Segnon, Mawuli; Gupta, Rangan

Book

Forecasting stock market volatility with regime-switching GARCH-MIDAS : the role of geopolitical risks

Reference: Segnon, Mawuli/Gupta, Rangan (2022). Forecasting stock market volatility with regime-switching GARCH-MIDAS : the role of geopolitical risks. Pretoria, South Africa : Department of Economics, University of Pretoria.
http://www.up.ac.za/media/shared/61/WP/wp_2022_03.zp214290.pdf.

University of Pretoria
Department of Economics Working Paper Series

Forecasting Stock Market Volatility with Regime-Switching GARCH-MIDAS: The Role of Geopolitical Risks

Mawuli Segnon
University of Münster
Rangan Gupta
University of Pretoria
Working Paper: 2022-03
January 2022

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Forecasting stock market volatility with Regime-Switching GARCH-MIDAS: The role of geopolitical risks

Mawuli Segnon[*]
Department of Economics, Institute for Econometric and Economic Statistics and Chair of Empirical Economics, University of Münster, Germany

and

Rangan Gupta
Department of Economics, University of Pretoria, South Africa

Abstract: We investigate the role of geopolitical risks (GPR) in forecasting stock market volatility in a robust autoregressive Markov-switching GARCH mixed data sampling (AR-MSGARCH-MIDAS) framework that accounts for structural breaks through regime switching and allows us to disentangle short- and long-run volatility components driven by geopolitical risks. An empirical out-of-sample forecasting exercise is conducted using unique data sets on Dow Jones Industrial Average (DJIA) index and geopolitical risks that cover the time period from January 3, 1899 to December 31, 2020. We find that geopolitical risks as explanatory variables can help to improve the accuracy of stock market volatility forecasts. Furthermore, our empirical results show that the macroeconomic variables such as output measured by recessions, inflation and interest rates contain information that is complementary to the one included in the geopolitical risks.

Keywords Geopolitical risks, Volatility forecasts, Markov-switching GARCH-MIDAS

JEL classification C52, C53, C58

[*]Corresponding author: Mawuli Segnon, Department of Economics, University of Münster, Germany. E-mail: segnon@uni-muenster.de.

1 Introduction

Forecasting valid stock market volatility is central to the option pricing theory, portfolio optimization, risk management and monetary policy. Since the introduction of the ARCH processes by Engle (1982) substantial progress has been made on modeling and forecasting the time variation of volatility. The main goals of this endeavor are: (i) to extend the original framework for properly capturing the *stylized facts* of financial markets and (ii) to allow for the modeling the economic sources of volatility, see Engle and Rangel (2008), Engle et al. (2013), Conrad and Loch (2015), Wei et al. (2017), Fang et al. (2018), Fang et al. (2020), Conrad and Kleen (2020), Wang et al. (2020), Wang et al. (2020), Ma et al. (2020), You and Liu (2020), Pan et al. (2017) and Salisu et al. (2022). While all these studies have shed light on the explanatory power of macroeconomic variables to improve the accuracy of stock or commodity market volatility forecasts, the empirical evidence on the role of geopolitical risks in enhancing the accuracy of stock market volatility forecasts is scare. However, the theoretical and empirical literature on the impacts of geopolitical shocks on the financial markets and their transmission channels is recently well-established, see Burch et al. (2003), Kollias et al. (2011b), Kollias et al. (2011a), Kollias et al. (2013), Kollias et al. (2013), Balcilar et al. (2017), Balcilar et al. (2018), Balcilar et al. (2018), Hanisch (2020), Bouri et al. (2022).

The findings of the recent studies on the relationship between financial markets, the economy and the geopolitical risks[2] indicate that geopolitical risks negatively affect the stock market returns, and, in turn, play an important role in the investment decisions making processes by investors at both national and international levels and can be viewed as one of key determinants of the state of the economy, see Dogan et al. (2021), Caldara and Iacoviello (2019), Hoque and Zaidi (2020), Smales (2021) and Elsayed and Helmi (2021). So, the natural question that arises is: Can geopolitical risks be helpful for forecasting future stock market volatility? This study aims to answer this specific question and fill this gap in the literature.

To answer this specific question we adopt an autoregressive Markov-switching GARCH-MIDAS (AR-MSGARCH-MIDAS) framework that can accounts for nonlinearities and structural breaks through regime switching. Our choice is motivated by the findings in recent studies that the relationship between returns, macroeconomic variables and geopolitical risks is nonlinear and may depend on the volatility regimes, macroeconomic characteristics and levels of stock market development, see e.g., Hoque and Zaidi (2020) and Conrad and Kleen (2020). The AR-MSGARCH-MIDAS framework allows us to model the stock market volatility as a product of short- and long-term components. The long-term component is driven by geopolitical risks or macroeconomic variables and the short-term one is modeled via the Markov-switching GARCH process, see Haas et al. (2004). The MSGARCH framework allows for multiple regimes that are needed in order to model different variance dynamics which govern the short-term volatility component. Recently introduced by

[2]We note that papers by Antonakakis et al. (2017), Apergis et al. (2018), Bouras et al. (2019) do not find any impact of geopolitical risks on stock market returns.

Schulte-Tillmann et al. (2021) the AR-MSGARCH-MIDAS framework has been successful in forecasting stock market volatility and outperforms the standard GARCH or MSGARCH model. Our objective here is to investigate in which extent geopolitical risks as explanatory variables may improve the accuracy stock market volatility forecasts. We use a unique data set on Dow Jones Industrial Average (DJIA) prices that covers the time period from January 03, 1899 to December 31, 2020. We also examine the complementarity of the information content in macroeconomic variables such outputs measured by recessions, inflation and interest rates.

Based on Patton (2011) findings we use two robust loss functions, namely the MSE and QLIKE and apply the equal predictive ability (EPA) test of Diebold and Mariano (1995), the asymptotic EPA of Giacomini and White (2006) and the model confidence set test of Hansen et al. (2011) to evaluate the relative forecasting performance of the AR-MSGARCH-MIDAS with geopolitical risks or macroeconomic variables at different forecasting horizons (one month up to four months). We find that (i) the AR-GARCH-MIDAS model with geopolitical risks such as GPRH, GPRHT and GPRHA or/and macroeconomic variables equally perform well over different forecasting horizons and across loss functions and especially outperform the standard AR-GARCH model for QLIKE, (ii) the AR-MSGARCH-MIDAS framework with geopolitical risk index or macroeconomic variables and the AR-MSGARCH show similar forecasting performance and (iii) the macroeconomic variables have complementary information content for the geopolitical risks, (iv) finally, we find that forecasts combination from models with a single variable also lead to improvement of the forecast accuracy over the AR-MSGARCH model.

The rest of the paper is organized as follows. Section 2 presents the descriptive analysis of our unique data set. Our econometric framework and statistical properties are described in Section 3. Section 4 presents the forecasting evaluation methodology. The empirical results for the in-sample and out-of-sample exercises are reported in Section 5. Finally, Section 6 concludes.

2 Data analysis

We use daily Dow Jones Industrial Average (DJIA) index prices and monthly US Consumer price index (CPI), interest rates, geopolitical risk indices. The data on DJIA is sourced from MeasuringWorth: *https://www.measuringworth.com/datasets/DJA/index.php* and cover the time period from January 03, 1899 to December 31, 2020. The GPR data is based on the work of Caldara and Iacoviello (2019).[3] The news-based GPR is constructed via the enumeration of the occurrences of words associated to geopolitical tensions in three leading international newspapers, namely the New York Times, the Chicago Tribune, and the Washington Post for which electronic access to all articles is available from 1899 through Pro Quest Historical Newspapers. For each newspaper Caldara and Iacoviello (2019) compute the index by counting the number of articles that contain the search terms for each month

[3]Geopolitical risk data are available for download from: *https://www.matteoiacoviello.com/gpr2019.htm.*

starting in 1899. The search identifies articles containing references to six groups of words. Group 1 consists of words associated with explicit mentions of geopolitical risk as well as mentions of military-related tensions involving large regions of the world or US involvement. Group 2 contains words directly related to nuclear tensions. Groups 3 and 4 are of mentions related to war threats and terrorist threats, respectively. Groups 5 and 6 capture press coverage of actual adverse geopolitical events (as opposed to just risks) which can be reasonably expected to lead to increases in geopolitical uncertainty (for example, terrorist acts or the beginnings of wars). Naturally, Groups 1 to 4 capture threats of geopolitical risk, while Groups 5 and 6 encompass actual acts of geopolitical risk.

To control for the general macroeconomic environment, we use the recession dummy as a measure of the state of economic activity (obtained from the FRED database of the Federal reserve Bank of St. Louis), month-on-month inflation rate (based on the underlying consumer price index (CPI) data derived from the data-segment of the website of Professor Robert J. Shiller at: *http://www.econ.yale.edu/ shiller/data.htm*), and finally a measure of short-term interest rate, whereby we use the risk-free rate from January, 1899 to February, 1921, which is then merged with the 3-month Treasury bill rate over the period of March, 1920 to December, 2020 (with both series downloaded from the website of Professor Amit Goyal at: *https://sites.google.com/view/agoyal145*).

We compute the percent continuously compounded returns

$$r_{i,t} = 100 * [\log p_{i,t} - \log p_{i-1,t}], \tag{1}$$

where $p_{i,t}$ denotes the price of the DJIA index at time i through period t.

Fig. 1 depicts the time evolution of DJIA index prices, and their log-returns and squared returns. Figs. 2 and 3 illustrate the macroeconomic variables and the geopolitical risks. The descriptive statistics of the log-returns, macroeconomic variables and geopolitical risks are reported in Table 2. The rejection of the null hypothesis of no autocorrelation in returns by the Ljung-Box test is in contraction to the efficient market hypothesis. While the return series exhibit negative skewness, the geopolitical risk indices, the inflation and interest rates are characterized by a positive skewness. All the time series exhibit excess kurtosis. These results show that the computed log-returns do not follow a Normal distribution. This observation is confirmed by the Jarque-Bera test, which rejects the null hypothesis of Normally distributed log-returns at any level of significance. The augmented Dickey-Fuller (ADF) unit-root test of Dickey and Fuller (1979) indicates the stationarity of DJIA log-returns. Fig. 4 shows the autocorrelation functions for log-returns, squared and absolute log-returns. We observe that the absolute and squared log-returns are highly correlated, and this observation is in conformity with the Ljung-Box statistics, $Q(5)$. Furthermore, the ARCH test conforms the presence of heteroscedasticity and therefore a significant ARCH effects in the returns.

Finally, we apply the modified iterated cumulative sum of squares (ICSS) algorithm to test whether multiple breaks occur in the second moment at the 5% significance level. We obtain six break points that occur between January 03, 1899 and December 31, 2020. These break points are reported in Table 1 and motivate the use of the Markov-switching GARCH framework that can take into account such structural breaks observed in the data through regime switching.

3 Theoretical framework

The results from the Section 2 motivate us to consider an AR-MSGARCH-MIDAS framework that models daily returns, $r_{i,t}$, with $i = 1, \ldots, N^{(t)}$ denoting a day within period $t = 1, \ldots, T$, as:

$$\phi(\mathrm{L}) r_{i,t} = \mu + \varepsilon_{i,t}, \tag{2}$$

where $\phi(\mathrm{L}) = 1 - \sum_{j=1}^{p} \phi_j \mathrm{L}^j$ is the lag polynomial, L is the lag operator, μ is a constant and the error term, $\varepsilon_{i,t}$, can be formalized as

$$\varepsilon_{i,t} = \sqrt{\tau_t g_{\Delta_{i,t},i,t}} \epsilon_{i,t}. \tag{3}$$

where $\epsilon_{i,t} | \mathfrak{F}_{i-1,t} \sim N(0,1)$ with $\mathfrak{F}_{i-1,t}$ is the information set up to day $(i-1)$ of period t, τ_t denotes the long-run volatility component and $g_{\Delta_{i,t},i,t}$ is the short-run volatility component with $\mathbb{E}\left(g_{\Delta_{i,t},i,t}\right) = 1$. $\{\Delta_{i,t}\}$ is a Markov chain with finite state $S = \{1, 2, \ldots, k\}$ and is independent of $\epsilon_{i,t}$, and with an irreducible, aperiodic $(k \times k)$ transition probability matrix, $\mathbf{P}$, that is,

$$\mathbf{P} = [p_{jl}] = \Pr\{\Delta_{i,t} = l | \Delta_{i-1,t} = j\}, \qquad j, l = 1, \ldots, k. \tag{4}$$

The stationary distribution of the Markov chain is given by $\pi_\infty = [\pi_\infty^1, \pi_\infty^2 \ldots, \pi_\infty^k]'$. Furthermore, we assume that the conditional unit-variance in regime j is a GARCH(1, 1) process:

$$g_{i,t}^{(j)} = \alpha_{0j} + \alpha_{1j} \frac{\varepsilon_{i-1,t}^2}{\tau_t} + \beta_j g_{i-1,t}^{(j)}, \qquad j = 1, 2, \ldots, \tag{5}$$

where $\alpha_{0j} = (1 - \alpha_{1j} - \beta_j) > 0$, $\alpha_{1j}, \beta_j \geq 0$ to guarantee positivity of the variance process.

To complete the modeling framework we adopt the following regression that enables us to incorporate a single explanatory variable in the long-run volatility component, τ_t,

$$\tau_t = m + \theta \sum_{q=1}^{Q} \varphi_q(\omega_1, \omega_2) X_{t-q}, \tag{6}$$

where $m > 0$, $\theta > 0$, and X_t is the variable of interest such as the historical index of geopolitical risk (GPRH), the geopolitical risk due to attacks (GPRHA) and the geopolitical risk due to threats (GPRHT), the output measured by recession indicators, the inflation and the interest rates. The importance of the specific lags of X_t with respect to the long-term volatility movements is measured by the weights $\varphi_q(\omega_1, \omega_2) \geq 0$, which are chosen according to the following Beta weighting scheme:

$$\varphi_q(\omega_1, \omega_2) = \frac{\left(\frac{q}{Q+1}\right)^{\omega_1 - 1} \cdot \left(1 - \frac{q}{Q+1}\right)^{\omega_2 - 1}}{\sum_{j=1}^{Q} \left(\frac{j}{Q+1}\right)^{\omega_1 - 1} \cdot \left(1 - \frac{j}{Q+1}\right)^{\omega_2 - 1}}. \tag{7}$$

that satisfies, by definition, that the weights $\varphi_q(\omega_1, \omega_2)$ are positive and sum up to one for $q = 1, \ldots, Q$. Furthermore, the parameter θ determines the sign of the effect of the lagged X_t on the long-term component. As noted by Ghysels et al. (2007) the Beta weighting scheme is very flexible, such that it can produce (i) equal weights for all lags q (for $\omega_1 = 1$ and $\omega_2 = 1$), (ii) monotonically declining weights for increasing lags q (for $\omega_1 = 1$ and $\omega_2 > 1$) and (iii) hump-shaped and convex patterns (for unrestricted parameters). In the second case the parameter ω_2 determines the rate of decline of the weights, i.e. the greater ω_2, the more rapidly the weights φ_q will decrease. For the third case the ratio of ω_1 and ω_2 governs, whether higher weight is put on more recent lags or on less recent lags.

