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The Roles of Global Supply Chain Pressure and Economic Conditions in Forecasting the VaR of Commodity Markets: A Quantile GARCH-MIDAS Approach

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Abstract

Accurately predicting the Value-at-Risk (VaR) in commodity markets is crucial for risk management, yet the volatility and cyclicality of commodity prices pose significant challenges. This paper innovatively incorporates the information content of the Global Supply Chain Pressure Index (GSCPI) and the Global Economic Conditions Index (GECON) into the quantile Genaralized Autoregressive Conditional Heteroskedasticty-Mixed Data Sampling (GARCH-MIDAS) framework to address the issue of mismatched data frequencies, and explores the impact of these monthly indicators on daily commodity returns volatility. We find that the MIDAS framework significantly outperforms the conditional autoregressive VaR by regression quantiles (CAViaR) model, with asymmetric models showing superior performance. Both GSCPI and GECON exhibit strong explanatory power for VaR forecasting, highlighting the important influence of global supply and demand conditions on returns volatility of the overall commodity market, as well as its various sub-sectors.

Keywords: VaR predictions, Quantiles-based mixed-frequency models, Commodity market

JEL Codes: C32, C53, E23, E32, Q02

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1 Introduction

Over the last two decades, and especially post the Global Financial Crisis in 2007-2009, commodity markets have witnessed a process of financialization that has resulted in increased participation of institutional investors (for example, hedge funds, pension funds, and insurance companies) in this sector (Ohashi & Okimoto, 2016; Silvennoinen & Thorp, 2013; Tang & Xiong, 2012). This, in turn, has resulted in the emergence of commodities as an alternative asset class, relative to the standard investment vehicles, held by investors in search of possible diversification benefits (Adams & Gluck, 2015; Cheng et al., 2015; Cheng & Xiong, 2014; Hamilton & Wu, 2015). In this regard, accurate estimation and prediction of a benchmark estimate of downside risk, such as the Value-at-Risk (VaR), is likely to play a critical role in investment decisions associated with commodities. Note that VaR provides a quantifiable threshold for potential portfolio losses within a specified confidence level and time horizon, making it indispensable for financial institutions.

With the global economy continuing to witness severe supply chain constraints ever since the outbreak of the COVID-19 pandemic due to ongoing multiple geopolitical acts and threats and ever-escalating climate risks (Burriel et al., 2024; Caldara et al., 2025), the objective of our paper is to predict (in- and out-of-sample) the VaR of the overall commodity market, as well as its various sub-sectors (agriculture, energy, metals), based on the information content of a measure of global supply chain bottlenecks. The Global Supply Chain Pressure index (GSCPI), as developed by Benigno et al. (2022) and used by us in this paper to capture supply bottlenecks, is expected to drive shortages emanating from disruption in transportation, and impact commodity price fluctuations (Diaz et al., 2023; Gozgor et al., 2023). Moreover, the GSCPI has been associated with negative effects on output (Ascari et al., 2024; Ginn, 2024; Ginn & Saadaoui, 2025), which, in turn, would affect commodity prices via the demand-channel (Chen & Huang, 2022; Zhang, 2021). Finally, being an overall proxy for rare disasters (Bouri et al., 2025; Polat et al., 2025), supply chain constraints reflected by the GSCPI can alter investor expectations and risk preferences (Gabaix, 2012; Gourio, 2012), and due to the financial attributes of the commodity market pointed out above, these changes can significantly impact commodity price movements via the dominant jump risks component (Demirer et al., 2018; Nel et al., 2024).

