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Volatility Forecasting Using Geopolitical Risk Indices: A GARCH-MIDAS Approach

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Abstract

This paper applies the GARCH-MIDAS (mixed data sampling) framework to examine if geopolitical risk indices (GPR) have predictive ability when forecasting stock market volatility in advanced economies. Stock market indices and country-specific GPR indices from 21 advanced economies are used to examine the out-of-sample predictability of short-term total variance and long-term variance. The main finding of this paper is that geopolitical risk indices have a predictive ability for stock market volatility in certain advanced economies, but not in all advanced economies. The improvement of forecasting ability is evident for both short-term total variance and long-term variance but is primarily related to long-term variance. The results are of practical relevance for both investors and risk managers.

Keywords: Geopolitical Risk, Stock Market Volatility, GARCH-MIDAS, Advanced Economies
JEL codes: C53; F51; G15; G17

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Contents

1 Introduction

This study investigates if information about geopolitical risk can improve the forecasting accuracy of stock market volatility. Forecasting stock market volatility is essential in risk management practices and investment decisions. Volatility is for example a key input when pricing derivative securities and can also serve as a good starting point for portfolio managers when assessing investment risk. The extensive literature and the attention to volatility forecasting from both academics and practitioners for over four decades can be viewed as an acknowledgement of its importance (Poon & Granger, 2003). The seminal work by Engle (1982) on autoregressive conditional heteroscedasticity (ARCH) models provided the starting point for models that could capture the stylized fact that the conditional variance of stock returns is time-varying. Bollerslev (1986) later extended the work of Engle (1982) by developing the generalized autoregressive conditional heteroscedasticity (GARCH) model.

Contributing to the literature of volatility forecasting can in principle be done in two ways, either by improving the econometric techniques or by developing a further understanding of what information to incorporate in the models under different settings. This study focuses on the latter alternative. The papers by Officer (1973) and Schwert (1989) are early examples of literature that addresses the question of why stock market volatility changes over time. Schwert (1989) investigates the linkages between the stock market volatility and the macroeconomic environment. More recent examples include Asgharian et al. (2013), Conrad and Loch (2015), and Engle et al. (2013). The previously mentioned studies have mainly focused on macroeconomic variables such as industrial production, short-term interest rates, and unemployment rates. However, it is intuitive to believe that other factors such as geopolitical risk also impact the stock market volatility by increasing the uncertainty about future cash flows and discount rates.

Geopolitical risk is however a challenging factor to measure. Caldara and Iacoviello (2022) address this problem by creating geopolitical risk (GPR) indices based on a news article methodology. Geopolitical risk is defined by Caldara and Iacoviello (2022) as the risk associated with adverse events related to wars, terrorism, and tensions between states and political actors that affect peaceful and normal international relations. Salisu et al. (2022a) provide evidence that the GPR index by Caldara and Iacoviello (2022) has a predictive ability for stock market volatility in emerging economies. One might expect that geopolitical risk plays a more important role in emerging economies than in advanced economies. This view is supported by the results in Zhang et al. (2023) that show how the effect of GPR on volatility is positive in advanced economies, but less pronounced than in emerging economies. However, Zhang et al. (2023) only report regression results and do not perform any out-of-sample forecasts to evaluate the predictive ability of GPR indices on stock market volatility in advanced economies. This gap in the literature gives rise to the research question of this study:

Do geopolitical risk indices have predictive ability when forecasting stock market volatility in advanced economies?

This paper uses an extension of the GARCH-MIDAS (mixed data sampling) model. The GARCH-MIDAS model decomposes the conditional variance into a short-term component and a long-term component, which enables combining data sampled at low frequency (GPR) and high frequency (stock returns). The country-specific GPR index is included in the long-term variance component in addition to the smoothed realized variance. The model including GPR is compared with the traditional GARCH-MIDAS-RV using the adjusted mean square prediction error (MSPE-adjusted) test for nested models by Clark and West (2007). The out-of-sample forecast accuracy is evaluated for both total variance and long-term variance. To the best of my knowledge, this is the first study that evaluates the out-of-sample predictive ability of GPR indices on stock market volatility in advanced economies. The empirical results in this study suggest that GPR indices have predictive ability in certain advanced economies for both short-term total variance and long-term variance, but how the predictive ability primarily relates to long-term variance.

The rest of this paper is outlined in the following way. Section 2 presents relevant previous literature related to geopolitical risk and volatility forecasting. Section 3 describes the methodology and data used, which covers the GARCH-MIDAS framework and the forecasting procedure. Section 4 contains the results and analysis. Lastly, Section 5 concludes and provides suggestions for future research.

2 Literature

This study relates to the literature on geopolitical risk and volatility forecasting using the GARCH-MIDAS methodology. Caldara and Iacoviello (2022) define geopolitical as the risk associated with adverse events related to wars, terrorism, and tensions between states and political actors that affect peaceful and normal international relations. The GPR indices created by Caldara and Iacoviello (2022) enable us to capture geopolitical risk in a continuous fashion and allow us to go beyond studying the effect of specific geopolitical events on stock market volatility (Choudhry, 2010; Nikkinen et al 2008; Schneider & Troeger, 2006). Choudhry (2010) investigated how US investors reacted to events during World War II that historians later labelled as important and found evidence for structural breaks in volatility. Nikkinen et al. (2008) examined how the terrorist attack of September 11 increased volatility across regions. Further examples of studies that investigate the linkage between terrorism and stock market volatility include Arin et al. (2008) and Corbet et al. (2018).