In order to investigate how a more than one explanatory variable (two explanatory variables) may affect the forecasting performance of our model, we adopt the following regression model for the long-term component:

$$\tau_t = m + \theta_1 \sum_{q=1}^{Q^{mv}} \varphi_q(\omega_1^{mv}, \omega_2^{mv}) X_{t-q}^{mv} + \theta_2 \sum_{q=1}^{Q^{gpr}} \varphi_q(\omega_1^{gpr}, \omega_2^{gpr}) X_{t-q}^{gpr}, \tag{8}$$

where the weights are computed as in Eq. (7). The subscripts mv and gpr are for macroeconomic variables and geopolitical risks, respectively.

Now we provide the conditions under which the AR-MSGARCH-MIDAS is strictly stationary.

Assumption 1. *Let $\{\epsilon_{i,t}\}$ be i.i.d. with $\mathbb{E}(\epsilon_{i,t}) = 0$, $\mathbb{E}(\epsilon_{i,t}^2) = 1$ and $\mathbb{E}(|\epsilon_{i,t}^2|^\nu) < \infty$ for some $\nu > 0$.*

Assumption 2. *Let τ_t be well specified and the explanatory variable $\{X_t\}$ be a strictly stationary and ergodic time series with $\mathbb{E}(|X_t|^\delta) < \infty$, where δ is sufficiently large to ensure that $\mathbb{E}(\tau_t^2) < \infty$. Additionally, $\{X_t\}$ is independent of $\{\epsilon_{i,t}\}$ for all t, and i.*

Assumption 3. *The roots of the characteristic polynomial $\phi(L)$ lie outside the unit circle. Let m and θ be positive and the weights $\varphi_q(\omega)$ are a nonnegative function of ω for all q with $\sum_{q=1}^{Q} \varphi_q(\omega) = 1$.*

Assumption 4.

$$\sum_{j=1}^{k} \pi_j \, \mathbb{E}\left[\ln(\alpha_{1j}\epsilon_{i,t} + \beta_j)\right] < 0. \tag{9}$$

Proposition 1. *Under Assumptions 1, 2, 3 and 4 the extended process $Z_{i,t} = (\varepsilon_{i,t}, \tau_t, g_{i,t}, \Delta_{i,t})'$ is geometrically ergodic and if it is initiated from its stationary distribution, then the process is strictly stationary and $\beta-$mixing with exponential decay.*

Proof. We follow Bauwens et al. (2010) and rewrite the model in its Markovian state space representation. We use the notation $g_{i,t} = h_{i-1,t}$ to make it clear that $g_{i,t}$ is a function of the information dated at time $i-1$ or earlier, not information dated at i. There exist two measurable functions $f : S \times R \to S$ and $f^+ : R_+ \times R_+ \to R_+$ such that $\Delta_{i,t} = f(\Delta_{i-1,t}, \xi_{i,t})$ where the error term $\xi_{i,t}$ is i.i.d. independent of $\varepsilon_{i,t}$, h_0 and τ_0 and $R_+ = (0, +\infty)$ and $\tau_t = f^+(\tau_{t-1})$. Let $\bar{\Delta}_{i,t} = \Delta_{i+1,t}$, $\eta_{i,t} = (\varepsilon_{i,t}, \xi_{i,t})'$ and $Z_{i,t}$ be defined on $D \subset R \times R_+ \times R_+ \times S$. From (3), (5) and (6) we have

$$Z_{i,t} = \begin{pmatrix} \varepsilon_{i,t} \\ h_{i,t} \\ \tau_t \\ \bar{\Delta}_{i,t} \end{pmatrix} = \begin{pmatrix} \sqrt{h_{\Delta_{i-1,t},i-1,t}\tau_t}\epsilon_{i,t} \\ \alpha_0 + \left(\varepsilon_{i,t}^2 \alpha_1 \mathbf{1}_{\Delta_{i-1,t}}' + \beta\right) h_{i-1,t} \\ f(\tau_{t-1}) \\ f(\bar{\Delta}_{i-1,t}, \xi_{i+1,t}) \end{pmatrix} = F(Z_{i-1,t}, \eta_{i,t}) \tag{10}$$

where $\alpha_i = [\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{ik}]'$, $i = 0, 1$; $\beta = diag(\beta_1, \beta_2, \ldots, \beta_k)$, $F : D \times R^2 \to D$ and $\mathbf{1}_{\{\cdot\}}$ denotes an indicator function, $\mathbf{1}_{\Delta_{i,t}} = \left(\mathbf{1}_{\{\Delta_{i,t}=1\}}, \mathbf{1}_{\{\Delta_{i,t}=2\}}, \ldots, \mathbf{1}_{\{\Delta_{i,t}=k\}}\right)'$. Since $\eta_{i,t}$ is independent of $Z_{i-1,t}$ it follows from (10) that $(\varepsilon_{i,t}, \tau_t, g_{i,t}, \Delta_{i,t})'$ forms a homogenous Markov chain. It follows that under Assumption 1, 2, and 3, Theorem 2.1. in Bauwens et al. (2010) applies and thus, $Z_{i-1,t}$ is geometrically ergodic and if it is initiated from its stationary distribution, then the process is strictly stationary and $\beta-$mixing with exponential decay. The proof of the proposition is similar to the proof of the Theorem 2.1 in Bauwens et al. (2010). We refer the reader to Bauwens et al. (2010). ■

Remark. *The conditions for the existence of moments and for the weak stationarity for the GARCH-MIDAS are studied in details by Wang and Ghysels (2015).*

4 Forecasting evaluation

To answer the question whether the information content in the geopolitical risks can help improve the accuracy of stock market volatility forecasts we split our data set into an estimation sample that covers the period from January 04, 1899 to December 29, 2000 and an out-of-sample that contains observation from January 2001 to December 31, 2020. We adopt a rolling forecasting scheme that keeps the estimation sample size constant over the out-of-sample period. Due to the different frequency of the geopolitical risk indices, we forecast the cumulative variance for 1 up to 4 months ahead. The optimal variance forecast for day h in period $t+s$ with $s \geq 1$ based on the information available at day $N^{(t)}$ in period t is given by

$$\hat{\sigma}^2_{h,t+s|N^{(t)},t} = \mathbb{E}_{N^{(t)},t}(\tau_{t+s} g_{h,t+s}) = \mathbb{E}_t(\tau_{t+s})\mathbb{E}_{N^{(t)},t}(g_{h,t+s}) = \tau_{t+s|t} g_{h,t+s|N^{(t)},t}. \tag{11}$$

For a horizon of $s = 1$, the forecast of the long-term component $\tau_{t+1|t}$ is predetermined by Eqs. 6 and 8. However, for larger horizons, i.e. $s > 1$, we cannot predict the long-term component without knowing the distribution of the geopolitical risk index X_t. Following Conrad and Loch (2015) we assume smooth movements in the low-frequency component and therefore, set $\tau_{t+s|t} = \tau_{t+1|t}$ for $s > 1$.

We aggregate the daily volatility forecast over the period $t+s$ in order to obtain the cumulative volatility forecast that is given by

$$\hat{\sigma}^2_{1:N^{(t+s)},t+s|N^{(t)},t} = \tau_{t+s|t} \sum_{i=1}^{N^{(t+s)}} g_{i,t+s|N^{(t)},t} \tag{12}$$

which is the subject of interest in our out-of-sample analysis. The closed-form formula for volatility forecasts from the MSGARCH model is available in Haas et al. (2004). Furthermore, the computation of the forecasts from the GARCH-MIDAS is explained in details in Conrad and Kleen (2020). To access the forecasting performance we employ two different loss functions, namely the mean squared error (MSE) and the Gaussian quasi-likelihood (QLIKE) that are more robust to imperfect volatility proxies, see Patton (2011), and are defined by

$$\begin{aligned} \text{MSE}(\sigma^2_{1:N^{(t+s)},t+s}, \hat{\sigma}^2_{1:N^{(t+s)},t+s|N^{(t)},t}) &= (\sigma^2_{1:N^{(t+s)},t+s} - \hat{\sigma}^2_{1:N^{(t+s)},t+s|N^{(t)},t})^2, \\ \text{QLIKE}(\sigma^2_{1:N^{(t+s)},t+s}, \hat{\sigma}^2_{1:N^{(t+s)},t+s|N^{(t)},t}) &= \ln\left(\hat{\sigma}^2_{1:N^{(t+s)},t+s|N^{(t)},t}\right) + \frac{\sigma^2_{1:N^{(t+s)},t+s}}{\hat{\sigma}^2_{1:N^{(t+s)},t+s|N^{(t)},t}}, \end{aligned} \tag{13}$$

where $\sigma_{1:N^{(t+s)},t+s}$ denotes a proxy for the variance.

We use aggregated squared returns as a proxy, although it is known that they are a noisy proxy. Patton (2011), however, shows that the ranking of the forecasting performance based on the MSE and QLIKE loss function is consistent as long as the proxy is conditionally unbiased. In order to test for equal (unconditional) predictive ability, we apply Giacomini and White (2006)'s test, that is applicable in the context of nested models. Based on the loss differential

$$d_{i,j}(t+s) = L(\sigma^2_{1:N^{(t+s)},t+s}, \hat{\sigma}^{2,(i)}_{1:N^{(t+s)},t+s|N^{(t)},t}) - L(\sigma^2_{1:N^{(t+s)},t+s}, \hat{\sigma}^{2,(j)}_{1:N^{(t+s)},t+s|N^{(t)},t}) \tag{14}$$

of two competing models i and j, the null hypothesis, $H_0 : \mathbb{E}\left(d_{i,j}(t+s)\right) = 0$ for all $t+s$, can be stated. The loss function $L(\cdot,\cdot)$ represents the previously defined MSE or QLIKE losses. The corresponding test statistic is given by

$$t_{ij} = \frac{\bar{d}_{ij}}{\sqrt{\widehat{\text{Var}}(\bar{d}_{ij})}}, \tag{15}$$

where $\bar{d}_{ij} = \frac{1}{T}\sum_{t=1}^{T} d_{ij}(t+s)$, T is the number of out-of-sample forecast periods. With regard to our application, we fix model j to the benchmark model and conduct the test sequentially against the specifications with long-term component for each model class separately.

In a second step we investigate the forecast accuracy inter model-wise and try to identify the set of models with superior forecasting performance based on Hansen et al. (2011)'s model confidence sets (MCS). According to their approach we eliminate sequentially the 'worst-performing' model from the initial set $\mathcal{M}$, that encompasses all model specifications, if the null hypothesis, $H_{0,\mathcal{M}} : \mathbb{E}(d_{ij}) = 0$ for all $i, j \in \mathcal{M}$, is rejected. The iterative testing procedure terminates, once the null hypothesis cannot be rejected anymore. Then, the set of surviving models is called the model confidence set $\widehat{\mathcal{M}}^{*}$. In order to approximate the nonstandard asymptotic distribution of the test statistic, $T_{\mathcal{M}} = \max_{i,j\in\mathcal{M}}|t_{ij}|$, a block-bootstrap can be applied, where the block length corresponds to the maximum number of significant lags that is obtained when fitting an AR(p) process to all loss differentials.

5 Empirical analysis

5.1 Estimation of AR-MSGARCH-MIDAS models

Prior to the estimation and forecasting exercises we determine the lag length p in AR-MSGARCH-MIDAS via the Bayesian information criterion (BIC). The optimal lag length is $p = 1$ and we select the number of regimes k to be two. We note that the optimal lag length in the AR specification is obtained by estimating standard GARCH(1,1) model for the error term. As with the standard GARCH(1,1) we estimate the AR-GARCH-MIDAS and AR-MSGARCH-MIDAS via the maximum likelihood approach. The estimation results are reported in Tables 3, 4, 5, and 6.

We start with specification involving the single series, such as GPRH, GPRHT, GPRHA, recessions, inflation and interest rates and experience different weighting scheme as described in Section 3. We note that we use the logarithm specification of the long-term component, τ_t. The advantage here is that the parameters m and θ are not restricted to be positive in the estimation process. The parameters, β, that quantifies the effect of past volatility on current volatility and α that measures the effect of past squared innovations on current volatility in the short-term component are well estimated. While the estimates of β in the AR-GARCH-MIDAS model specifications are in the range from 0.893 to 0.898 and lower than those of β in AR-MSGARCH-MIDAS model specifications (they are in the range from 0.910 to 0.911). The most interesting parameters are the slope parameters θ in the MIDAS filter. For all explanatory variables except for GPRHT the sign of θ is positive and seems to be independent on the weighting schemes, see Tables 3 and 5. This implies that an increase in geopolitical risks or inflation or a decrease in output (recessions) leads to high stock market volatility. In the case of GPRHT our estimation results suggest that an increase in GPRHT may reduce stock market volatility. The estimation results for specifications involving geopolitical risks combined with macroeconomic variables are reported in Tables 4 and 6. The results are similar to those of specification involving the single series.

5.2 Forecasting results

Tables 7 and 9 report the relative MSE and QLIKE of volatility forecasts at different horizons for the AR-GARCH-MIDAS and AR-MSGARCH-MIDAS specifications with a single and two explanatory variables to the MSE and QLIKE of the standard AR-GARCH and AR-MSGARCH, the Giacomini and White (2006)'s test and the equally predictive ability (EPA) test results. The framework of Giacomini and White (2006)'s test is appropriate for nested models and, thus, can be used to produce valid results. Although the EPA of Diebold and Mariano (1995) test is designed for non-nested models we also apply it and the results are robust and reported in Tables 7 and 9. According MSE, the AR-GARCH-MIDAS with a single geopolitical risk or macroeconomic explanatory variable (or a combination of geopolitical risks and macroeconomic variables) dominates the standard AR-GARCH at the 2M (2-Month) ahead forecasting horizon and beyond, see Table 7. Based on QLIKE criterion the results suggest that the AR-GARCH-MIDAS cannot yield to better results that the standard AR-GARCH model at all forecasting horizons. These results have been confirmed by the Giacomini and White (2006) and EPA test results. According the MSE criterion only the AR-MSGARCH-MIDAS with GPRH or interest rates seem to produce lower values than the AR-MSGARCH. Furthermore, we observe that interest rates has complementary information for GPHRT and GPHRA. All the remaining AR-MSGARCH-MIDAS specifications and AR-MSGARCH perform equally well across loss functions and over forecasting horizons, see Table 9. Furthermore, Table 8 also reports the MSE and QLIKE ratios of the AR-MSGARCH-MIDAS with/or without a single variable relative to the AR-GARCH-MIDAS with/or without a single variable. We find that for MSE in most cases loss ratios are larger than 1 and for QLIKE they are lower than 1. The advantage of a Markov switching framework seems here to be mixed. The results also suggest that the importance of the explanatory variables in the out-of-sample forecasting exercises depends on the frameworks (AR-MSGARCH-MIDAS or AR-GARCH-MIDAS) in which they are conducted.

We apply the model confidence set (MCS) test in order to investigate the relative forecasting performance of our proposed models and 5,000 bootstrap replications at each stage were sufficient in order to produce stable p-values. For MSE the MCS test results show that both specifications, namely the AR-GARCH-MIDAS and AR-MSGARCH-MIDAS with a single explanatory variable or a combination of geopolitical risks (GPRH, GPRHT and GPRHA) with a macroeconomic variables (recessions, inflation or interest rates) perform relatively well at the 1M, 2M and 3M forecasting horizons. For QLIKE the MCS test results indicate that forecasts from the simple AR-MSGARCH at the 2M and 3M forecasting horizons are better than those from AR-MSGARCH-MIDAS with a single explanatory variable. It seems that single variables do not have explanatory power in the AR-MSGARCH-MIDAS framework. However, we observe that a combination of the GPRHT or GPRHA with output measured by recessions or inflation rates significantly affects the forecasting performance. At the 1M forecasting horizon the AR-MSGARCH-MIDAS with GPRH or GPRHT combined with output measured by recessions or interest rates outperforms the simple AR-MSGARCH and AR-MSGARCH-MIDAS with single variables. At the 4M ahead horizon forecasts from the AR-MSGARCH-MIDAS and from the AR-MSGARCH are excluded from $M_{90\%}$.

