749	0.1678	0.0915	0.2552
	20-day	0.2852	0.3036	0.2825	0.1882	0.2428	0.2492	0.2517	0.2542	0.2542	0.3489	0.2549	0.3716	0.3701
							Platinum							
long	1-day	0.5275	0.3959	0.3755	0.4946	0.3854	0.3481	0.3863	0.3496	0.3493	0.3238	0.3750	0.4654	0.5890
	5-day	0.3424	0.2143	0.1088	0.1946	0.1762	0.1381	0.2327	0.1074	0.1600	0.1123	0.1356	0.2942	0.4215
	20-day	0.6303	0.4262	0.3569	0.5533	0.3946	0.4017	0.5559	0.3885	0.3724	0.3261	0.4003	0.6276	0.6961
short	1-day	0.7805	0.6911	0.6263	0.6671	0.6558	0.6815	0.5459	0.6582	0.6820	0.6552	0.6548	0.7223	0.7601
	5-day	0.6449	0.5750	0.4126	0.5417	0.5893	0.5027	0.5158	0.5358	0.5337	0.4698	0.5076	0.6313	0.7133
	20-day	0.8711	0.7506	0.6516	0.7504	0.6583	0.6789	0.8057	0.6524	0.6771	0.6775	0.6806	0.8739	0.8763
							GSCI							
long	1-day	0.0418	0.1139	0.0445	-0.0353	0.1125	0.0671	0.0921	0.1288	0.0428	0.0521	0.0469	0.1406	-0.2155*
	5-day	-0.2504*	-0.1028	-0.2147*	-0.1969*	-0.0830	-0.2230*	-0.1662	-0.1691	-0.1816	-0.1724	-0.2110*	-0.0288	-0.5244***
	20-day	-0.0735	0.0112	-0.1044	-0.1204	-0.0260	-0.1315	0.0239	-0.1159	-0.0951	0.0242	-0.0661	0.1866	-0.4334***
short	1-day	0.5911	0.6308	0.5595	0.5965	0.6295	0.5687	0.6049	0.6345	0.5709	0.5318	0.6305	0.7020	0.5131
	5-day	0.4320	0.4476	0.4306	0.3997	0.4742	0.4118	0.4814	0.4733	0.4093	0.4075	0.4088	0.5421	0.2356
	20-day	0.5258	0.5530	0.5354	0.4405	0.5473	0.4856	0.5882	0.4873	0.5458	0.5468	0.5412	0.5976	0.2830

Table 25: Results for the Expected Shortfall "direct" backtest Z_2 of Acerbi & Szekely (2014) 0.975% confidence.