How the stock market volatility reacts to adverse events is closely related to the well-known asymmetry effect first examined by Black (1976), which reveals how bad news increases volatility more than good news. One theoretical explanation for asymmetric volatility is the leverage hypothesis of how a drop in stock value increases the market-based financial leverage ratio and hence makes the stock riskier and more volatile. This can be demonstrated by a simple model presented by Christie (1982). First, assume we have Modigliani and Miller world including a constant interest rate, no dividends, and that there only exists a single class of riskless debt. Second, by assuming that the firm's assets have a constant volatility one can show that

$$\sigma_{S,t} = \sigma_V(1 + LR_t) \tag{1}$$

where σ represents the standard deviation of returns. The market-based financial leverage ratio is denoted $LR = D/S(V)$. Time is denoted by t and D, S, V are the market values of debt, equity, and firm. Equation (1) show how the volatility of equity (σ_s) is a positive increasing function of LR. The elasticity (θ_s) of the volatility of equity with respect to the stock price is given by

$$\theta_s = (\partial\sigma_s/\sigma_s)/(\partial S/S) = -[LR/(LR+1)] \tag{2}$$

where $-1 \leq \theta_s \leq 0$. The elasticity is zero for an unlevered firm and is equal to -1 when the leverage ratio goes to infinity. A decline in the stock price would for a levered firm lead to an increase in the volatility of equity. If the stock price decreases by 1%, the volatility of equity can increase by up to 1% under this scenario. The leverage hypothesis is one potential theoretical channel through which geopolitical risk might affect volatility, given that geopolitical risk also affects stock returns. Salisu et al. (2022b) find evidence for a negative relation between stock returns and GPR in advanced economies. Based on the empirical results by Salisu et al. (2022b), it is expected that higher values of GPR are associated with higher stock market volatility. However, it should be emphasized that forecasting ability using GPR indices is the main focus of this study and not causal inference.

The forecasting ability of GPR indices on stock market volatility has previously been examined by Salisu et al. (2022a) using data from 11 emerging economies. Salisu et al. (2022a) employ the GARCH-MIDAS framework that decomposes the conditional variance into a long-term and short-term component where the GPR index is incorporated in the long-term component. The results in Salisu et al. (2022a) show that GPR offers improved out-of-sample forecasting of stock market volatility in emerging markets. Improved out-of-sample forecasting of volatility by incorporating GPR in a GARCH-MIDAS model is also found by Ndako et al. (2021) when using data of Islamic stocks in Indonesia and Malaysia. The study by Bouras et al. (2019) is another example of a study that investigates stock market volatility and GPR in emerging economies. Bouras et al. (2019) estimate a panel GARCH model and find that country-specific GPR has a weak statistical effect on volatility while the impact from global GPR is both statistically and economically stronger than the country-specific.

In contrast to the previously mentioned studies by Bouras et al. (2019), Ndako et al. (2021), and Salisu et al. (2022a) that focus on emerging economies the study by Zhang et al. (2023) investigates how GPR affects volatility in a global perspective. Zhang et al.

(2023) use a biased-corrected LSDV estimator and find evidence that the effect of GPR on stock market volatility is more pronounced in emerging economies, countries at peace, and crude oil exporters. The finding of a more significant effect for crude oil exporters can be related to the studies by Liu et al. (2019) and Mei et al. (2020) who find evidence that GPR is useful when predicting oil price volatility.

3 Methodology and Data

This section begins by describing the GARCH-MIDAS framework, followed by a discussion of the data. Lastly, the estimation and forecasting strategy is presented which includes a description of the forecast evaluation.

3.1 GARCH-MIDAS Framework

The GARCH-MIDAS model presented by Engle et al. (2013) is employed to examine the predictive ability of geopolitical risk indices when forecasting stock market volatility in advanced economies. Previous studies that examine the predictive ability of macroeconomic variables in volatility forecasting frequently use the GARCH-MIDAS framework (Asgharian et al. 2013; Conrad and Loch, 2015; Girardin and Joyeux, 2013; Virk et al. 2024). In the context of using GPR indices, this study follows Salisu et al. (2022a) by using a GARCH-MIDAS approach. An alternative to the GARCH-MIDAS approach would be to include the GPR index in an extended version of Corsi's (2009) heterogenous autoregressive (HAR) model. For comparability with previous literature, this study focuses on the GARCH-MIDAS model.

The GARCH-MIDAS model is a component model that uses mixed data sampling (MIDAS). The model decomposes the conditional variance into a short-term transitory component modelled by a unit variance GARCH(1,1) and into a long-term component. MIDAS (mixed data sampling) regression models were first introduced by Ghysels et al. (2007). The MIDAS framework offers a way to incorporate variables such as the GPR index that are sampled at a monthly frequency along with the stock returns sampled at a daily frequency. In the GARCH-MIDAS model, the GPR index enters the specification of the long-term component without restricting the analysis of volatility to the same frequency as the GPR index. Formally, to describe the GARCH-MIDAS model we denote daily log returns for day i in month t by

$$r_{i,t} = 100 \times \log \left(\frac{P_{i,t}}{P_{i-1,t}} \right) \tag{3}$$

where $P_{i,t}$ represents the price for day i in month t. The log return is assumed to be described by the following mean equation

$$r_{i,t} = \mu + \sqrt{\tau_t \cdot g_{i,t}} \cdot \varepsilon_{i,t} \qquad \forall i = 1, ..., N_t \tag{4}$$

where $\varepsilon_{i,t}|\Phi_{i-1,t} \sim N(0,1)$ and $\Phi_{i-1,t}$ is the information set up to day $(i-1)$ in month t and N_t is the number of trading days in month t. Equation (4) expresses the variance as a multiplicative process of the long-term component τ_t and the short-term component $g_{i,t}$. Engle et al. (2013) specify the short-term component $g_{i,t}$ as a GARCH(1,1) process.