We also examine the question whether forecasts from our competing volatility models with a single explanatory variable may be combined to produce a new predictor that is more accurate than the individual forecasts. To do that we apply the forecast encompassing tests developed by Harvey et al. (1998) for non-nested models and its adjusted version by Clark and West (2007) for nested ones. The results are reported in Tables 11, 12 and 13. The null hypothesis that forecasts from AR-MSGARCH-MIDAS with a single variable such as GPRH or GPRHT or GPRHA or recessions or inflation or interest rates do encompass those of the AR-GARCH-MIDAS with a single variable (GPRH or GPRHT or GPRHA or recessions or inflation or interest rates) models cannot be rejected at the 5% confidence level in most cases. This indicates that in most cases the AR-MSGARCH-MIDAS model should not contribute useful information to the AR-GARCH-MIDAS forecasts while the opposite is excepted for the cases where the null hypothesis is rejected.

The results of encompassing tests motivate us to explore the predictive capacity of combined forecasts from AR-MSGARCH-MIDAS and AR-GARCH-MIDAS (with single variable) in a linear way in the hope of generating superior predictions, see Aiolfi and Timmermann (2006). The new predictions $\sigma_{n,t}$ are obtained by

$$\sigma_{n,t} = (1 - \hat{\varsigma})\sigma_{1,t} + \hat{\varsigma}\sigma_{2,t}, \tag{16}$$

where $\sigma_{1,t}$ and $\sigma_{2,t}$ are the single forecasts from the model 1 and model 2, respectively. $\hat{\varsigma}$ is the optimal weight of model 2 that is obtained from the following regression

$$\xi_{1,t} = \varsigma\,(\xi_{1,t} - \xi_{2,t}) + \epsilon_t, \tag{17}$$

where $\xi_{1,t}$ denotes the forecasting error from the model 1, that is AR-MSGARCH-MIDAS with single variable or AR-MSGARCH in this study and $\xi_{2,t}$ is that from AR-GARCH-MIDAS with single variable or AR-GARCH, and ϵ_t an *iid* Normally distributed error term.

We access the relative forecasting performance of the combined forecasts from competing volatility models with a single explanatory variable by applying the MCS test and the results are reported in Tables 14 and 15. We note that the optimal forecasts according to *eqs.* (16) and (17) have implicitly been calculated under an MSE criterion, so they need not be the optimal combinations for QLIKE. We observe results for the MSE and QLIKE of the combined forecasts that are hardly different from the previous results for AR-MSGARCH-MIDAS and AR-GARCH-MIDAS with single or bivariate explanatory variables across forecasting horizons. These results tend to confirm the tendency that our encompassing test cannot reject the null hypothesis. If AR-MSGARCH-MIDAS with a single explanatory variable or without encompasses these alternative forecasts from the AR-GARCH-MIDAS with a single explanatory variable or without, the forecast combination should not be superior which is indeed what we mostly observe. However, it also seems that for QLIKE at the 1-Month forecasting horizon, the forecast combination help improving the forecasting accuracy.

6 Conclusion

This paper has analyzed the explanatory power of geopolitical risks and their complementarity with macroeconomic variables such output measured by recessions, inflation and interest rates in forecasting stock market volatility in a robust AR-MSGARCH-MIDAS framework. We have utilized two loss functions, namely the MSE and QLIKE and applied the Giacomini and White (2006) and the model confidence set (MCS) tests in order to evaluate the relative forecasting of the AR-MSGARCH-MIDAS with single geopolitical risks or macroeconomic variables or both combined. Our empirical results show that AR-MSGARCH-MIDAS and AR-GARCH-MIDAS perform as well as the AR-MSGARCH and AR-GARCH models and sometimes outperform them. However, it seems that the explanatory power of the geopolitical risks such as GPRH, GPRHA and GPRHT depends on the modeling framework. They are less informative in the AR-MSGARCH-MIDAS framework than the AR-GARCH-MIDAS one. Combined with recessions, inflation or interest rates the geopolitical risk indices can yield to improvement of the forecasting accuracy. Forecast combinations from models with a single explanatory variables have produced accurate predictors and can be used as an alternative to the models with two or more explanatory variables.

References

Aiolfi, M. and A. Timmermann (2006). Persistence in forecasting performance and conditional combination strategies. *Journal of Econometrics 135*, 1–53.

Antonakakis, N., R. Gupta, C. Kollias, and S. Papadamou (2017). Geopolitical risks and the oil-stock nexus over 1899-2016. *Finance Research Letters 23*, 165–173.

Apergis, N., M. Bonato, R. Gupta, and C. Kyei (2018). Does geopolitical risks predict stock returns and volatility of leading defense companies? evidence from a nonparametric approach. *Defence and Peace Economics 29*, 684–696.

Balcilar, M., M. Bonato, R. Demirer, and R. Gupta (2018). Geopolitical risks and stock market dynamics of the BRICS. *Economic Systems 42*, 295–306.

Balcilar, M., R. Gupta, C. Pierdzioch, and M. E. Wohar (2017). Do terror attacks affect the dollar-pound exchange rate? a nonparametric causality-in-quantiles analysis. *North American Journal of Economics and Finance 41*, 44–56.

Balcilar, M., R. Gupta, C. Pierdzioch, and M. E. Wohar (2018). Terror attacks and stock-market fluctuations: Evidence based on a nonparametric causality-in-quantiles test for the g7 countries. *European Journal of Finance 24*, 333–346.

Bauwens, L., A. Preminger, and J. V. K. Rombouts (2010). Theory and inference for a markov switching GARCH model. *The Econometrics Journal 13*, 218–244.

Bouras, C., C. Christou, R. Gupta, and T. Suleman (2019). Geopolitical risks, returns and volatility in emerging stock markets: Evidence from a panel GARCH model. *Emerging Markets Finance and Trade 55*, 1841–1856.

Bouri, E., O. Cepni, R. Gupta, and N. Jalkh (2022). Geopolitical risks and stock market volatility in the G7 countries: A century of evidence from a time-varying nonparametric panel data model. In A. Basuchoudhary and G. Schulze (Eds.), *Handbook for the Economics of Terrorism*. Forthcoming.

Burch, T. R., D. R. Emery, and M. E. Fuerst (2003). What can "Nine-Eleven" tell us about closed-end fund discounts and investor sentiment? *The Financial Review 38*, 515–529.

Caldara, D. and M. Iacoviello (2019). Measuring geopolitical risk. Working Paper, Board of Governors of the Federal Reserve.

Clark, T. E. and K. D. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics 2*, 84–108.

Conrad, C. and O. Kleen (2020). Two are better than one: Volatility forecasting using multiplicative component garch-midas models. *Journal of Applied Econometrics 35*, 19–45.

Conrad, C. and K. Loch (2015). Anticipating long-term stock market volatility. *Journal of Applied Econometrics 30*, 1090–1114.

Dickey, D. A. and W. A. Fuller (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association 74*, 427–431.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics 13*, 253–263.

Dogan, E., M. T. Majeed, and T. Luni (2021). Analyzing the impacts of geopolitical risk and economic uncertainty on natural resources rents. *Resources Policy 72*, 102056.

Elsayed, A. H. and M. H. Helmi (2021). Volatility transmission and spillover dynamics across financial markets: The role of geopolitical risk. *Annals of Operations Research 305*, 1–22.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica 50*, 987–1008.

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

Engle, R. F. and J. Rangel (2008). The spline-garch model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies 21*, 1187–1222.

Fang, T., B. Chen, H. Yu, and Y. Qian (2018). The importance ofglobal economic policy uncertainty in predicting gold futuresmarket volatility: A GARCH-MIDAS approach. *Journal of Futures Markets 38*, 413–422.

Fang, T., T.-H. Lee, and Z. Su (2020). Predicting the long-term stockmarket volatility: A GARCH-MIDAS model with variable selection. *Journal of Empirical Finance 58*, 36–49.

Ghysels, E., A. Sinko, and R. Valkanov (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews 26*, 53–90.

Giacomini, R. and H. White (2006). Tests of conditional predictive ability. *Econometrica 74*, 1545–1578.

Haas, M., S. Mittnik, and M. S. Paolella (2004). A new approach to markov-switching garch models. *Journal of Financial Econometrics 2*, 493–530.

Hanisch, M. (2020). From iran to russia to hong kong: Geopolitical risks are weighing on the german economy. DIW Weekly Report ISSN 2568-7697, Deutsches Institut fÃ¼r Wirtschaftsforschung (DIW), Berlin.

Hansen, P. R., A. Lunde, and J. M. Nason (2011). The model confidence set. *Econometrica 79*, 453–497.

Harvey, D. I., S. J. Leybourne, and P. Newbold (1998). Tests for forecast encompassing. *Journal of Business & Economic Statistics 16*, 254–259.

Hoque, M. E. and M. A. S. Zaidi (2020). Global and country-specific geopolitical risk uncertainty and stock return of fragile emerging economies. *Borsa Istanbul Review 20*, 197–213.

Kollias, C., S. Papadamou, and V. Arvanitis (2013). Does terrorism affect the stock-bond covariance? evidence from european countries. *Southern Economic Journal 79*, 832–848.

Kollias, C., S. Papadamou, and A. Stagiannis (2011a). Stock markets and terrorist attacks: comparative evidence from a large and a small capitalization market. *European Journal of Political Economy 27*, S64–S77.

Kollias, C., S. Papadamou, and A. Stagiannis (2011b). Terrorism and capital markets: the effects of the madrid and london bomb attacks. *International Review of Economics and Finance 20*, 532–541.

Kollias, C., S. Papadamou, and A. Stagiannis (2013). The effects of terrorism and war on the oil and prices stock indices relationship. *Energy Economics 40*, 743–752.

Ma, F., X. Lu, L. Wang, and J. Chevallier (2020). Global economic policy uncertainty and gold futures market volatility: Evidence from markov regime-switching GARCH-MIDAS models. *Journal of Forecasting 40*, 1070–1085.

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

Patton, A. J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics 160*, 246–256.

Salisu, A., R. Gupta, E. Bouri, and Q. Ji (2022). Mixed-frequency forecasting of crude oil volatility based on the information content of global economic conditions. *Journal of Forecasting 41*, 134–157.

Sansó, A., V. Aragó, and J. L. C. i Silvestre (2004). Testing for changes in the unconditional variance of financial time series. *Revista de Economia Financiera*, 32–53.

Schulte-Tillmann, B., M. Segnon, and B. wilfling (2021). Multiplicative decomposition of financial market volatility: Multi-Component volatility models. University of Münster.

Smales, L. A. (2021). Geopolitical risk and volatility spillovers in oil and stock markets. *The Quarterly Review of Economics and Finance 80*, 358–366.

Wang, F. and E. Ghysels (2015). Econometric analysis of volatility component models. *Econometric Theory 31*, 362–393.

Wang, L., F. Ma, and G. Liu (2020). Forecasting stock volatility in the presence of extreme shocks: Short-term and long-term effects. *Journal of Forecasting 39*, 797–810.

Wang, L., F. Ma, J. Liu, and L. Yang (2020). Forecasting stock price volatility: New evidence from the GARCH-MIDAS model. *International Journal of Forecasting 36*, 684–694.

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

You, Y. and X. Liu (2020). Forecasting short-run exchange rate volatility with monetary fundamentals: A GARCH-MIDAS approach. *Journal of Banking & Finance 116*, 105849.

Table 1: Structural breaks in the variance processes of DJIA price returns

No. of break points	Date (dd/mm/yyyy)			Standard deviation
	04/01/1899	–	**22/08/1910**	1.060
	23/08/1910	–	**27/07/1914**	0.657
	28/07/1914	–	**21/01/1921**	1.179
6	22/01/1921	–	**15/11/1928**	0.827
	16/11/1928	–	**17/09/1931**	1.969
	18/09/1931	–	**21/11/1932**	3.287
	22/11/1932	–	31/12/2020	1.022

Note: The bold dates represent the structural break points obtained from the modified iterated cumulated squares algorithm suggested by Sansó et al. (2004).

Table 2: Descriptive Statistics of the returns, inflation, interest rates and geopolitical risks

	Returns	Inflation rates	Interest rates	GPRH	GPRHA	GPRHT
Min	-25.632	-4.163	0.010	5.110	0.000	0.000
Max	14.273	6.736	16.300	618.530	2484.240	470.190
Mean	0.020	0.250	3.441	86.475	151.208	66.471
Std	1.093	0.773	2.736	69.940	241.466	53.191
Skewness	-0.582	0.360	1.127	2.267	4.099	2.349
Kurtosis	24.653	12.297	5.209	10.662	23.428	13.012
JB stat($\times 10^3$)	646.210	5.300	0.607	4.831	29.535	7.457
ARCH(5)($\times 10^3$)	3.651	0.136	1.400	0.726	0.906	0.574
ADF	-130.730	-18.531	-3.255	-8.788	-6.702	-10.209
Q(5)($\times 10^3$)	0.057	0.445	6.835	4.120	5.185	3.401
$Q^2(5)$($\times 10^3$)	6.279	0.211	6.245	2.157	3.127	1.461
$Q^{abs}(5)$($\times 10^3$)	1.382	-	-	-	-	-

Note: $Q^2(5)$ and $Q^{abs}(5)$ denote the Ljung-Box test statistics for squared and absolute returns, respectively.

Table 3: Parameter estimates of AR-GARCH-MIDAS

Variables	α_0	α_1	β	μ	ϕ_1	m	θ	ω_1	ω_2	*LLH*	*BIC*
Recessions	-	0.092	0.897	0.016	0.072	0.149	0.220	1	5.193	-41968	84009
	(-)	(0.008)	(0.009)	(0.004)	(0.006)	(0.145)	(0.117)	–	(2.374)	–	–
	-	0.092	0.897	0.016	0.072	0.148	0.224	1.010	5.690	-41968	84019
	(-)	(0.008)	(0.009)	(0.004)	(0.006)	(0.145)	(0.128)	(0.077)	(3.982)	–	–
Inflation	-	0.092	0.897	0.017	0.072	0.158	0.202	1	1.010	-41970	84012
	(-)	(0.008)	(0.009)	(0.005)	(0.006)	(0.169)	(0.166)	–	(1.439)	–	–
	-	0.092	0.897	0.017	0.072	0.154	0.215	1.010	1.010	-41969	84022
	(-)	(0.008)	(0.009)	(0.004)	(0.006)	(0.155)	(0.157)	(0.038)	(0.999)	–	–
Interest rate	-	0.092	0.895	0.016	0.072	-0.036	0.057	1	49.208	-41960	83993
	(-)	(0.009)	(0.009)	(0.004)	(0.007)	(0.233)	(0.023)	–	(285.345)	–	(-) –
	-	0.092	0.895	0.016	0.072	-0.036	0.057	1.010	49.914	-41960	84003
	(-)	(0.008)	(0.009)	(0.004)	(0.006)	(0.021)	(0.018)	(0.434)	(83.392)	–	–
GPRH	-	0.092	0.897	0.016	0.072	0.134	0.001	1	4.179	-41970	84014
	(-)	(0.009)	(0.009)	(0.004)	(0.006)	(0.222)	(0.0009)	–	(3.757)	–	–
	-	0.092	0.897	0.016	0.072	0.135	9.626E-4	1.010	4.177	-41970	84024
	(-)	(0.100)	(0.100)	(0.038)	(0.028)	(9.485)	(0.086)	(55.033)	(178.121)	–	–
GPRHT	-	0.092	0.898	0.016	0.072	0.219	1E-4	1	3.899	-41972	84017
	(-)	(0.008)	(0.009)	(0.004)	(0.006)	(0.143)	(0.001)	–	(6.409)	–	–
	-	0.092	0.898	0.017	0.072	0.288	-1.1E-3	1.010	1.010	-41971	84026
	(-)	(0.008)	(0.009)	(0.005)	(0.006)	(0.214)	(0.001)	(0.064)	(0.904)	–	–
GPRHA	-	0.092	0.897	0.016	0.072	0.155	3E-4	1	3.039	-41970	84012
	(-)	(0.008)	(0.009)	(0.004)	(0.006)	(0.181)	(2E-4)	–	(0.975)	–	–
	-	0.092	0.897	0.016	0.072	0.154	3.444E-4	1.010	3.227	-41969	84022
	(-)	(0.008)	(0.009)	(0.005)	(0.006)	(0.166)	(2.375E-4)	(0.068)	(1.835)	–	–
AR-GARCH	0.013	0.092	0.898	0.016	0.087	-	-	-	-	-41886	83825
	(0.002)	(0.008)	(0.009)	(0.005)	(0.007)	(-)	(-)	(–)	(-)	–	–

The parameter estimates for each explanatory variable that enters the specification via the restricted and unrestricted weighting scheme are reported in this table. The number in parentheses are the associated standard errors. The log-likelihood value and the Bayesian Information Criterion are abbreviated by *LLH* and *BIC*, respectively.

Table 4: Parameter estimates of an AR-GARCH-MIDAS with combined variables

Variables	α_1	β	μ	ϕ_1	m	θ_1	θ_2	ω_1^{mv}	ω_2^{mv}	ω_1^{gpr}	ω_2^{gpr}	*LLH*	*BIC*
GPRH+Recessions	0.092	0.896	0.016	0.072	0.006	0.273	1.4E-3	1	1.010	1	3.937	-41966	84026
	(0.008)	(0.009)	(0.004)	(0.007)	(0.008)	(0.188)	(8.519E-4)	–	(12.088)	–	(3.743)	–	–
	0.092	0.896	0.016	0.072	0.009	0.275	1.3E-3	1.010	5.428	1.107	3.539	-41964	84043
	(0.008)	(0.009)	(0.005)	(0.006)	(0.023)	(0.127)	(7.543E-4)	(0.077)	(5.463)	(0.046)	(2.214)	–	–
GPRH+Inflation	0.092	0.897	0.016	0.072	0.106	0.168	6.840E-4	1	1.010	1	4.458	-41969	84031
	(0.009)	(0.008)	(0.006)	(0.006)	(0.295)	(0.188)	(0.001)	–	(1.245)	–	(9.614)	–	–
	0.092	0.897	0.017	0.072	0.114	0.189	5.190E-4	1.010	1.015	1.103	4.293	-41969	84052
	(0.008)	(0.009)	(0.007)	(0.006)	(0.353)	(0.201)	(0.001)	(0.071)	(2.088)	(0.142)	(10.230)	–	–
GPRH+Interest rate	0.093	0.895	0.016	0.072	-0.156	0.060	1.2E-3	1	1.010	1	3.871	-41957	84008
	(0.008)	(0.009)	(0.004)	(0.006)	(0.180)	(0.021)	(7.988E-4)	–	(1.692)	–	(2.485)	–	–
	0.092	0.895	0.016	0.072	-0.148	0.058	1.2E-3	1.010	50.010	1.010	3.811	-41957	84028
	(0.008)	(0.009)	(0.005)	(0.006)	(0.170)	(0.019)	(8.427E-4)	(0.642)	(76.827)	(0.284)	(1.730)	–	–
GPRHT+Recessions	0.092	0.897	0.016	0.072	0.095	0.242	8.594E-4	1	1.010	1	50.009	-41968	84029
	(0.008)	(0.009)	(0.005)	(0.006)	(0.097)	(0.144)	(8.008E-4)	–	(2.339)	–	(24.656)	–	–
	0.092	0.897	0.016	0.072	0.143	0.227	8.369E-5	1.010	5.673	1.109	3.821	-41968	84050
	(0.008)	(0.009)	(0.005)	(0.006)	(0.100)	(0.153)	(0.001)	(0.084)	(4.651)	(0.257)	(6.998)	–	–
GPRHT+Inflation	0.092	0.897	0.017	0.072	0.226	0.214	-1.2E-3	1	1.010	1	1.010	-41968	84030
	(0.008)	(0.009)	(0.004)	(0.006)	(0.153)	(0.155)	(7.943E-4)	–	(1.176)	–	(1.799)	–	–
	0.092	0.897	0.017	0.072	0.261	0.234	-0.002	1.010	1.010	3.930	1.032	-41966	84046
	(0.008)	(0.009)	(0.004)	(0.006)	(0.184)	(0.174)	(0.001)	(0.041)	(1.177)	(2.422)	(1.585)	–	–
GPRHT+Interest rate	0.092	0.896	0.016	0.072	-0.084	0.059	7.762E-4	1	1.010	1	50.010	-41959	84011
	(0.009)	(0.009)	(0.005)	(0.006)	(0.369)	(0.028)	(8.785E-4)	–	(5.154)	–	(76.476)	–	–
	0.092	0.895	0.016	0.072	-0.037	0.057	6.312E-6	1.010	49.521	1.103	3.807	-41959	84034
	(0.009)	(0.009)	(0.005)	(0.006)	(0.369)	(0.028)	(8.785E-4)	–	(5.154)	–	(76.476)	–	–
GPRHA+Recessions	0.092	0.896	0.016	0.072	0.073	0.228	3.720E-4	1	1.010	1	3.026	-41966	84026
	(0.014)	(0.009)	(0.016)	(0.009)	(0.677)	(0.696)	(2.252E-4)	–	(29.873)	–	(10.208)	–	–
	0.092	0.896	0.016	0.072	0.056	0.248	4.202E-4	1.010	5.626	1.147	3.974	-41963	84040
	(0.016)	(0.009)	(0.015)	(0.007)	(1.165)	(0.126)	(4.799E-4)	(0.153)	(14.873)	(1.651)	(19.390)	–	–
GPRHA+Inflation	0.092	0.897	0.016	0.072	0.126	0.148	2.437E-4	1	1.010	1	3.063	-41968	84030
	(0.009)	(0.009)	(0.005)	(0.006)	(0.227)	(0.234)	(2.235E-4)	–	(3.127)	–	(1.439)	–	–
	0.092	0.896	0.016	0.072	0.111	0.122	3.644E-4	1.010	1.010	10.344	50.009	-41965	84044
	(0.009)	(0.009)	(0.005)	(0.007)	(0.216)	(0.227)	(2.131E-4)	(0.141)	(4.770)	(10.072)	(54.746)	–	–
GPRHA+Interest rate	0.093	0.894	0.016	0.072	-0.150	0.064	4.472E-4	1	1.010	1	2.821	-41955	84004
	(0.008)	(0.009)	(0.004)	(0.006)	(0.137)	(0.021)	(1.803E-4)	–	(2.456)	–	(1.034)	–	–
	0.093	0.893	0.016	0.072	-0.159	0.063	4.919E-4	1.010	49.585	10.389	50.008	-41950	84015
	(0.009)	(0.009)	(0.004)	(0.006)	(0.185)	(0.022)	(1.592E-4)	(1.884)	(144.104)	(6.560)	(36.163)	–	–
GPRHA+GPRHT	0.092	0.897	0.016	0.072	0.232	-1.4E-3	3.858E-4	1	1.010	1	2.943	-41968	84029
	(0.008)	(0.009)	(0.005)	(0.006)	(0.171)	(0.001)	(1.964E-4)	–	(3.010)	–	(1.075)	–	–
	0.092	0.897	0.016	0.072	0.226	-0.002	4.697E-4	1.010	1.010	3.889	11.124	-41966	84046
	(0.009)	(0.009)	(0.011)	(0.008)	(0.308)	(0.004)	(2.065E-4)	(0.092)	(7.241)	(26.995)	(123.756)	–	–

The parameter estimates for each explanatory variable that enters the specification via the restricted and unrestricted weighting scheme are reported in this table. The number in parentheses are the associated standard errors. The log-likelihood value and the Bayesian Information Criterion are abbreviated by *LLH* and *BIC*, respectively.

Table 5: Parameter estimates of AR-MSGARCH-MIDAS

Variables	α_{01}	α_{02}	α_{11}	α_{12}	β_1	β_2	μ	ϕ_1	p_{11}	p_{22}	m	θ	ω_1	ω_2	*LLH*	*BIC*
Recessions	-	-	0.650	0.089	0.000	0.910	0.032	0.070	0.100	0.961	2.003	0.267	1	3.961	-41345	82825
	(-)	(-)	(2.281)	(0.049)	(0.143)	(0.051)	(0.007)	(0.008)	(0.128)	(0.006)	(6.364)	(0.262)	–	(4.840)	–	–
	-	-	0.646	0.089	0.000	0.911	0.032	0.070	0.101	0.961	1.999	0.280	17.407	50.007	-41343	82831
	(-)	(-)	(1.675)	(0.034)	(0.219)	(0.036)	(0.005)	(0.008)	(0.128)	(0.006)	(4.470)	(0.119)	(34.625)	(92.613)	–	–
Inflation	-	-	0.650	0.089	0.000	0.911	0.032	0.070	0.101	0.961	1.991	0.186	1	1.010	-41346	82826
	(-)	(-)	(1.100)	(0.023)	(0.053)	(0.025)	(0.005)	(0.006)	(0.079)	(0.003)	(3.125)	(0.171)	–	(0.871)	–	–
	-	-	0.089	0.648	0.911	0.000	0.032	0.070	0.961	0.101	1.996	0.155	1.939	1.092	-41346	82837
	(-)	(-)	(0.030)	(1.439)	(0.031)	(0.049)	(0.006)	(0.007)	(0.004)	(0.109)	(4.068)	(0.501)	(22.269)	(3.834)	–	–
Interest rates	-	-	0.089	0.654	0.911	0.000	0.032	0.070	0.961	0.100	1.994	0.023	1	49.786	-41346	82827
	(-)	(-)	(0.007)	(0.318)	(0.008)	(0.025)	(0.004)	(0.006)	(0.005)	(0.041)	(0.994)	(0.021)	–	(185.057)	–	–
	-	-	0.089	0.654	0.911	0.000	0.032	0.070	0.961	0.101	1.994	0.023	1.010	49.930	-41346	82838
	(-)	(-)	(0.062)	(2.729)	(0.065)	(0.170)	(0.009)	(0.010)	(0.003)	(0.131)	(8.748)	(0.130)	(0.398)	(177.032)	–	–
GPRH	-	-	0.644	0.089	0.000	0.911	0.032	0.070	0.101	0.960	1.904	1.400E-3	1	2.354	-41345	82826
	(-)	(-)	(158.470)	(3.717)	(15.903)	(3.905)	(0.610)	(0.333)	(6.326)	(0.076)	(468.202)	(0.097)	–	(82.298)	–	–
	-	-	0.089	0.641	0.911	0.000	0.032	0.070	0.960	0.102	1.844	1.900E-3	17.587	50.009	-41340	82826
	(-)	(-)	(0.113)	(4.705)	(0.119)	(0.509)	(0.019)	(0.010)	(0.007)	(0.270)	(13.566)	(5.900E-3)	(112.604)	(326.330)	–	–
GPRHT	-	-	0.649	0.089	0.000	0.911	0.032	0.070	0.101	0.960	2.130	-1.100E-3	1	1.010	-41347	82828
	(-)	(-)	(1.835)	(0.039)	(0.008)	(0.041)	(0.006)	(0.008)	(0.122)	(0.004)	(5.229)	(0.001)	–	(1.201)	–	–
	-	-	0.089	0.646	0.911	0.000	0.032	0.070	0.961	0.102	2.056	6.059E-8	1.407	2.042	-41347	82840
	(-)	(-)	(0.061)	(2.953)	(0.064)	(0.086)	(0.008)	(0.010)	(0.008)	(0.229)	(8.693)	(1.900E-3)	(24.094)	(13.872)	–	–
GPRHA	-	-	0.090	0.647	0.910	0.000	0.032	0.070	0.959	0.100	1.934	4.755E-4	1	2.004	-41344	82824
	(-)	(-)	(0.044)	(1.958)	(0.046)	(0.070)	(0.007)	(0.007)	(0.005)	(0.133)	(5.462)	(3.983E-4)	–	(1.773)	–	–
	-	-	0.646	0.089	0.000	0.911	0.032	0.070	0.102	0.961	2.055	2.592E-9	1.402	1.913	-41347	82840
	(-)	(-)	(1.299)	(0.027)	(0.053)	(0.028)	(0.005)	(0.007)	(0.102)	(0.004)	(3.638)	(6.546E-5)	(0.000)	(3.454)	–	–
AR-MSGARCH	0.100	0.023	0.090	0.647	0.910	0.000	0.032	0.070	0.959	0.100	1.934	4.755E-4	1	2.004	-41344	82824
	(-)	(-)	(0.044)	(1.958)	(0.046)	(0.070)	(0.007)	(0.007)	(0.005)	(0.133)	(5.462)	(3.983E-4)	–	(1.773)	–	–

The parameter estimates for each explanatory variable that enters the specification via the restricted and unrestricted weighting scheme are reported in this table. The number in parentheses are the associated standard errors. The log-likelihood value and the Bayesian Information Criterion are abbreviated by *LLH* and *BIC*, respectively.