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{5}$$

Engle et al. (2013) provides various specifications of the long-term component τ_t where Equation (6) shows the most basic one.

$$\tau_t = m + \theta \sum_{k=1}^{K} \rho_k(\omega_1, \omega_2) RV_{t-k} \tag{6}$$

RV_t is the monthly realized variance defined as $RV_t = \sum_{i=1}^{N_t} r_{i,t}^2$. An alternative is to specify the long-term component in log form to ensure non-negative τ_t. This study follows Asgharian et al. (2013) by using a fixed time span such that τ_t is updated on a monthly frequency.

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \rho_k(\omega_1, \omega_2) RV_{t-k} \tag{7}$$

The model specification in Equation (7) will be used as a benchmark model and referred as GARCH-MIDAS-RV.

$$\log(\tau_t) = m + \theta_1 \sum_{k=1}^{K} \rho_k(\omega_{11}, \omega_{21}) RV_{t-k} + \theta_2 \sum_{k=1}^{K} \rho_k(\omega_{12}, \omega_{22}) GPR_{t-k} \tag{8}$$

The model specification in Equation (8) will throughout this study be referred to as

GARCH-MIDAS-RV+GPR. The MIDAS slope coefficients θ_1 and θ_2 indicates the predictive ability of RV and GPR. If the coefficient θ_2 is equal to zero, then Equation (8) reduces to Equation (7) such that the GARCH-MIDAS-RV model is nested inside the GARCH-MIDAS-RV+GPR. Engle et al. (2013) show how Equation (7) and Equation (8) in a sense can be thought of as regression models apart from not imposing orthogonality between the regressors and the residuals. The weighting scheme used in Equation (7) and Equation (8) is the beta lag polynomial in Equation (9).

$$\rho_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(j/K)^{\omega_1 - 1}(1 - j/K)^{\omega_2 - 1}} \tag{9}$$

Finally, the conditional variance of $r_{i,t}$ is presented by Equation (10).

$$\sigma_{i,t}^2 = \tau_t \cdot g_{i,t} \tag{10}$$

3.2 Data

The dataset consists of stock market indices for 21 advanced economies and their respective GPR index. The stock market indices have been selected with the ambition to be broad measures of each country's stock market performance without losing too many observations due to the start date of the index (see Appendix A). All stock market data are obtained from Bloomberg. The GPR indices were created by Caldara and Iacoviello (2022) and downloaded from the website of Iacoviello (2024). There exist country-specific GPR indices for 44 countries of which 21 countries are classified as advanced economies according to IMF (2023). The GPR indices by Caldara and Iacoviello (2022) are constructed by an automated text-search methodology using electronic archives for 10 newspapers. The newspapers are the Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post. The indices were created by calculating the share of articles related to adverse geopolitical events. The country-specific GPR indices have a start date in the year 1985 and are measured at a monthly frequency.

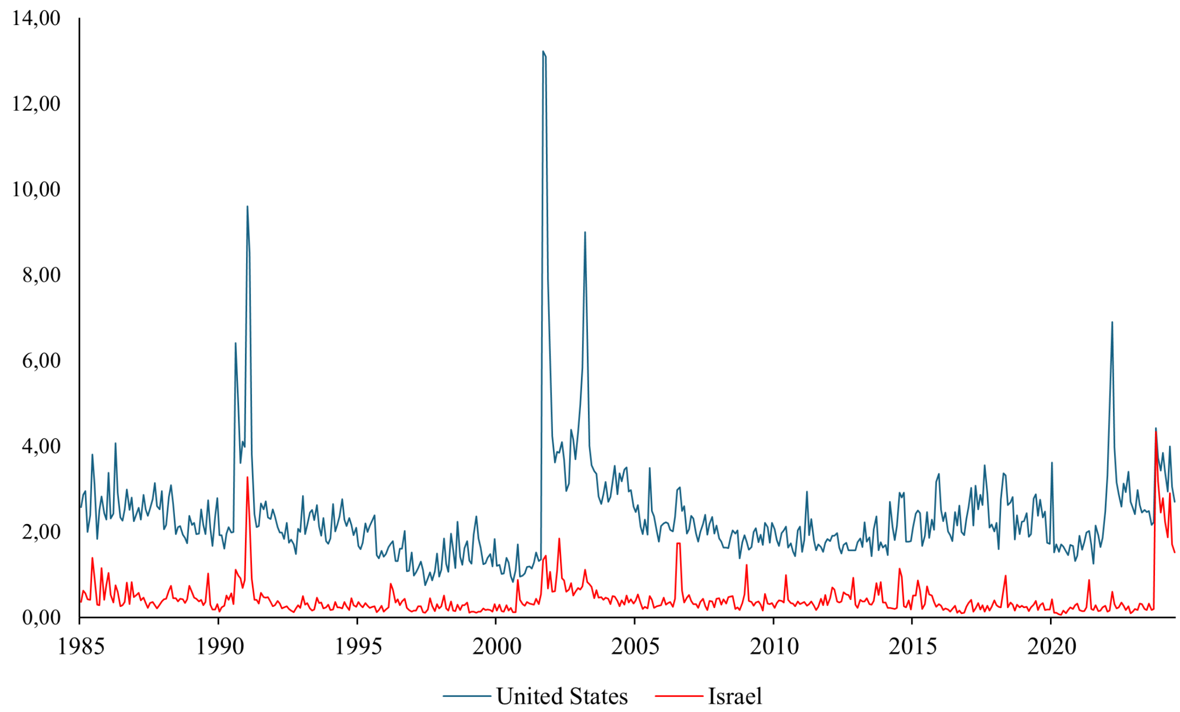

Figure 1: GPR Indices For Two Selected Countries

Notes: This figure displays the GPR indices for the United States and Israel between January 1985 and June 2024. The vertical axis displays GPR values.

Figure 1 illustrates how the country-specific GPR indices have evolved for two of the countries in the sample since the start date in 1985. In Figure 1, one can see that the GPR index for the United States has its highest peaks around historical events such as the Gulf War 1990, the 11 September Attacks 2001, the Iraq War 2003, and the Russian invasion of Ukraine 2022. Figure 1 further show how the GPR index for Israel recently peaked during the outbreak of the Israel-Hamas War 7 October 2023. That Israel has lower GPR values than the United States indicates that the absolute levels of the country-specific GPR indices are not directly comparable across countries. This remark is further discussed in the result section.

3.3 Estimation and Forecasting Strategy

The parameters are estimated using the maximum likelihood method. The log-likelihood function in Equation (11) is maximized using numerical optimization.

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\left[\log(2\pi) + \log(g_{i,t}\tau_t) + \frac{(r_{i,t}-\mu)^2}{g_{i,t}\tau_t}\right] \tag{11}$$

The estimation and forecast evaluation are carried out using MATLAB[1]. Before estimating the models, one must decide the number of lags to be used in the MIDAS equation. According to Conrad and Kleen (2020), the forecast performance is relatively insensitive to misspecification of the lag length. Asgharian et al. (2013) find that the optimal value of the likelihood function reaches its highest value around 36 lags. Based on the findings by Conrad and Kleen (2020) and Asgharian et al. (2013) this study uses 36 lags throughout all estimations.

Another choice is to decide the weights ω_1 and ω_2 in Equation (9). There exist three alternative ways of doing this.

(i) Estimating both ω_1 and ω_2 within the model.

(ii) Fixing ω_1 a priori and estimating ω_2 within the model.

(iii) Fixing both ω_1 and ω_2 a priori.

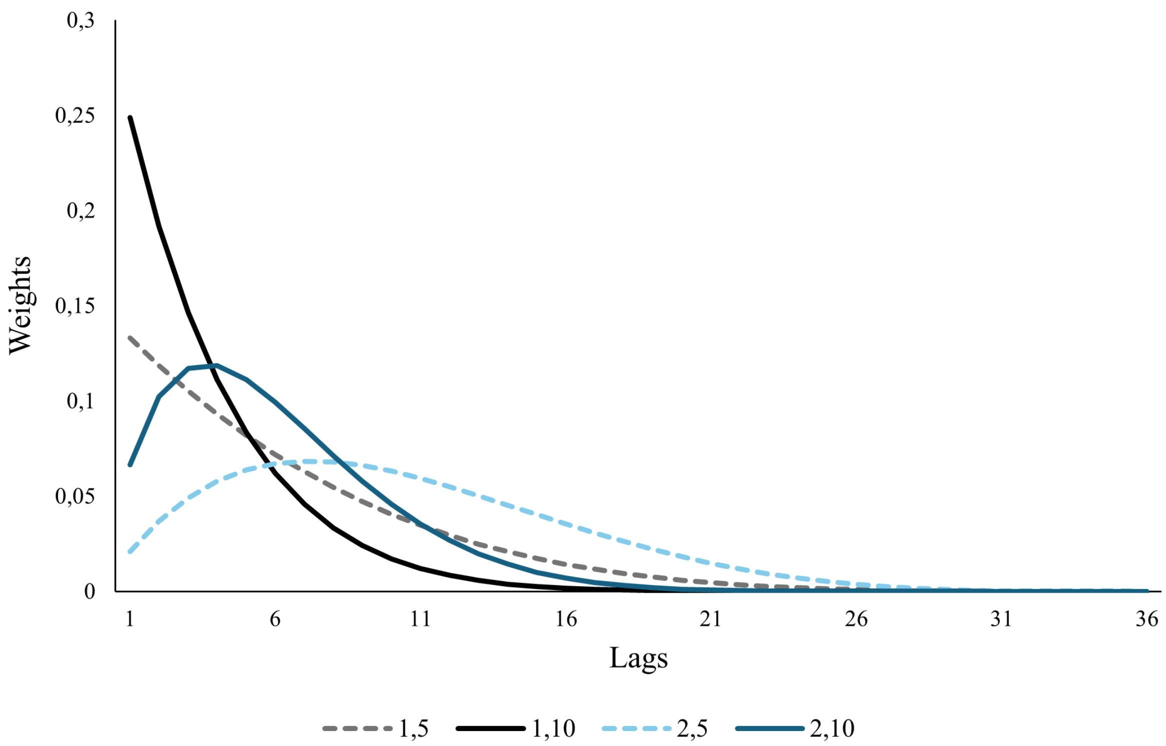

Figure 2: Lag Structure for Different Values of ω_1 and ω_2.

Notes: This figure displays the weighting function for different values of ω_1 and ω_2. For $\omega_1 = 1$ or $\omega_1 = 2$ and $\omega_2 = 5$ or $\omega_2 = 10$.

[1]The code is based on the MIDAS Matlab Toolbox and is extended to incorporate two regressors.

Figure 2 illustrates how the weight function is monotonically decreasing if ω_1 is equal to one. Given that $\omega_1 = 1$, then larger values of ω_2 results in that more weight is put on the most recent lags. The weight function is also able to produce a hump-shaped weighting scheme. Alternative (i) can sometimes produce counterintuitive weighting schemes such as a hump-shaped weighting scheme. It is most reasonable to assume a monotonically decreasing weight function for both RV and GPR. Hence, ω_1 will be fixed a priori to a value equal to one. The value of ω_2 is estimated within the model since there are no theoretical arguments to be made about its value. In summary, alternative (ii) will be used, which is in line with previous studies by Asgharian et al. (2013) and Engle et al. (2013).