Table 6: Parameter estimates of an AR-MSGARCH-MIDAS with combined variables

Variables	α_{11}	α_{12}	β_1	β_2	μ	ϕ_1	p_{11}	p_{22}	m	θ_1	θ_2	ω_1^{mv}	ω_2^{mv}	ω_1^{gpr}	ω_2^{gpr}	*LLH*	*BIC*
GPRH+Recessions	0.653	0.090	0.000	0.910	0.032	0.070	0.098	0.959	1.821	0.322	1.6E-3	1	1.248	1	2.451	-41343	82842
	(3.199)	(0.078)	(0.161)	(0.082)	(0.009)	(0.019)	(0.247)	(0.014)	(9.514)	(0.528)	(0.003)	(-)	(36.289)	(-)	(3.481)	–	–
GPRH+Inflation	0.647	0.089	0.000	0.911	0.032	0.070	0.101	0.960	1.890	0.130	1.1E-3	1	1.253	1	2.556	-41345	82845
	(1.639)	(0.034)	(0.041)	(0.036)	(0.008)	(0.007)	(0.119)	(0.005)	(4.974)	(3.226)	(0.008)	(-)	(47.497)	(-)	(2.041)	–	–
GPRH+Interest rate	0.089	0.652	0.910	0.000	0.032	0.070	0.960	0.100	1.839	0.023	1.4E-3	1	1.414	1	2.466	-41345	82845
	(0.014)	(0.590)	(0.014)	(0.148)	(0.004)	(0.006)	(0.003)	(0.053)	(1.746)	(0.075)	(9.709E-4)	(-)	(6.975)	(-)	(0.720)	–	–
GPRHT+Recessions	0.436	0.090	0.381	0.910	0.032	0.070	0.126	0.957	2.025	0.219	1.048E-4	1	2.436	1	9.544	-41338	82831
	(0.098)	(0.008)	(0.213)	(0.008)	(0.004)	(0.005)	(0.044)	(0.003)	(0.703)	(0.142)	(7.455E-4)	(-)	(2.486)	(-)	(22.216)	–	–
GPRHT+Inflation	0.089	0.653	0.911	0.000	0.032	0.070	0.960	0.100	2.074	0.198	-1.3E-3	1	1.010	1	1.010	-41345	82846
	(0.052)	(2.259)	(0.055)	(0.207)	(0.007)	(0.009)	(0.005)	(0.156)	(6.910)	(0.413)	(2.2E-3)	(-)	(1.169)	(-)	(0.987)	–	–
GPRHT+Interest rate	0.437	0.090	0.386	0.910	0.032	0.070	0.125	0.957	2.063	0.024	-7.309E-4	1	9.967	1	1.010	-41338	82832
	(0.095)	(0.008)	(0.196)	(0.008)	(0.004)	(0.005)	(0.044)	(0.002)	(0.736)	(0.025)	(5.795E-4)	(-)	(30.869)	(-)	(0.659)	–	–
GPRHA+Recessions	0.090	0.655	0.910	0.000	0.032	0.070	0.958	0.098	1.864	0.315	5.099E-4	1	1.386	1	1.860	-41342	82840
	(0.192)	(8.386)	(0.202)	(0.563)	(0.028)	(0.036)	(0.025)	(0.552)	(23.614)	(1.012)	(6.818E-4)	(-)	(22.430)	(-)	(6.531)	–	–
GPRHA+Inflation	0.649	0.090	0.000	0.910	0.032	0.070	0.100	0.959	1.914	0.107	4.142E-4	1	1.309	1	2.028	-41344	82843
	(2.663)	(0.062)	(0.093)	(0.066)	(0.009)	(0.010)	(0.167)	(0.006)	(7.802)	(0.238)	(5.657E-4)	(-)	(6.348)	(-)	(2.003)	–	–
GPRHA+Interest rate	0.658	0.090	0.000	0.910	0.032	0.070	0.099	0.959	1.830	0.031	5.368E-4	1	1.443	1	1.892	-41343	82842
	(3.834)	(0.084)	(0.071)	(0.089)	(0.010)	(0.013)	(0.318)	(0.013)	(12.094)	(0.233)	(2.885E-4)	(-)	(34.257)	(-)	(4.095)	–	–
GPRHA+GPRHT	0.090	0.652	0.910	0.000	0.032	0.070	0.959	0.099	2.029	-0.002	5.164E-4	1	1.031	1	1.691	-41344	82843
	(0.070)	(3.029)	(0.074)	(0.042)	(0.009)	(0.011)	(0.008)	(0.211)	(8.655)	(0.003)	(4.755E-4)	(-)	(2.399)	(-)	(0.972)	–	–

The parameter estimates for each explanatory variable that enters the specification via the restricted and unrestricted weighting scheme are reported in this table. The number in parentheses are the associated standard errors. The log-likelihood value and the Bayesian Information Criterion are abbreviated by *LLH* and *BIC*, respectively.

Table 7: MSE and QLIKE losses for monthly forecast horizons using DJIA prices from January 04, 1899 to December 29, 2000 as in-sample period and DJIA prices January 02, 2001 to December 31, 2020 as out-of-sample period.

Variables	MSE				QLIKE			
	Forecast horizon							
	1M	*2M*	*3M*	*4M*	*1M*	*2M*	*3M*	*4M*
	AR-GARCH-MIDAS							
Recessions	1.076	0.844	0.844	0.827	2.803	1.308	1.057	0.970
	[0.465]	[0.699]	[0.560]	[0.453]	[0.000]	[0.001]	[0.016]	[0.098]
	(0.184)	(0.174)	(0.380)	(0.508)	(0.000)	(0.001)	(0.022)	(0.153)
Inflation	1.201	0.944	0.946	0.929	3.317	1.513	1.213	1.106
	[0.460]	[0.719]	[0.603]	[0.502]	[0.000]	[0.001]	[0.020]	[0.084]
	(0.183)	(0.165)	(0.365)	(0.364)	(0.000)	(0.001)	(0.025)	(0.125)
Interest rates	1.201	0.944	0.946	0.927	3.302	1.517	1.213	1.102
	[0.461]	[0.718]	[0.597]	[0.487]	[0.000]	[0.001]	[0.015]	[0.065]
	(0.183)	(0.153)	(0.337)	(0.346)	(0.000)	(0.001)	(0.018)	(0.091)
GPRH	1.202	0.946	0.948	0.930	3.356	1.535	1.224	1.111
	[0.460]	[0.725]	[0.611]	[0.506]	[0.000]	[0.002]	[0.020]	[0.070]
	(0.182)	(0.143)	(0.322)	(0.321)	(0.000)	(0.002)	(0.023)	(0.103)
GPRHT	1.201	0.944	0.946	0.928	3.309	1.514	1.211	1.101
	[0.461]	[0.720]	[0.602]	[0.494]	[0.000]	[0.001]	[0.023]	[0.093]
	(0.184)	(0.170)	(0.383)	(0.495)	(0.000)	(0.001)	(0.030)	(0.138)
GPRHA	1.204	0.949	0.954	0.940	3.678	1.636	1.283	1.161
	[0.455]	[0.744]	[0.654]	[0.568]	[0.000]	[0.001]	[0.009]	[0.029]
	(0.178)	(0.112)	(0.246)	(0.140)	(0.000)	(0.001)	(0.008)	(0.037)
	AR-GARCH-MIDAS with combined variables							
GPRH+Recessions	1.199	0.941	0.942	0.924	3.176	1.479	1.191	1.090
	[0.464]	[0.703]	[0.570]	[0.464]	[0.000]	[0.001]	[0.015]	[0.062]
	(0.182)	(0.147)	(0.324)	(0.281)	(0.000)	(0.001)	(0.018)	(0.098)
GPRH+Inflation	1.202	0.946	0.947	0.931	3.427	1.542	1.225	1.117
	[0.458]	[0.725]	[0.605]	[0.511]	[0.000]	[0.001]	[0.013]	[0.046]
	(0.180)	(0.133)	(0.291)	(0.186)	(0.000)	(0.001)	(0.015)	(0.065)
GPRH+Interest rates	1.202	0.946	0.949	0.933	3.387	1.552	1.237	1.123
	[0.459]	[0.728]	[0.620]	[0.521]	[0.000]	[0.002]	[0.015]	[0.052]
	(0.181)	(0.131)	(0.289)	(0.221)	(0.000)	(0.001)	(0.016)	(0.071)
GPRHT+Recessions	1.201	0.945	0.948	0.933	3.496	1.576	1.246	1.133
	[0.459]	[0.721]	[0.607]	[0.515]	[0.000]	[0.001]	[0.008]	[0.024]
	(0.177)	(0.112)	(0.237)	(0.135)	(0.000)	(0.001)	(0.007)	(0.032)
GPRHT+Inflation	1.205	0.951	0.956	0.944	3.880	1.685	1.308	1.186
	[0.453]	[0.751]	[0.666]	[0.592]	[0.000]	[0.001]	[0.007]	[0.024]
	(0.176)	(0.099)	(0.208)	(0.116)	(0.000)	(0.001)	(0.006)	(0.032)
GPRHT+Interest rates	1.205	0.951	0.957	0.943	3.854	1.697	1.319	1.188
	[0.453]	[0.754]	[0.673]	[0.589]	[0.000]	[0.001]	[0.006]	[0.021]
	(0.176)	(0.099)	(0.210)	(0.119)	(0.000)	(0.001)	(0.005)	(0.023)
GPRHA+Recessions	1.199	0.940	0.941	0.922	3.129	1.458	1.178	1.082
	[0.465]	[0.699]	[0.561]	[0.457]	[0.000]	[0.001]	[0.016]	[0.084]
	(0.184)	(0.178)	(0.397)	(0.397)	(0.000)	(0.001)	(0.022)	(0.135)
GPRHA+Inflation	1.201	0.943	0.943	0.925	3.273	1.491	1.195	1.092
	[0.461]	[0.712]	[0.580]	[0.476]	[0.000]	[0.001]	[0.015]	[0.074]
	(0.183)	(0.174)	(0.382)	(0.399)	(0.000)	(0.001)	(0.020)	(0.111)
GPRHA+Interest rates	1.201	0.946	0.949	0.932	3.354	1.543	1.235	1.123
	[0.460]	[0.726]	[0.620]	[0.521]	[0.000]	[0.001]	[0.014]	[0.054]
	(0.183)	(0.152)	(0.340)	(0.317)	(0.000)	(0.001)	(0.016)	(0.074)
GPRHA+GPRHT	1.204	0.951	0.956	0.945	3.786	1.679	1.297	1.184
	[0.453]	[0.755]	[0.670]	[0.603]	[0.000]	[0.001]	[0.006]	[0.022]
	(0.178)	(0.109)	(0.313)	(0.118)	(0.000)	(0.001)	(0.005)	(0.028)

Note: MSE and QLIKE for all specifications are computed relative to the MSE and QLIKE of an out-of-sample AR-MSGARCH forecasts. The entries in brackets and parentheses are the p-values of the Giacomini and White and EPA tests, respectively.

Table 8: Relative MSE and QLIKE losses for monthly forecast horizons using DJIA prices from January 04, 1899 to December 29, 2000 as in-sample period and DJIA prices January 02, 2001 to December 31, 2020 as out-of-sample period.

Variables	MSE				QLIKE			
	Forecast horizon							
	1M	*2M*	*3M*	*4M*	*1M*	*2M*	*3M*	*4M*
Recessions	1.047	1.522	1.634	1.781	0.321	0.687	0.857	0.940
Inflation	1.002	1.274	1.349	1.515	0.304	0.660	0.833	0.921
Interest rates	0.792	1.035	1.110	1.235	0.305	0.665	0.849	0.941
GPRH	0.715	0.975	1.088	1.134	0.300	0.655	0.833	0.917
GPRHT	1.025	1.304	1.359	1.502	0.307	0.667	0.825	0.916
GPRHA	0.926	1.278	1.423	1.557	0.273	0.612	0.798	0.881
Without	0.986	1.046	1.151	1.417	1.006	0.995	0.993	1.001

Note: The entries in Table are the MSE and QLIKE ratios of the AR-MSGARCH-MIDAS specification with/or without single variable relative to the AR-GARCH-MIDAS specification with/or without single variable.

Table 9: MSE and QLIKE losses for monthly forecast horizons and EPA test results using DJIA prices from January 04, 1899 to December 29, 2000 as in-sample period and DJIA prices January 02, 2001 to December 31, 2020 as out-of-sample period.

Variables	MSE				QLIKE			
	Forecast horizon							
	1M	*2M*	*3M*	*4M*	*1M*	*2M*	*3M*	*4M*
	AR-MSGARCH-MIDAS							
Recessions	1.273	1.369	1.335	1.158	0.996	1.006	1.018	1.015
	[0.101]	[0.145]	[0.180]	[0.462]	[0.262]	[0.713]	[0.606]	[0.708]
	(0.250)	(0.116)	(0.341)	(0.396)	(0.228)	(0.609)	(0.054)	(0.815)
Inflation	1.221	1.151	1.108	0.993	1.003	1.004	1.017	1.017
	[0.075]	[0.172]	[0.373]	[0.949]	[0.439]	[0.800]	[0.626]	[0.690]
	(0.187)	(0.334)	(0.614)	(0.773)	(0.312)	(0.573)	(0.321)	(0.697)
Interest rates	0.964	0.934	0.912	0.808	1.002	1.013	1.037	1.036
	[0.713]	[0.420]	[0.432]	[0.056]	[0.707]	[0.666]	[0.487]	[0.542]
	(0.166)	(0.674)	(0.622)	(0.073)	(0.823)	(0.647)	(0.164)	(0.669)
GPRH	0.871	0.881	0.895	0.744	1.002	1.010	1.026	1.018
	[0.369]	[0.574]	[0.667]	[0.298]	[0.731]	[0.427]	[0.462]	[0.644]
	(0.555)	(0.446)	(0.492)	(0.283)	(0.876)	(0.537)	(0.695)	(0.878)
GPRHT	1.249	1.178	1.116	0.984	1.009	1.015	1.006	1.007
	[0.048]	[0.094]	[0.373]	[0.872]	[0.362]	[0.470]	[0.835]	[0.841]
	(0.119)	(0.197)	(0.621)	(0.662)	(0.097)	(0.268)	(0.067)	(0.555)
GPRHA	1.131	1.160	1.179	1.032	0.997	1.006	1.031	1.021
	[0.270]	[0.159]	[0.259]	[0.813]	[0.382]	[0.723]	[0.460]	[0.641]
	(0.419)	(0.307)	(0.427)	(0.848)	(0.507)	(0.165)	(0.224)	(0.536)
	AR-MSGARCH-MIDAS with combined variables							
GPRH+Recessions	1.481	1.451	1.435	1.254	1.008	1.001	1.009	1.017
	[0.091]	[0.132]	[0.153]	[0.321]	[0.156]	[0.896]	[0.716]	[0.643]
	(0.153)	(0.255)	(0.309)	(0.551)	(0.362)	(0.292)	(0.045)	(0.439)
GPRH+Inflation	1.319	1.301	1.265	1.117	1.010	1.014	1.016	1.012
	[0.156]	[0.140]	[0.220]	[0.529]	[0.127]	[0.393]	[0.600]	[0.722]
	(0.226)	(0.239)	(0.370)	(0.784)	(0.137)	(0.078)	(0.150)	(0.819)
GPRH+Interest rates	1.088	1.072	1.075	0.941	1.001	1.013	1.041	1.038
	[0.224]	[0.266]	[0.540]	[0.556]	[0.906]	[0.608]	[0.422]	[0.491]
	(0.452)	(0.392)	(0.551)	(0.224)	(0.804)	(0.354)	(0.516)	(0.575)
GPRHT+Recessions	1.323	1.375	1.291	1.125	0.998	1.001	0.981	0.999
	[0.057]	[0.162]	[0.231]	[0.531]	[0.635]	[0.932]	[0.183]	[0.968]
	(0.164)	(0.260)	(0.438)	(0.436)	(0.411)	(0.073)	(0.027)	(0.761)
GPRHT+Inflation	1.034	1.053	1.073	0.931	1.000	1.022	1.051	1.042
	[0.205]	[0.301]	[0.552]	[0.502]	[0.971]	[0.405]	[0.282]	[0.378]
	(0.432)	(0.450)	(0.602)	(0.136)	(0.772)	(0.277)	(0.138)	(0.383)
GPRHT+Interest rates	0.869	0.870	0.881	0.753	1.034	1.074	1.117	1.114
	[0.488]	[0.418]	[0.539]	[0.168]	[0.024]	[0.186]	[0.140]	[0.209]
	(0.380)	(0.727)	(0.446)	(0.166)	(0.055)	(0.343)	(0.240)	(0.406)
GPRHA+Recessions	0.928	1.017	1.034	0.864	0.999	1.000	1.018	1.002
	[0.779]	[0.958]	[0.907]	[0.631]	[0.686]	[0.978]	[0.627]	[0.952]
	(0.961)	(0.309)	(0.484)	(0.248)	(0.487)	(0.544)	(0.498)	(0.621)
GPRHA+Inflation	1.129	1.140	1.157	1.015	0.997	1.004	1.029	1.024
	[0.262]	[0.183]	[0.294]	[0.909]	[0.425]	[0.799]	[0.488]	[0.599]
	(0.393)	(0.353)	(0.434)	(0.848)	(0.415)	(0.464)	(0.348)	(0.643)
GPRHA+Interest rates	0.947	0.904	0.886	0.809	1.005	1.022	1.044	1.047
	[0.536]	[0.175]	[0.297]	[0.052]	[0.476]	[0.524]	[0.459]	[0.478]
	(0.298)	(0.330)	(0.525)	(0.090)	(0.727)	(0.544)	(0.523)	(0.612)
GPRHA+GPRHT	1.055	1.095	1.078	0.951	1.000	1.018	1.023	1.036
	[0.280]	[0.401]	[0.568]	[0.688]	[0.928]	[0.525]	[0.567]	[0.504]
	(0.343)	(0.363)	(0.635)	(0.123)	(0.561)	(0.735)	(0.282)	(0.633)

Note: MSE and QLIKE for all specifications are computed relative to the MSE and QLIKE of an out-of-sample AR-MSGARCH forecasts. The entries in brackets and in parentheses are the p-values of the Giacomini-White and of the EPA tests, respectively.