This study uses pseudo-out-of-sample forecasts to evaluate the predictive ability of GPR on stock market volatility in a GARCH-MIDAS framework. Two types of forecasts are made, a one-step ahead forecast of total variance and a forecast of long-term variance. Total variance is forecasted by the estimated value of $\sigma_{i,t}^2 = \tau_t \cdot g_{i,t}$, which is compared to realized daily volatility computed as $r_{i,t}^2$. The long-term variance is predicted by the estimated value of τ_t. This is motivated by $E[r_{i,t} - E(r_{i,t}|\Phi_{N^{(t-1)},t-1})]^2 = E[g_{i,t}\tau_t\varepsilon_{i,t}^2|\Phi_{N^{(t-1)},t-1}] = \tau_t \cdot E[g_{i,t}|\Phi_{N^{(t-1)},t-1}] = \tau_t$, assuming that $E[g_{i,t}|\Phi_{N^{(t-1)},t-1}]$ converges to its unconditional expectation equal to one given that i is large and $\alpha + \beta < 1$. The predicted long-term variance is compared to realized monthly volatility measured as $\sum_{i=1}^{21} r_{i,t}^2$. Since, τ_t is daily variance, it needs to be transformed into monthly variance by multiplying with 21. The last 2520 observations are used for the out-of-sample forecast evaluation which is approximately 10 years. There is a tradeoff when deciding the length of the forecast evaluation window. The forecast evaluation window must be long enough to make a robust statistical evaluation of the forecast performance, while still leaving sufficiently many observations at the beginning of the full sample for the first estimation window as the maximum likelihood requires large samples. The parameters are estimated using an expanding estimation window and the estimated parameters are updated once every 252 trading days.

The forecasting accuracy is measured by the mean squared prediction error (MSPE) which is defined by Equation (12), where T is the length of the forecast evaluation window.

$$\frac{1}{T}\sum_{t=1}^{T}[\sigma_{t+1}^2 - E_t(\sigma_{t+1}^2)]^2 \tag{12}$$

The DM-test by Diebold and Mariano (1995) is a standard test of equal forecast accuracy between two competing models. However, the standard DM-test is not appropriate when the models are nested such as the GARCH-MIDAS-RV and the GARCH-MIDAS-RV+GPR. Under the null hypothesis of equal MSPE i.e., the data is generated by the parsimonious model, then the larger model introduces noise into its forecasts by estimating unnecessary parameters whose population values are zero. The MSPE from the parsimonious model is under the null hypothesis therefore expected to be *smaller* than the MSPE from the larger model. Clark and West (2007) present a procedure how to adjust the forecast errors from the larger model so that a modified DM-test can be used for nested models. Denote the forecast from the parsimonious model with $f_{1,t}$ and its forecast error with $e_{1,t}$. The corresponding notation for the larger model is $f_{2,t}$ and $e_{2,t}$. Equation (13) presents how a new series z_t is created.

$$z_t = (e_{1,t})^2 - \left[(e_{2,t})^2 - (f_{1,t} - f_{2,t})^2\right] \quad \forall t = 1, ..., T \tag{13}$$

Any discrepancy between $f_{1,t}$ and $f_{2,t}$ is under the null hypothesis due to parameter estimation error. This discrepancy is squared and subtracted from the larger model's squared forecast error $(e_{2,t})^2$. To perform the test, z_t is regressed on a constant and using the t-statistics to test for a zero coefficient. The alternative hypothesis is that the data is generated by the larger model. The null hypothesis is rejected if the t-statistic is sufficiently positive since the test is one-sided. The test presented by Clark and West (2007) will be referred to as MSPE-adjusted in the result section.

4 Results and Analysis

This section begins with an analysis of descriptive statistics. Thereafter, the results from the forecasting of the total variance and long-term variance are presented and analysed.

4.1 Preliminary Analysis

Table 1 presents summary statistics of the 21 countries' stock market indices. When looking at the standard deviation of daily returns, one can see that Taiwan and Hong Kong SAR are the two most volatile stock markets, while Australia and Canada are the two least volatile stock markets. Table 1 also displays the stylized facts that stock returns are negatively skewed and have fat tails. Australia and Hong Kong SAR are the countries with the highest kurtosis, which is an interesting observation given the previous description that Australia is one of the least volatile stock markets while Hong Kong SAR is one of the most volatile stock markets. In addition, one can notice how Taiwan is the country with the highest standard deviation but the lowest kurtosis. The description above indicates that there is no clear relationship between extreme events (kurtosis) and volatility (standard deviation). In Table 1, we also can see the result from the ARCH-LM test when using 5 respectively 10 lags. All 21 countries show evidence of conditional heteroscedasticity for 5 and 10 lags.

Table 2 presents summary statistics over the country-specific GPR for the 21 advanced economies used in this study. One can see that the United Kingdom and the United States are the two countries with the highest mean GPR. This is not surprising given that 6 respectively 3 newspapers are from the United States and United Kingdom out of the total 10 newspapers that the GPR indices are based on. The implication is that the level of GPR is not directly comparable across countries. If we look at the minimum values in Table 2, then we see that the minimum values for Denmark, Finland, Hong Kong SAR, Portugal, Switzerland, and Taiwan are zero. There seems to be a tendency that the smaller countries are less covered by the 10 newspapers which results in lower GPR values. This raises the question of how reliable the country-specific GPR indices are for smaller countries compared to the larger countries that seem to be more covered in the 10 newspapers. However, as forecasting accuracy is the core of this study, any potential measurement error of the underlying geopolitical risk is only of indirect importance through its impact on forecasting accuracy.