Table 10: Model confidence sets (MCS) results.

Variables	MSE				QLIKE			
	Forecast horizon							
	1M	*2M*	*3M*	*4M*	*1M*	*2M*	*3M*	*4M*
	AR-GARCH-MIDAS							
Recessions	0.343	0.483	0.118	0.088*	0.189	0.713	0.560	0.083*
Inflation	0.306	0.358	0.568	0.494	0.712	0.996	0.560	0.999
Interest rates	0.306	0.375	0.377	0.596	0.296	0.808	0.525	0.608
GPRH	0.306	0.343	0.242	0.206	0.729	1.000	0.560	0.765
GPRHT	0.307	0.375	1.000	1.000	0.688	0.996	1.000	1.000
GPRHA	0.302	0.269	0.168	0.135	0.729	0.889	0.431	0.452
Without	0.618	0.269	0.132	0.135	0.029*	0.058*	0.101	0.305
	AR-GARCH-MIDAS with combined explanatory variables							
GPRH + Recessions	0.335	0.439	0.108	0.088*	0.620	0.933	0.560	0.979
GPRH + Inflation	0.306	0.275	0.223	0.152	0.729	0.996	0.559	0.534
GPRH + Interest rates	0.306	0.269	0.173	0.149	0.712	0.956	0.508	0.561
GPRHT + Recessions	0.306	0.269	0.915	0.270	0.729	0.947	0.466	0.487
GPRHT + Inflation	0.283	0.269	0.168	0.112	0.729	0.843	0.392	0.426
GPRHT + Interest rates	0.269	0.269	0.132	0.112	0.652	0.697	0.294	0.357
GPRHA + Recessions	0.456	0.519	0.110	0.088*	0.090*	0.641	0.560	0.075*
GPRHA + Inflation	0.314	0.375	0.105	0.088*	0.457	0.956	0.560	0.999
GPRHA + Interest rates	0.306	0.343	0.204	0.149	0.353	0.769	0.482	0.561
GPRHA + GPRHT	0.293	0.269	0.132	0.119	0.502	0.764	0.417	0.383
	AR-MSGARCH-MIDAS							
Recessions	0.269	0.939	0.119	0.088*	0.013*	0.033*	0.062*	0.222
Inflations	0.306	0.187	0.132	0.091*	0.003*	0.039*	0.065*	0.184
Interest rates	0.660	0.269	0.132	0.091*	0.003*	0.028*	0.047*	0.128
GPRH	0.931	0.802	0.132	0.091*	0.003*	0.025*	0.055*	0.199
GPRHT	0.306	0.156	0.132	0.091*	0.003*	0.018*	0.082*	0.237
GPRHA	0.618	0.167	0.132	0.091*	0.010*	0.030*	0.042*	0.171
Without	0.681	0.269	0.132	0.091*	0.004*	0.309	0.148	0.281
	AR-MSGARCH-MIDAS with combined explanatory variables							
GPRH + Recessions	0.254	0.939	0.126	0.089*	1.000	0.078*	0.068*	0.151
GPRH + Inflation	0.301	1.000	0.132	0.091*	0.003*	0.020*	0.058*	0.209
GPRH + Interest rates	0.631	0.254	0.132	0.091*	0.004*	0.022*	0.038*	0.092*
GPRHT + Recessions	0.269	0.939	0.121	0.088*	0.008*	0.129	0.192	0.332
GPRHT + Inflation	0.641	0.231	0.132	0.091*	0.004*	0.016*	0.035*	0.065*
GPRHT + Interest rates	1.000	0.887	0.132	0.091*	0.729	0.015*	0.560	0.561
GPRHA + Recessions	0.875	0.264	0.132	0.091*	0.005*	0.530	0.074*	0.258
GPRHA + Inflation	0.612	0.229	0.132	0.091*	0.006*	0.047*	0.045*	0.119
GPRHA + Interest rates	0.813	0.583	0.132	0.091*	0.003*	0.019*	0.039*	0.108
GPRHA + GPRHT	0.381	0.939	0.128	0.088*	0.004*	0.019*	0.051*	0.116

Note: The entries are MCS p-values. The forecasts excluded from $\hat{M}^*_{90\%}$ are identified by one asterisk.

Table 11: Encompassing test results for non-nested models at different forecasting horizons

	Forecast horizons															
	1M	2M	3M	4M	1M	2M	3M	4M	1M	2M	3M	4M	1M	2M	3M	4M
Model 1 vs.	Model 2															
AR-MSGARCH-MIDAS	AR-GARCH-MIDAS															
GPRH	Recessions				Inflation				Interest rates				Without			
ENC-T	1.684	2.448	1.949	1.978	1.683	2.453	1.948	1.958	1.684	2.457	1.956	1.987	-0.277	0.952	1.716	1.643
	(0.047)	(0.008)	(0.026)	(0.025)	(0.047)	(0.008)	(0.026)	(0.026)	(0.047)	(0.007)	(0.026)	(0.024)	(0.609)	(0.171)	(0.044)	(0.051)
$\hat{\varsigma}$	0.242	0.477	0.633	0.724	0.241	0.472	0.622	0.707	0.241	0.472	0.622	0.706	-0.130	0.242	0.584	0.647
	[1.318]	[3.943]	[6.651]	[11.510]	[1.316]	[3.901]	[6.473]	[10.731]	[1.315]	[3.909]	[6.521]	[11.138]	[−0.291]	[0.635]	[1.669]	[1.773]
GPRHT	Recessions				Inflation				Interest rates				Without			
ENC-T	1.3021	1.303	1.270	1.290	1.302	1.302	1.268	1.286	1.302	1.303	1.271	1.292	1.753	1.498	1.328	1.315
	(0.097)	(0.097)	(0.103)	(0.099)	(0.097)	(0.097)	(0.103)	(0.100)	(0.097)	(0.097)	(0.103)	(0.099)	(0.040)	(0.068)	(0.093)	(0.095)
$\hat{\varsigma}$	0.516	0.720	0.755	0.849	0.515	0.715	0.749	0.840	0.515	0.715	0.748	0.839	2.318	1.563	1.424	1.500
	[3.006]	[5.728]	[9.019]	[8.828]	[2.995]	[5.615]	[8.616]	[8.412]	[2.996]	[5.623]	[8.664]	[8.465]	[3.245]	[2.1387]	[2.9871]	[4.6076]
GPRHA	Recessions				Inflation				Interest rates				Without			
ENC-T	1.123	1.368	1.415	1.386	1.123	1.369	1.416	1.384	1.123	1.370	1.419	1.389	1.206	1.391	1.453	1.431
	(0.131)	(0.086)	(0.079)	(0.084)	(0.131)	(0.086)	(0.079)	(0.084)	(0.131)	(0.086)	(0.079)	(0.083)	(0.115)	(0.083)	(0.074)	(0.077)
$\hat{\varsigma}$	0.458	0.685	0.780	0.884	0.457	0.681	0.773	0.874	0.457	0.681	0.773	0.873	1.347	1.581	1.718	1.676
	[2.184]	[5.053]	[12.394]	[13.200]	[2.178]	[4.983]	[11.789]	[12.251]	[2.178]	[4.987]	[11.820]	[12.323]	[1.398]	[2.250]	[5.007]	[7.748]
Without	Recessions				Inflation				Interest rates				Without			
ENC-T	0.944	1.304	1.609	2.009	0.942	1.302	1.606	2.003	0.943	1.305	1.614	2.019	2.644	1.489	1.835	2.647
	(0.173)	(0.097)	(0.055)	(0.023)	(0.174)	(0.097)	(0.055)	(0.023)	(0.173)	(0.097)	(0.054)	(0.022)	(0.004)	(0.069)	(0.034)	(0.004)
$\hat{\varsigma}$	0.347	0.596	0.652	0.798	0.346	0.592	0.646	0.792	0.346	0.592	0.646	0.789	0.338	0.749	0.864	1.081
	[1.311]	[3.362]	[5.011]	[8.711]	[1.306]	[3.316]	[4.910]	[8.455]	[1.307]	[3.323]	[4.950]	[8.516]	[1.363]	[1.512]	[2.270]	[4.731]

Note: we test the null hypothesis that forecasts from model 1 encompass those of model 2 and ENC-T denotes the associated test statistics. The values in parentheses are the p-values of the tests. $\hat{\varsigma}$s are the estimates of the slope parameter ς in the forecast encompassing regression 17. The values in square brackets are the t-statistics computed using White heteroscedasticity robust standard errors.

Table 12: Encompassing test results for non-nested models at different forecasting horizons

	Forecast horizons															
	1M	2M	3M	4M	1M	2M	3M	4M	1M	2M	3M	4M	1M	2M	3M	4M
Model 1 vs.	Model 2															
AR-MSGARCH-MIDAS	AR-GARCH-MIDAS															
Recessions	GPRH				GPRHT				GPRHA				Without			
ENC-T	1.606	1.646	1.644	1.614	1.606	1.647	1.645	1.617	1.606	1.648	1.646	1.611	1.686	1.655	1.679	1.632
	(0.055)	(0.051)	(0.051)	(0.054)	(0.055)	(0.050)	(0.051)	(0.054)	(0.055)	(0.050)	(0.051)	(0.054)	(0.047)	(0.050)	(0.047)	(0.052)
$\hat{\varsigma}$	0.519	0.728	0.779	0.839	0.519	0.728	0.780	0.841	0.518	0.725	0.774	0.831	1.690	1.888	1.681	1.556
	[3.807]	[8.585]	[14.221]	[12.485]	[3.808]	[8.597]	[14.252]	[12.484]	[3.802]	[8.507]	[13.856]	[12.134]	[3.193]	[6.370]	[9.983]	[9.456]
Inflation	GPRH				GPRHT				GPRHA				Without			
ENC-T	1.220	1.292	1.308	1.338	1.220	1.293	1.309	1.341	1.220	1.294	1.310	1.335	1.554	1.488	1.351	1.362
	(0.112)	(0.099)	(0.096)	(0.091)	(0.112)	(0.099)	(0.096)	(0.091)	(0.112)	(0.099)	(0.096)	(0.092)	(0.061)	(0.069)	(0.089)	(0.087)
$\hat{\varsigma}$	0.501	0.689	0.730	0.835	0.501	0.690	0.732	0.838	0.500	0.684	0.723	0.823	1.606	1.213	1.325	1.494
	[2.690]	[4.802]	[7.718]	[8.486]	[2.690]	[4.814]	[7.748]	[8.532]	[2.684]	[4.744]	[7.485]	[8.097]	[2.146]	[1.867]	[2.679]	[4.551]
Interest rates	GPRH				GPRHT				GPRHA				Without			
ENC-T	1.074	1.265	1.356	1.420	1.074	1.265	1.355	1.424	1.075	1.268	1.358	1.412	-0.032	1.407	1.716	1.667
	(0.142)	(0.104)	(0.088)	(0.079)	(0.142)	(0.104)	(0.088)	(0.078)	(0.142)	(0.103)	(0.088)	(0.080)	(0.513)	(0.080)	(0.044)	(0.049)
$\hat{\varsigma}$	0.294	0.539	0.624	0.762	0.294	0.541	0.627	0.767	0.293	0.534	0.615	0.745	-0.020	0.328	0.870	1.415
	[1.272]	[2.844]	[5.299]	[6.222]	[1.273]	[2.852]	[5.322]	[6.260]	[1.271]	[2.814]	[5.144]	[5.927]	[−0.022]	[2.546]	[1.491]	[2.184]

Note: we test the null hypothesis that forecasts from model 1 encompass those of model 2 and ENC-T denotes the associated test statistics. The values in parentheses are the p-values of the tests. $\hat{\varsigma}$s are the estimates of the slope parameter ς in the forecast encompassing regression 17. The values in square brackets are the t-statistics computed using White heteroscedasticity robust standard errors.

Table 13: Encompassing test results for non-nested models at different forecasting horizons

	Forecast horizons															
	1M	2M	3M	4M	1M	2M	3M	4M	1M	2M	3M	4M	1M	2M	3M	4M
Model 1 vs.	Model 2															
AR-MSGARCH-MIDAS	AR-GARCH-MIDAS															
GPRH	GPRH				GPRHT				GPRHA				Without			
ENC-T	1.679	2.445	1.938	1.950	1.682	2.458	1.951	1.967	1.678	2.437	1.929	1.923	-	-	-	-
	(0.047)	(0.008)	(0.027)	(0.026)	(0.047)	(0.007)	(0.026)	(0.025)	(0.047)	(0.008)	(0.028)	(0.028)	(–)	(–)	(–)	(–)
$\hat{\varsigma}$	0.241	0.470	0.621	0.706	0.241	0.472	0.623	0.709	0.240	0.466	0.610	0.686	-	-	-	-
	[1.310]	[3.848]	[6.370]	[10.585]	[1.314]	[3.883]	[6.466]	[10.858]	[1.307]	[3.796]	[6.124]	[9.520]	[–]	[–]	[–]	[–]
GPRHT	GPRH				GPRHT				GPRHA				Without			
ENC-T	1.301	1.300	1.266	1.283	1.302	1.301	1.267	1.288	1.301	1.298	1.263	1.275	-	-	-	-
	(0.097)	(0.098)	(**0.104**)	(**0.100**)	(0.097)	(0.097)	(**0.103**)	(**0.100**)	(0.097)	(0.098)	(**0.104**)	(**0.102**)	(–)	(–)	(–)	(–)
$\hat{\varsigma}$	0.515	0.714	0.748	0.839	0.515	0.716	0.750	0.842	0.514	0.710	0.741	0.829	-	-	-	-
	[2.992]	[5.594]	[8.596]	[8.416]	[2.993]	[5.610]	[8.633]	[8.456]	[2.982]	[5.509]	[8.301]	[8.052]	[–]	[–]	[–]	[–]
GPRHA	GPRH				GPRHT				GPRHA				Without			
ENC-T	1.123	1.368	1.414	1.382	1.123	1.369	1.416	1.385	1.123	1.369	1.415	-	-	-	-	-
	(**0.131**)	(0.086)	(0.079)	(0.084)	(**0.131**)	(0.086)	(0.079)	(0.084)	(0.131)	(0.086)	(0.079)	(0.085)	(–)	(–)	(–)	(–)
$\hat{\varsigma}$	0.456	0.680	0.772	0.873	0.457	0.681	0.774	0.876	0.455	0.676	0.765	0.861	-	-	-	-
	[2.176]	[4.966]	[11.725]	[12.228]	[2.177]	[4.976]	[11.794]	[12.347]	[2.172]	[4.913]	[11.211]	[11.363]	[–]	[–]	[–]	[–]
Without	GPRH				GPRHT				GPRHA				Without			
ENC-T	0.942	1.300	1.602	1.997	0.942	1.302	1.606	2.008	0.942	1.303	1.607	1.993	-	-	-	-
	(**0.174**)	(0.097)	(0.055)	(0.024)	(**0.174**)	(0.097)	(0.055)	(0.023)	(**0.174**)	(0.097)	(0.055)	(0.024)	(–)	(–)	(–)	(–)
$\hat{\varsigma}$	0.346	0.591	0.645	0.791	0.346	0.592	0.647	0.793	0.344	0.586	0.639	0.781	-	-	-	-
	[1.304]	[3.302]	[4.901]	[8.460]	[1.305]	[3.311]	[4.910]	[8.477]	[1.302]	[3.273]	[4.854]	[8.222]	[–]	[–]	[–]	[–]

Note: we test the null hypothesis that forecasts from model 1 encompass those of model 2 and ENC-T denotes the associated test statistics. The values in parentheses are the p-values of the tests. $\hat{\varsigma}$s are the estimates of the slope parameter ς in the forecast encompassing regression 17. The values in square brackets are the t-statistics computed using White heteroscedasticity robust standard errors.

Table 14: Model confidence sets (MCS) results.

Model 1	Model 2	MSE				QLIKE			
		Forecast horizon							
		1M	*2M*	*3M*	*4M*	*1M*	*2M*	*3M*	*4M*
Model with a single explanatory variable									
AR-GARCH-MIDAS									
Recessions		0.165	0.281	0.378	0.148	0.000*	0.633	0.613	0.529
Inflation		0.794	0.281	0.375	0.137	0.000*	0.788	0.159	0.388
Interest rates		0.794	0.275	0.375	0.144	0.000*	0.648	0.613	0.327
GPRH		0.727	0.268	0.359	0.135	0.015*	0.850	1.000	0.354
GPRHT		1.000	0.281	0.376	0.141	0.000*	0.788	0.189	0.447
GPRHA		0.710	0.216	0.359	0.131	0.000*	0.776	0.613	0.278
Without		0.359	0.127	0.318	0.130	0.000*	0.429	0.566	0.624
AR-MSGARCH-MIDAS									
Recessions		0.185	0.436	0.856	0.172	0.000*	0.406	0.492	0.624
Inflation		0.213	0.122	0.234	0.212	0.807	0.419	0.514	0.624
Interest rates		0.408	0.281	0.305	0.256	0.807	0.397	0.432	0.580
GPRH		0.600	0.281	0.345	0.256	0.807	0.383	0.529	0.624
GPRHT		0.197	0.436	0.210	0.212	1.000	0.374	0.550	0.624
GPRHA		0.248	0.119	0.875	0.212	0.000*	0.388	0.383	0.624
Without		0.437	0.145	0.327	0.180	0.000*	0.471	0.566	0.624
Combined forecasts from models with a single explanatory variable									
AR-MSGARCH-MIDAS	AR-GARCH-MIDAS								
GPRH	Recessions	0.345	0.426	0.418	0.122	0.002*	0.866	0.486	0.624
GPRH	Inflation	0.313	0.281	0.578	0.130	0.001*	0.866	0.434	0.624
GPRH	Interest rates	0.313	0.346	0.578	0.131	0.000*	0.866	0.438	0.624
GPRH	AR-GARCH	0.313	0.127	0.357	1.000	0.000*	0.443	0.533	0.624
GPRHT	Recessions	0.336	1.000	0.247	0.256	0.057	0.149	0.529	0.624
GPRHT	Inflation	0.328	0.436	0.280	0.256	0.044*	0.074*	0.529	0.624
GPRHT	Interest rates	0.325	0.436	0.298	0.256	0.050*	0.117	0.529	0.624
GPRHT	AR-GARCH	0.619	0.436	0.169	0.212	0.000*	0.866	0.613	0.624
GPRHA	Recessions	0.460	0.160	0.875	0.212	0.033*	0.251	0.425	0.624
GPRHA	Inflation	0.460	0.197	0.164	0.212	0.027*	0.209	0.392	0.624
GPRHA	Interest rates	0.460	0.239	0.171	0.212	0.025*	0.225	0.401	0.624
GPRHA	AR-GARCH	0.227	0.436	0.875	0.194	0.451	0.564	0.269	0.414
AR-MSGARCH	Recessions	0.408	0.281	0.412	0.212	0.018*	0.354	0.568	0.772
AR-MSGARCH	Inflation	0.408	0.281	0.558	0.256	0.022*	0.292	0.566	0.624
AR-MSGARCH	Interest rates	0.408	0.281	0.578	0.256	0.017*	0.285	0.568	0.858
AR-MSGARCH	AR-GARCH	0.408	0.281	0.352	0.160	0.000*	0.503	0.566	0.624
Recessions	GPRH	0.464	0.436	0.875	0.192	0.244	0.271	0.518	0.624
Recessions	GPRHT	0.568	0.436	0.856	0.190	0.235	0.327	0.518	0.624
Recessions	GPRHA	0.464	0.436	0.875	0.193	0.336	0.241	0.462	0.624
Recessions	AR-GARCH	0.647	0.436	0.825	0.150	0.451	0.550	0.529	0.624
Inflation	GPRH	0.348	0.128	0.342	0.256	0.199	0.339	0.486	0.624
Inflation	GPRHT	0.355	0.128	0.338	0.256	0.103	0.365	0.529	0.624
Inflation	GPRHA	0.346	0.136	0.349	0.256	0.192	0.379	0.440	0.624
Inflation	AR-GARCH	0.176	0.436	0.186	0.212	0.807	0.454	0.566	1.000
Interest rates	GPRH	0.296	0.281	0.578	0.116	0.004*	0.046	0.373	0.593
Interest rates	GPRHT	0.303	0.281	0.578	0.113	0.000*	0.866	0.362	0.612
Interest rates	GPRHA	0.271	0.281	0.587	0.121	0.001*	0.093	0.308	0.563
Interest rates	AR-GARCH	0.345	0.151	0.336	0.212	0.000*	0.440	0.486	0.484
GPRH	GPRH	0.310	0.281	0.549	0.130	0.014*	0.850	0.428	0.624
GPRH	GPRHT	0.313	0.304	0.567	0.130	0.000*	0.852	0.473	0.624
GPRH	GPRHA	0.305	0.281	0.571	0.130	0.008*	0.850	0.212	0.602
GPRHT	GPRH	0.315	0.436	0.267	0.256	0.107	0.052*	0.529	0.624
GPRHT	GPRHT	0.324	0.436	0.261	0.256	0.052*	0.061*	0.529	0.624
GPRHT	GPRHA	0.313	0.436	0.291	0.256	0.064*	1.000	0.481	0.624
GPRHA	GPRH	0.446	0.180	0.155	0.212	0.040*	0.175	0.377	0.624
GPRHA	GPRHT	0.446	0.170	1.000	0.212	0.028*	0.195	0.415	0.624
GPRHA	GPRHA	0.446	0.259	0.177	0.212	0.033*	0.160	0.237	0.620
AR-MSGARCH	GPRH	0.372	0.281	0.492	0.256	0.024*	0.225	0.566	0.624
AR-MSGARCH	GPRHT	0.408	0.281	0.448	0.212	0.020*	0.301	0.566	0.653
AR-MSGARCH	GPRHA	0.369	0.281	0.578	0.256	0.024*	0.184	0.566	0.624

Note: The entries are MCS p-values. The forecasts excluded from $\hat{M}^*_{90\%}$ are identified by one asterisk.

Table 15: Model confidence sets (MCS) results.

Model 1	Model 2	MSE				QLIKE			
		Forecast horizon							
		1M	*2M*	*3M*	*4M*	*1M*	*2M*	*3M*	*4M*
		AR-GARCH-MIDAS with combined explanatory variables							
GPRH	Recessions	0.845	0.270	0.344	0.116	0.001*	0.537	0.499	0.226
GPRH	Inflation	0.845	0.270	0.334	0.309	0.002*	0.850	0.499	0.148
GPRH	Interest rates	0.845	0.257	0.323	0.188	0.001*	0.790	0.499	0.167
GPRHT	Recessions	0.845	0.224	0.321	1.000	0.001*	0.559	0.499	0.862
GPRHT	Inflation	0.727	0.198	0.316	0.184	0.022*	0.674	0.492	0.648
GPRHT	Interest rates	0.697	0.177	0.312	0.184	0.001*	0.449	0.480	0.644
GPRHA	Recessions	0.165	0.270	0.344	0.119	0.001*	0.434	1.000	0.328
GPRHA	Inflation	0.160	0.270	0.339	0.112	0.001*	0.606	0.065	0.299
GPRHA	Interest rates	1.000	0.270	0.330	0.370	0.001*	0.462	0.499	0.184
GPRHA	GPRHT	0.811	0.183	0.318	0.184	0.001*	0.494	0.480	0.769
		AR-MSGARCH-MIDAS with combined explanatory variables							
GPRH	Recessions	0.171	0.467	0.588	0.128	0.459	0.394	0.476	0.533
GPRH	Inflation	0.176	0.467	0.874	0.137	0.654	0.355	0.413	0.644
GPRH	Interest rates	0.330	0.122	0.143	0.182	0.001*	0.366	0.109	0.351
GPRHT	Recessions	0.845	0.371	0.588	0.125	0.001*	0.380	0.480	0.644
GPRHT	Inflation	0.391	0.467	0.850	0.137	0.001*	0.047*	0.074*	0.208
GPRHT	Interest rates	0.544	0.270	0.211	0.184	0.329	0.966	0.594	1.000
GPRHA	Recessions	0.482	0.130	0.151	0.184	0.001*	0.400	0.466	0.644
GPRHA	Inflation	0.191	0.467	0.874	0.143	0.001*	0.374	0.354	0.426
GPRHA	Interest rates	0.470	0.270	0.301	0.184	0.001*	0.346	0.350	0.403
GPRHA	GPRHT	0.184	0.467	0.588	0.128	0.001*	0.335	0.366	0.377
	Combined forecasts from models with a single explanatory variable								
AR-MSGARCH-MIDAS	AR-GARCH-MIDAS								
GPRH	Recessions	0.330	0.304	0.345	0.184	0.017*	0.966	0.435	0.644
GPRH	Inflation	0.313	0.273	0.463	0.184	0.015*	0.966	0.373	0.644
GPRH	Interest rates	0.330	0.304	0.497	0.184	0.003*	0.966	0.391	0.644
GPRH	AR-GARCH	0.323	0.125	0.290	0.184	0.001*	0.385	0.476	0.644
GPRHT	Recessions	0.338	1.000	0.157	0.184	0.125	0.062*	0.476	0.644
GPRHT	Inflation	0.343	0.467	0.181	0.184	0.076*	0.034*	0.466	0.644
GPRHT	Interest rates	0.330	0.119	0.203	0.184	0.092*	0.054*	0.476	0.644
GPRHT	AR-GARCH	0.645	0.467	0.140	0.145	0.001*	0.966	0.480	0.644
GPRHA	Recessions	0.470	0.148	0.874	0.149	0.053*	0.155	0.354	0.628
GPRHA	Inflation	0.421	0.188	1.000	0.159	0.035*	0.138	0.274	0.610
GPRHA	Interest rates	0.460	0.210	0.134	0.182	0.031*	0.145	0.325	0.621
GPRHA	AR-GARCH	0.182	0.467	0.850	0.133	1.000	0.428	0.127	0.254
AR-MSGARCH	Recessions	0.405	0.270	0.344	0.182	0.025*	0.322	0.480	0.644
AR-MSGARCH	Inflation	0.396	0.270	0.348	0.184	0.026*	0.253	0.480	0.644
AR-MSGARCH	Interest rates	0.396	0.270	0.463	0.184	0.025*	0.240	0.480	0.644
AR-MSGARCH	AR-GARCH	0.421	0.270	0.275	0.128	0.001*	0.413	0.480	0.644
Recessions	GPRH	0.515	0.467	0.588	0.129	0.459	0.223	0.435	0.644
Recessions	GPRHT	0.524	0.467	0.588	0.128	0.459	0.275	0.442	0.644
Recessions	GPRHA	0.495	0.467	0.816	0.129	0.459	0.184	0.397	0.644
Recessions	Without	0.667	0.325	0.588	0.125	0.654	0.420	0.476	0.644
Inflation	GPRH	0.355	0.134	0.252	0.184	0.459	0.313	0.410	0.644
Inflation	GPRHT	0.355	0.132	0.236	0.184	0.254	0.332	0.456	0.644
Inflation	GPRHA	0.347	0.137	0.265	0.184	0.397	0.223	0.396	0.637
Inflation	Without	0.162	0.467	0.149	0.137	0.001*	0.393	0.480	0.644
Interest rates	GPRH	0.227	0.270	0.588	0.184	0.016*	0.025*	0.191	0.484
Interest rates	GPRHT	0.247	0.270	0.542	0.184	0.002*	0.966	0.168	0.512
Interest rates	GPRHA	0.208	0.270	0.588	0.184	0.005*	0.026*	0.150	0.452
Interest rates	Without	0.366	0.139	0.223	0.140	0.001*	0.378	0.413	0.271
GPRH	GPRH	0.290	0.272	0.348	0.184	0.020*	0.946	0.358	0.644
GPRH	GPRHT	0.296	0.284	0.373	0.184	0.008*	0.966	0.403	0.644
GPRH	GPRHA	0.270	0.270	0.408	0.184	0.018*	0.943	0.083*	0.575
GPRHT	GPRH	0.330	0.467	0.168	0.184	0.397	0.029*	0.464	0.644
GPRHT	GPRHT	0.330	0.467	0.162	0.184	0.117	0.040*	0.476	0.644
GPRHT	GPRHA	0.330	0.467	0.190	0.184	0.221	1.000	0.383	0.644
GPRHA	GPRH	0.421	0.171	0.874	0.169	0.070*	0.096*	0.229	0.596
GPRHA	GPRHT	0.421	0.158	0.874	0.154	0.038*	0.124	0.343	0.621
GPRHA	GPRHA	0.421	0.238	0.138	0.182	0.065*	0.077*	0.094*	0.575
Without	GPRH	0.384	0.270	0.345	0.184	0.026*	0.203	0.476	0.644
Without	GPRHT	0.386	0.270	0.345	0.184	0.025*	0.295	0.480	0.644
Without	GPRHA	0.379	0.270	0.584	0.184	0.030*	0.131	0.476	0.644

Note: The entries are MCS p-values. The forecasts excluded from $\hat{M}^*_{90\%}$ are identified by one asterisk.