Table 1: Summary Statistics of Stock Returns

Country	Mean	Std. Dev	Skewness	Kurtosis	ARCH(5)	ARCH(10)
Australia	0.024	0.989	-3.205	81.986	251.711***	315.543***
Belgium	0.016	1.157	-0.420	13.511	978.317***	1160.293***
Canada	0.022	0.983	-1.096	23.473	2336.123***	2432.782***
Denmark	0.043	1.167	-0.314	8.685	1395.629***	1513.876 ***
Finland	0.024	1.530	-0.342	11.340	769.362***	951.632***
France	0.017	1.353	-0.275	9.408	1290.556 ***	1496.228***
Germany	0.031	1.387	-0.346	9.714	1183.479***	1394.794***
Hong Kong SAR	0.028	1.619	-2.032	55.841	235.199***	276.639***
Israel	0.047	1.397	-0.525	8.207	567.120***	721.597***
Italy	0.015	1.490	-0.483	10.259	820.798***	911.982***
Japan	0.012	1.419	-0.287	10.453	1235.021***	1365.398***
Netherlands	0.024	1.292	-0.331	11.883	2061.431***	2190.531***
Norway	0.023	1.426	-0.855	17.639	1173.144***	1316.148***
Portugal	0.010	1.141	-0.470	10.657	790.937***	916.594***
South Korea	0.031	1.560	-0.146	8.866	1461.316***	1595.048***
Spain	0.017	1.366	-0.346	10.761	989.380***	1095.319***
Sweden	0.032	1.397	-0.069	7.912	1127.240***	1311.132***
Switzerland	0.026	1.092	-0.686	12.925	1611.410***	1645.866***
Taiwan	0.035	1.623	-0.133	7.219	1901.973***	2312.435***
United Kingdom	0.019	1.089	-0.572	13.382	1744.494***	1852.172***
United States	0.035	1.154	-1.182	28.416	1116.876***	1189.748***

Notes: This table presents the mean, standard deviation (Std. Dev), skewness, kurtosis, and the test statistics for the ARCH-LM test using 5 respectively 10 lags. The ARCH-LM test's null hypothesis is no conditional heteroscedasticity. The ARCH-LM test statistic is TR^2 which follows a χ^2_p when p lags are used, shown at 1% (***) significance level. Stock returns are computed as $100 \times \log(P_{i,t}/P_{i-1,t})$.

Table 2: Summary Statistics of Country-specific GPR

Country	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
Australia	0.089	0.071	0.005	0.515	2.153	9.480
Belgium	0.149	0.130	0.018	1.016	3.074	16.440
Canada	0.229	0.160	0.057	1.724	4.102	30.681
Denmark	0.035	0.035	0.000	0.400	3.815	30.327
Finland	0.036	0.061	0.000	0.619	5.960	46.641
France	0.529	0.318	0.141	2.799	2.908	15.342
Germany	0.400	0.276	0.082	2.662	3.444	22.567
Hong Kong SAR	0.049	0.060	0.000	0.482	3.358	17.438
Israel	0.404	0.428	0.054	4.337	4.712	32.271
Italy	0.141	0.092	0.028	0.645	2.176	9.607
Japan	0.234	0.161	0.050	1.237	2.582	12.041
Netherlands	0.080	0.057	0.011	0.447	2.615	12.823
Norway	0.051	0.044	0.003	0.472	3.772	27.420
Portugal	0.023	0.024	0.000	0.245	4.578	37.041
South Korea	0.249	0.221	0.037	1.816	2.944	15.192
Spain	0.100	0.094	0.017	1.150	5.816	51.002
Sweden	0.052	0.050	0.003	0.549	4.369	33.607
Switzerland	0.060	0.055	0.000	0.510	3.893	25.524
Taiwan	0.060	0.079	0.000	0.740	3.271	18.313
United Kingdom	0.964	0.623	0.234	5.995	4.017	27.651
United States	2.353	1.248	0.751	13.229	4.341	31.650

Notes: This table presents the mean, standard deviation (Std. Dev), minimum value (Min), maximum value (Max), skewness, and kurtosis of the country-specific GPR indices.

4.2 Forecasting Total Variance

This subsection presents the out-of-sample forecasting results of total variance using the GARCH-MIDAS-RV+GPR model and the benchmark model GARCH-MIDAS-RV. Table 3 presents the results from the forecasting of total variance, which shows the short-term predictive ability of GPR.

Table 3: Total Variance Forecast Evaluation

Country	$MSPE_{RV}$	$MSPE_{RV+GPR}$	MSPE-adjusted	Standard error
Australia	8.447	8.395	0.073	0.062
Belgium	33.095	29.602	7.037	6.503
Canada	26.142	26.517	-0.224	0.715
Denmark	10.962	11.097	-0.020	0.074
Finland	12.443	12.536	0.120	0.127
France	24.488	24.987	-0.185	0.653
Germany	25.139	25.233	-0.003	0.083
Hong Kong SAR	13.656	13.785	-0.043	0.139
Israel	26.223	17.100	19.326	17.446
Italy	81.322	80.808	3.065*	2.150
Japan	14.243	13.941	0.507*	0.348
Netherlands	14.411	14.369	0.055**	0.031
Norway	8.425	8.682	0.083	0.145
Portugal	13.291	13.269	0.082**	0.045
South Korea	7.746	7.706	0.389**	0.230
Spain	43.884	43.282	0.696	0.564
Sweden	13.903	13.996	0.077	0.064
Switzerland	9.417	9.375	0.076	0.065
Taiwan	5.375	5.680	0.024	0.067
United Kingdom	13.114	13.170	0.023	0.063
United States	22.513	22.676	-0.151	0.139

Notes: This table presents the MSPE for GARCH-MIDAS-RV and GARCH-MIDAS-RV+GPR from the forecasting of total variance. In addition, the table displays the resulting coefficient from the MSPE-adjusted test presented by Clark and West (2007), together with its associated standard errors corrected with the Newey-West estimator, and shown at 10% (*), 5% (**), and 1% (***) significance levels.