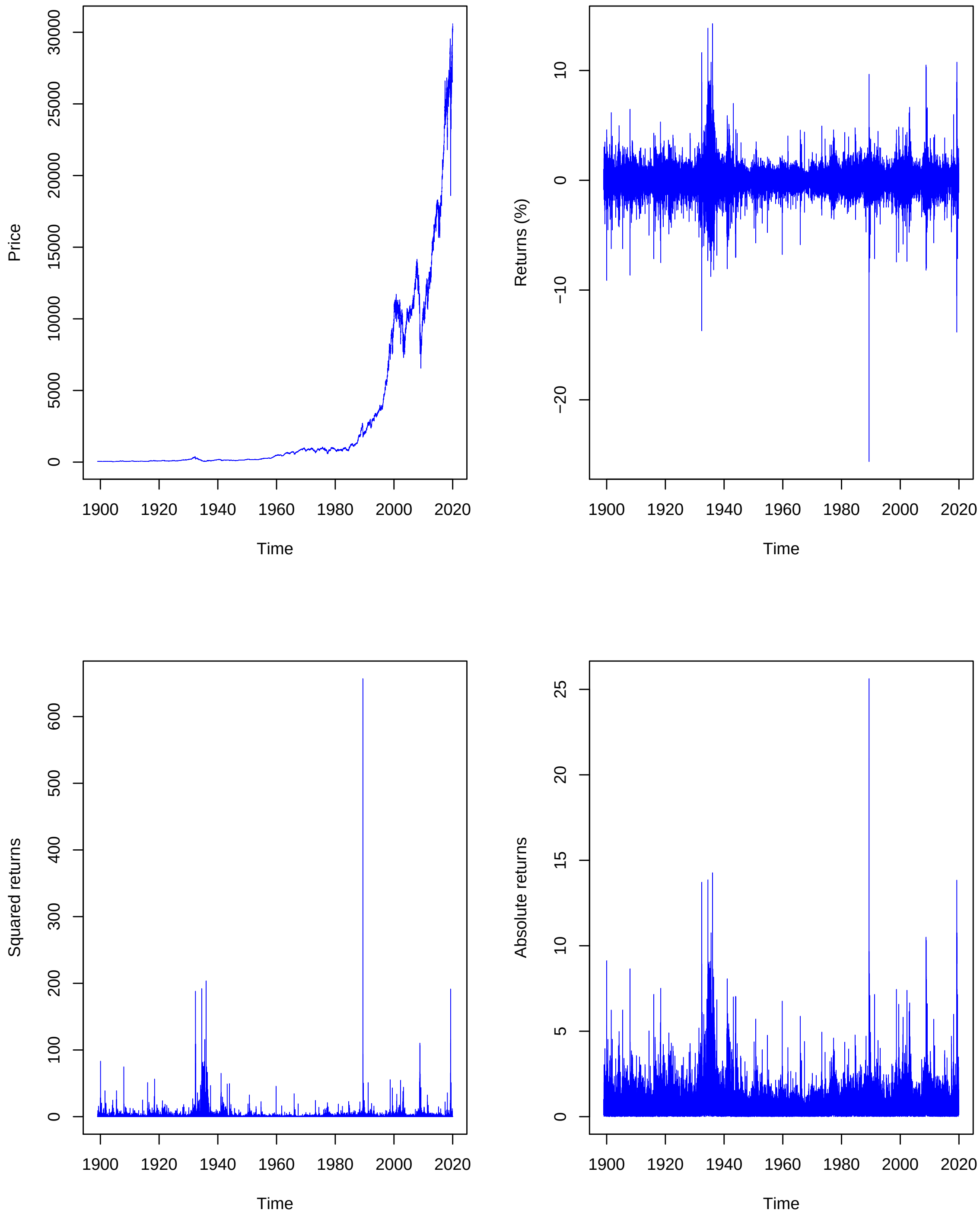

Figure 1: Plot of DJIA prices, returns, squared and absolute returns

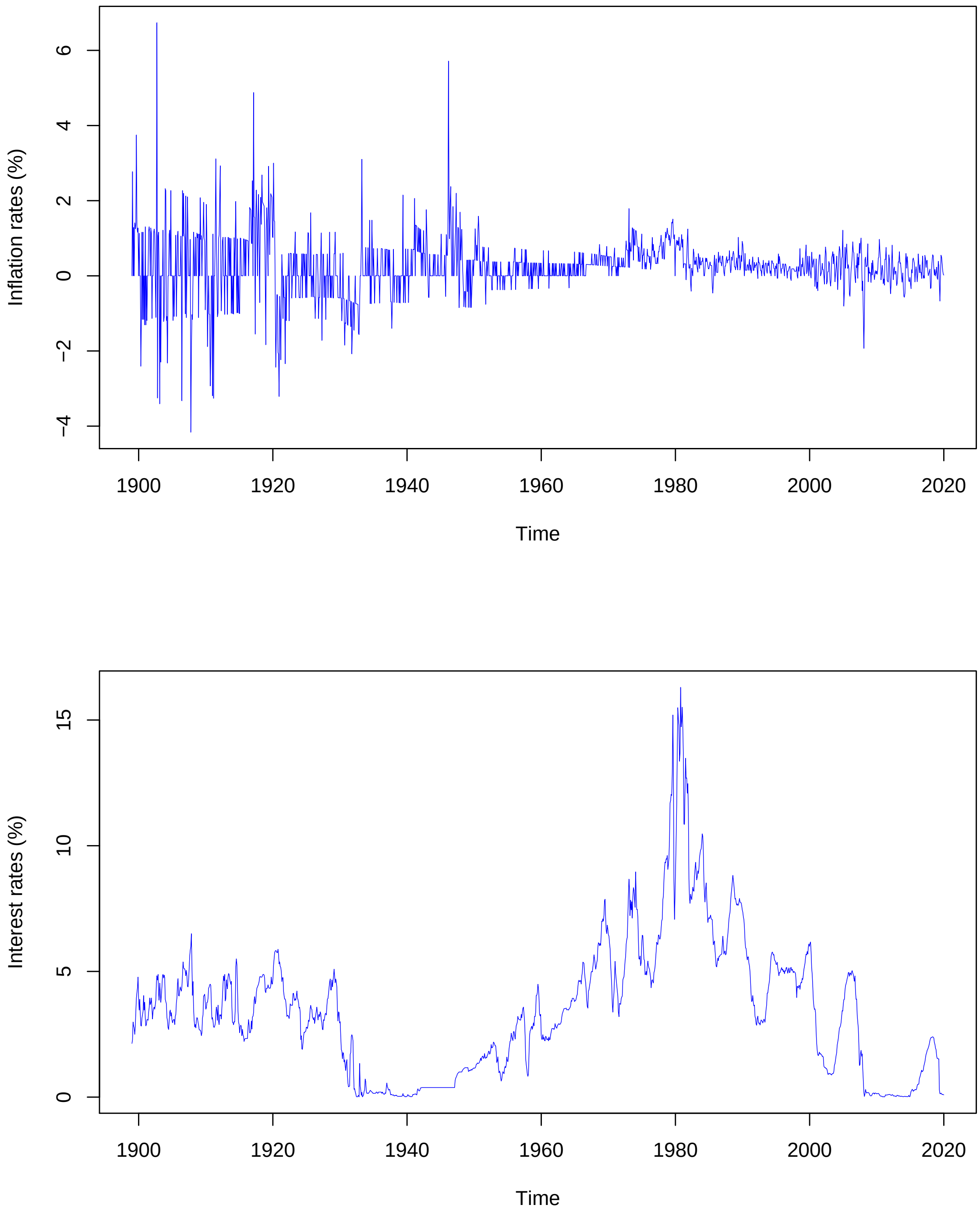

Figure 2: Plot of macroeconomic variables such as inflation and interest rates

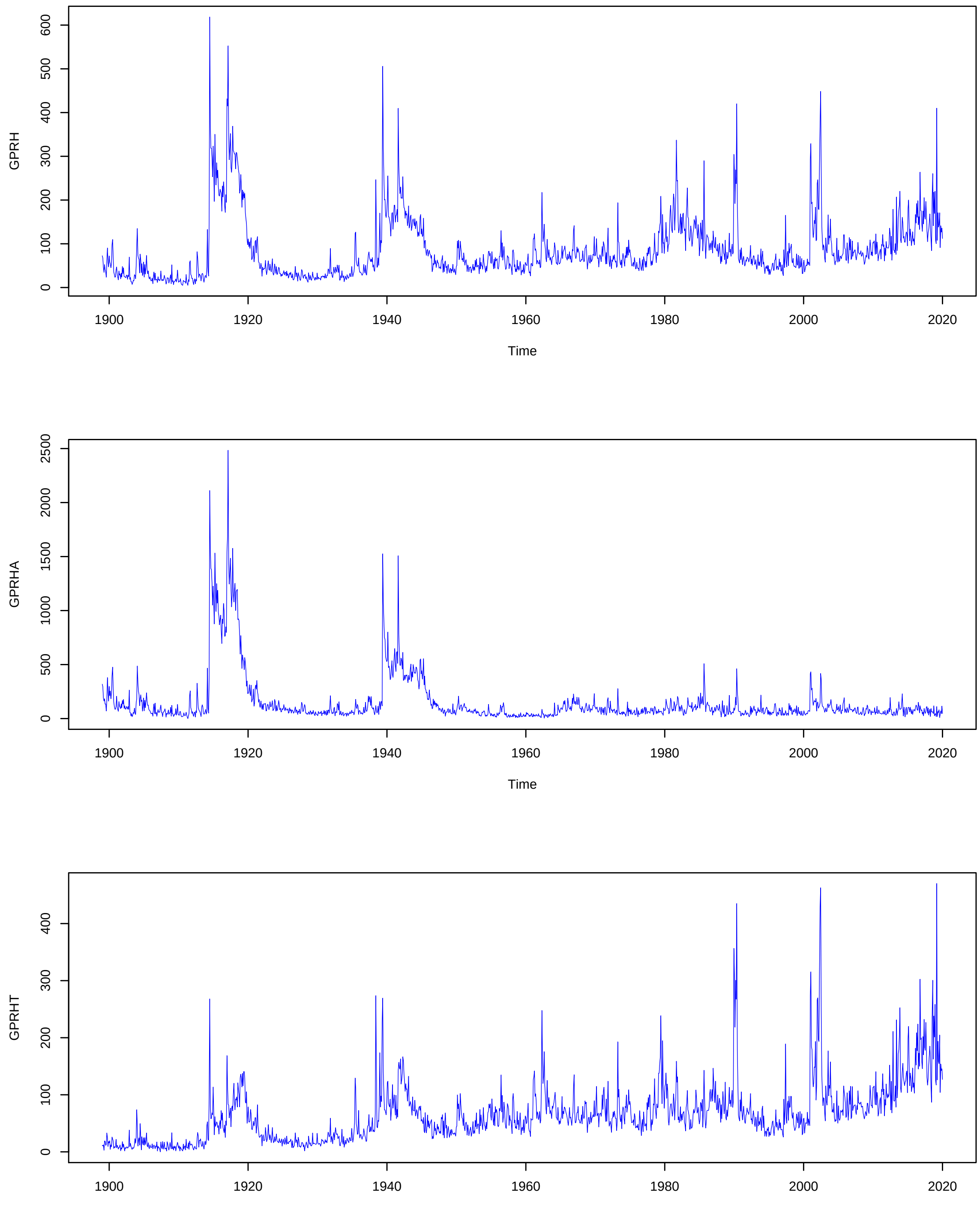

Figure 3: Plot of geopolitical risk indices

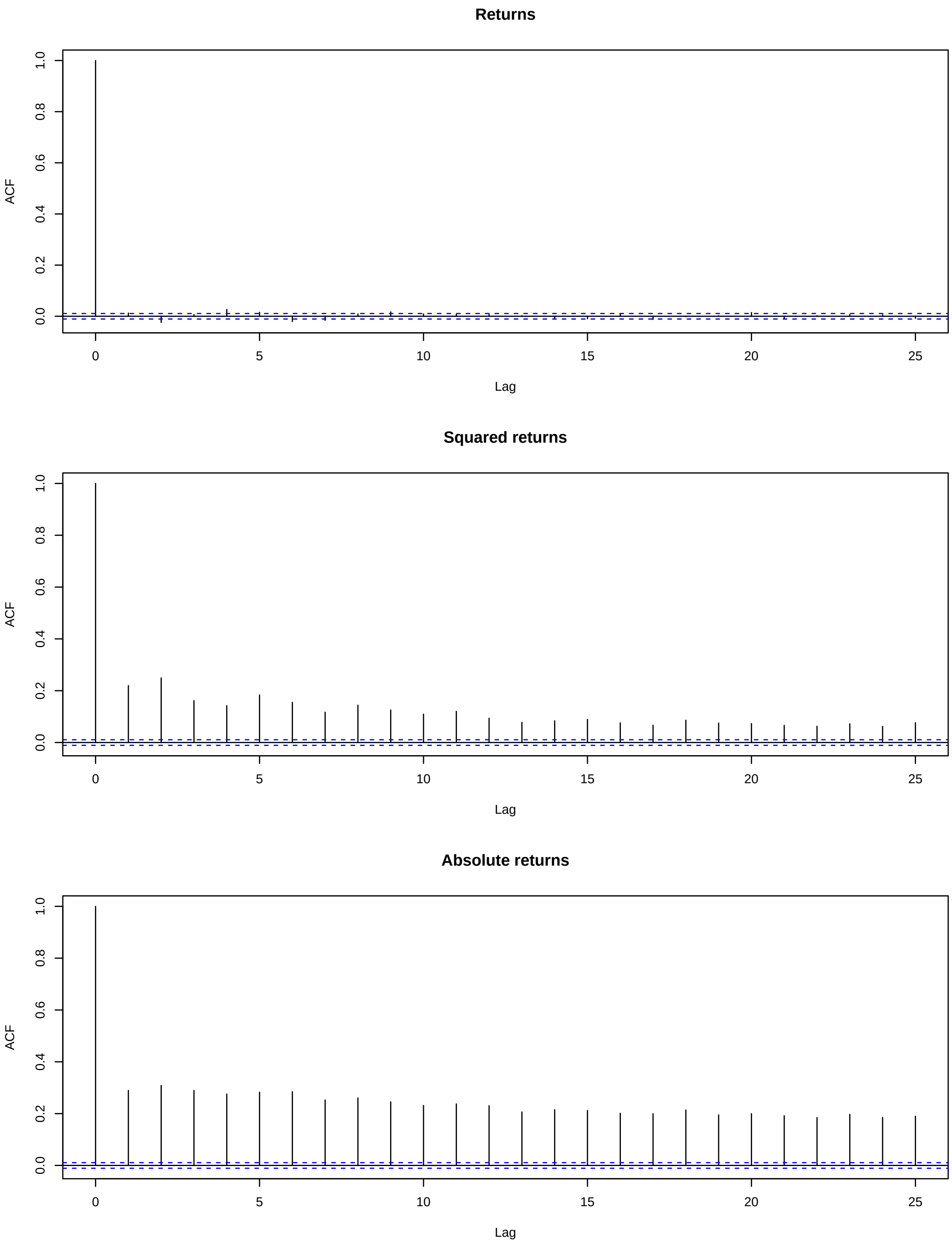

Figure 4: Plot of autocorrelation functions