In Table 3 we can see that the GARCH-MIDAS-RV+GPR has lower MSPE than the benchmark model in 10 of the total 21 countries without considering the statistical significance. Next, considering the MSPE-adjusted test we reject the null hypothesis for Italy and Japan at a 10% significance level, and for Netherlands, Portugal, and South Korea at a 5% significance level. The results indicate that country-specific GPR has predictive power when forecasting stock market volatility at short-term horizon in some advanced economies. One potential reason why GPR has predictive power in some countries while not in some countries is that the 21 advanced economies are a heterogeneous group with differences in the type of geopolitical risk. This argument can be related to the evidence in Salisu et al. (2022a) that act-related GPR offers better forecast performance than treat-related GPR for emerging economies. However, one should be cautious when interpreting the results based on a 10% significance level in a one-sided test, due to the risk of type I error.

4.3 Forecasting Long-term Variance

Table 4 presents the results from the forecasting of long-term variance. We can see that the GARCH-MIDAS-RV+GPR has lower MSPE than the benchmark model in 8 of the 21 countries without considering the statistical significance. However, when considering the MSPE-adjusted test the null hypothesis is rejected in 12 of the total 21 countries. For Canada, Portugal, Spain, and the United Kingdom we reject that the data is generated by the benchmark model but nevertheless, the benchmark models have the lowest MSPEs due to the noise associated with the additional parameters in GARCH-MIDAS-RV+GPR. This can be interpreted as that GPR has predictive ability in these countries, but the noise associated with the estimation of additional parameters offsets the benefits of including GPR.

Table 4 further shows how we reject the null hypothesis for France, Japan, and the Netherlands, at a 1% significance level, for Finland, Italy, and South Korea at a 5% significance level, and finally for Taiwan and the United States at a 10% significance level. In Table 5, one can see that MSPEs for both GARCH-MIDAS-RV and GARCH-MIDAS-RV+GPR are overall relatively large. The large values of MSPE are not surprising given that MSPE is a quadratic loss function, and the out-of-sample period includes subperiods of high volatility e.g. the COVID-19 stock market crash.

Table 4: Long-term Variance Forecast Evaluation

Country	MSPE_{RV}	MSPE_{RV+GPR}	MSPE-adjusted	Standard error
Australia	1465.320	1502.526	64.294	49.905
Belgium	2525.325	3286.747	77.738	308.485
Canada	6255.623	6293.693	132.393**	63.896
Denmark	670.959	1537.057	-238.826	134.109
Finland	1713.484	1465.414	622.871**	329.130
France	3125.260	2985.372	435.828***	184.209
Germany	3012.013	3234.743	12.134	79.760
Hong Kong SAR	866.102	2008.057	-24.890	257.440
Israel	2164.986	2166.425	-1.426	0.690
Italy	7332.686	6705.129	1603.199**	770.178
Japan	1922.360	1681.609	1214.954***	340.360
Netherlands	1588.378	1528.173	265.692***	96.733
Norway	1140.381	1693.358	106.036	222.548
Portugal	1387.585	1621.007	387.491***	113.659
South Korea	8667.906	7559.622	17920.712**	9560.559
Spain	3254.969	3270.244	333.596***	99.703
Sweden	15398.826	25598.019	-1877.142	2603.891
Switzerland	987.436	1107.699	42.074	46.293
Taiwan	2917.324	2687.219	5680.856*	3872.575
United Kingdom	1666.103	1761.131	47.192*	34.820
United States	4321.307	4229.810	180.410*	117.082

Notes: This table presents the MSPE for GARCH-MIDAS-RV and GARCH-MIDAS-RV+GPR from the forecasting of long-term variance. In addition, the table displays the resulting coefficient from the MSPE-adjusted test presented by Clark and West (2007), together with its associated standard errors corrected with the Newey-West estimator, and shown at 10% (*), 5% (**), and 1% (***) significance levels.

Furthermore, Table 4 shows how the models failed to produce reasonable forecasts of long-term variance in the Swedish stock market. This highlights the drawback of using methods that require numerical optimization since the log-likelihood function does not always converge to a global optimum. To address this problem the optimization algorithm is changed to an algorithm based on simulated annealing that during each iteration generates random trial points to avoid getting trapped on a local optimum (Goffe et al. 1994). As the simulated annealing algorithm uses random trial points in the optimization process it is not guaranteed to repeatedly converge to the same solution. The forecasting procedure of Swedish long-term variance using simulated annealing fails to systematically estimate the parameters in a way that produces reasonable forecast accuracy (see Appendix B). Consequently, no inference is made on the long-term variance for Sweden to avoid data mining bias.

The forecasting results for both total variance and long-term variance are summarized in Table 5. When comparing the MSPE-adjusted test for total variance and long-term variance we find that we reject that the data is generated by the benchmark model for 12 countries in the evaluation of long-term variance, while only for 5 countries in the evaluation of total variance. This indicates that the inclusion of country-specific GPR improves the prediction ability more for long-term horizon forecasts compared to short-term horizon forecasts. However, this is expected given how the GARCH-MIDAS-RV+GPR is specified. The only impact GPR has on total variance is indirect through its effect on long-term variance. The indirect impact of GPR on total variance is highlighted in Table 5 by the fact that all five countries with a significant MSPE-adjusted test for total variance also have a significant MSPE-adjusted test for long-term variance. That the inclusion of additional variables in a GARCH-MIDAS framework primarily benefits the predictability of long-term variance is in line with previous research (Asgharian et al. 2013; Virk et al. 2024).

Table 5: Summary of Forecasting Results

	Total Variance		Long-term Variance	
Country	MSPE-difference	MSPE-adjusted	MSPE-difference	MSPE-adjusted
Australia	+	+	−	+
Belgium	+	+	−	+
Canada	−	−	−	+**
Denmark	−	−	−	−
Finland	−	+	+	+**
France	−	−	+	+***
Germany	−	−	−	+
Hong Kong SAR	−	−	−	−
Israel	+	+	−	−
Italy	+	+*	+	+**
Japan	+	+*	+	+***
Netherlands	+	+**	+	+***
Norway	−	+	−	+
Portugal	+	+**	−	+***
South Korea	+	+**	+	+**
Spain	+	+	−	+***
Sweden	−	+	−	−
Switzerland	+	+	−	+
Taiwan	−	+	+	+*
United Kingdom	−	+	−	+*
United States	−	−	+	+*

Notes: This table presents a summary of the forecasting of total variance and long-term variance. MSPE-difference shows the sign of the difference between the MSPE from GARCH-MIDAS-RV and the MSPE from GARCH-MIDAS-RV+GPR, where a plus sign means that the GARCH-MIDAS-RV+GPR have the lowest MSPE. In addition, the table displays the sign of coefficient from the MSPE-adjusted test presented by Clark and West (2007) and shown at 10% (*), 5% (**), and 1% (***) significance levels.

In Table 5, one can see that there is no evidence of GPR having predictive ability in Australia, Belgium, Denmark, Germany, Hong Kong SAR, Israel, Norway, Sweden, and Switzerland. The absence of GPR forecasting ability in some countries is to a certain extent consistent with the evidence in Zhang et al. (2023) that GPR affects countries differently. For example, Zhang et al. (2023) found that GPR has a smaller impact on volatility in countries that are at war. This could explain why this study finds no predictive ability in a country like Israel that has a long history of wars. In Table 5, we see that Finland is the only one of the Nordic countries where the predictive ability of GPR is significant, which could be related to a larger exposure to geopolitical risk due to the border against Russia. Previous research by Salisu et al. (2022a) found evidence of GPR having out-of-sample predictability of volatility in emerging economies, while Zhang et al. (2023) provided evidence that GPR has a less significant effect on volatility in advanced economies compared to emerging economies. Given the combination of results in Salisu et al. (2022a) and Zhang et al. (2023), one could argue that this study's result of GPR having out-of-sample predictive ability of stock market volatility in some advanced economies is coherent with previous research.

5 Conclusion

This study has examined if geopolitical risk indices have predictive ability when forecasting stock market volatility in advanced economies by using a GARCH-MIDAS approach. Stock market indices from 21 advanced economies were used to perform the analysis. In addition to the smoothed realized variance, the long-term variance component included the country-specific geopolitical risk index. An expanding estimation window was used to estimate the parameters and make pseudo-out-of-sample forecasts of total variance and long-term variance. The forecasting ability of the model was compared to the traditional GARCH-MIDAS-RV.

The results indicate that geopolitical risk indices do have a predictive ability for stock market volatility in certain advanced economies but not in all advanced economies. This study contributes by highlighting that geopolitical risk indices have a mixed predictive ability among advanced economies, which demonstrates the importance of evaluating the forecasting ability separately for each country. The empirical findings further show that geopolitical risk indices can improve the forecasting accuracy for both short-term total variance and long-term variance, but how the improvements are primarily related to long-term variance. The results of this study are of practical relevance for both investors and risk managers in their assessment of market risk.

Future research on this topic should consider including the geopolitical risk indices in a heterogeneous autoregressive (HAR) model, since the GARCH-MIDAS framework requires estimation of a large number of parameters using numerical optimization which may not always find the global optimum of the log-likelihood function. Another area that future research should consider is to investigate potential structural breaks in the relationship between geopolitical risk and stock market volatility, and the economic significance of including geopolitical risk indices in forecasts of stock market volatility.

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Appendix A

Table 6: Description of Stock Market Indices

Country	Stock Index	Data Coverage
Australia	AS30	Jan., 1985 - June 2024
Belgium	BEL20	Dec., 1990 - June 2024
Canada	SPTSX	Jan., 1985 - June 2024
Denmark	MXDK	Jan., 1985 - June 2024
Finland	HEX	Jan., 1987 - June 2024
France	CAC	July, 1987 - June 2024
Germany	DAXS	Jan., 1985 - June 2024
Hong Kong SAR	HSI	Jan., 1985 - June 2024
Israel	TA-125	Dec., 1991 - June 2024
Italy	IT30	Jan., 1992 - June 2024
Japan	NKY	Jan., 1985 - June 2024
Netherlands	AEX	Jan., 1985 - June 2024
Norway	MXNO	Jan., 1985 - June 2024
Portugal	PSI20	Dec., 1992 - June 2024
South Korea	KOSPI	Jan., 1985 - June 2024
Spain	IBEX	Jan., 1987 - June 2024
Sweden	OMXS30	Sept., 1986 - June 2024
Switzerland	MXCH	Jan., 1985 - June 2024
Taiwan	TWSE	Jan., 1985 - June 2024
United Kingdom	UKX	Jan., 1985 - June 2024
United States	SPX	Jan., 1985 - June 2024

Notes: This table presents the 21 advanced economies with their corresponding stock market index used in this study. The table also displays the time periods of each stock market index.

Appendix B

Table 7: Sweden Long-term Variance Using Simulated Annealing Algorithm

Attempt	MSPE_{RV}	MSPE_{RV+GPR}
Attempt 1	190992.020	1654129.381
Attempt 2	32501.364	10236.336
Attempt 3	25644.804	2630.030
Attempt 4	73276.937	10503.047
Attempt 5	619415.432	1614.875
Attempt 6	1279.282	1675198.449
Attempt 7	1129190.114	1369.011
Attempt 8	3308.581	1713.874
Attempt 9	2037973.703	1355.751
Attempt 10	1455.591	1936.302

Notes: This table presents the long-term variance forecasting performance for Sweden when using the simulated annealing algorithm (Goffe et al. 1994). The first column displays the MSPE for GARCH-MIDAS-RV and the second column displays the MSPE for GARCH-MIDAS-RV+GPR.