Besides the GSCPI, for the sake of comparison from the perspective of a global predictor, we also use a measure of Global Economic Conditions (GECON), recently created by Baumeister et al. (2022), which has been shown to explain variability of commodity prices (Baumeister et al., 2022; Salisu et al., 2020, 2022; Wang et al., 2022). We also combine the information carried by GSCPI and GECON, based on a Principal Component Analysis (PCA), in our prediction experiment, to check if this scenario performs better than the two predictors considered individually from the perspective of VaR. VaR estimation are generally based on parametric, nonparametric, and semi-parametric approaches. In this regard, the parametric approaches are generally associated with the variance-covariance method involving the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-family models, besides the RiskMetrics variance model of J.P. Morgan. Under the assumption that the pattern of historical returns or simulated returns from a stochastic process is indicative of future returns, the non-parametric approaches are captured by historical simulation, as well as the Monte Carlo simulation method. As far as Semi-parametric methods are concerned, while they do not require assumptions about return distributions, some parameters still needs to be estimated. Given this, Bali (2003) proposes the extreme value theory approach as a semi-parametric method to evaluate VaR. With quantile regressions (Koenker & Bassett, 1978) being an alternative semi-parametric method that can directly obtain an estimate of the left-tailed quantile (i.e., VaR), Engle & Manganelli (2004) proposed a conditional autoregressive VaR by regression quantiles (CAViaR) model, which allows one to capture the dynamic evolution of VaR.

The literature associated with VaR predictions of the commodities, with strong focus on the oil market, has primarily relied on the parametric approach in univariate settings (see, Junior et al. (2022); Laporta et al. (2018); Lux et al. (2016); Lyu et al. (2025) for detailed discussions in this regard), and we add to this line of research from multiple directions. First, we incorporate the role of predictors capturing global demand and supply conditions in a semi-parametric quantile regression (QR) setting in predicting VaR for a wide coverage of the commodity sector. Second, and more importantly, with the GSCPI and GECON variables available monthly, instead of using a common-frequency approach, and thereby standing the chance to lose valuable information through temporal aggregation (Clements & Galvão, 2008) contained in the daily price data of the commodities, we rely on a mixed-frequency method. In particular, inspired by the GARCH-Mixed Data Sampling (MIDAS) model (Engle et al., 2013), we utilize the semi-parametric quantile regression-based GARCH-MIDAS model for VaR prediction (QR-GARCH-MIDAS) of Xu et al. (2021), allowing direct estimation of VaR using mixed-frequency information. Intuitively speaking, the GARCH-MIDAS approach is motivated by the argument that there are different components to volatility, namely, one pertaining to short-term fluctuations and the other to a long-run aspect, with the latter likely to be affected by slow-moving predictors, like the GSCPI and GECON, associated with the global economy. While the GARCH-MIDAS model can predict VaR using mixed-frequency information, but it requires assuming a distribution of returns, which we achieve via its QR-GARCH-MIDAS version. Finally, our study can be considered as an extension of the empirical implementation part of Xu et al. (2021), who analyzed the role of a monthly metric of uncertainty in VaR prediction of the oil market. Recall that, we are considering the overall commodity market and its sub-sectors, based on broader measures (i.e., beyond uncertainty) of demand-supply conditions prevailing globally, with GSCPI and GECON capturing not only various types of disaster risks but also economic- and financial-state of major economies of the world.

The rest of our paper is organized as follows: Section 2 outlines the data, while Section 3 outlines our econometric approach. Section 4 presents the results from our predictive analyses with Section 5 concluding the paper.

2 Data Description

The S&P GSCI serves as a benchmark for investment in the commodity markets and as a measure of performance of the market over time. It is a tradable index that is readily available to market participants. In this regard, we obtain daily data from Datastream for indexes covering the overall market, as well as the sub-sectors of precious metals, energy, non-energy, industrial metals, and agriculture, which, in turn, is further broken down into livestock, softs, and grains. We take log-differences to compute logarithmic returns of these indexes, and serve as our dependent variables.

As far the GSCPI of Benigno et al. (2022) is concerned, it is a summary indicator of global supply chain pressure based on Purchasing Managers' Index (PMI) surveys for manufacturing firms in China, the euro area, Japan, Korea, Taiwan, the United Kingdom (UK), and the United States (US), measures of transportation costs such as the HARPEX and the Baltic Dry Index and an indicator of airfreight costs. [1] Regarding the GECON index of Baumeister et al. (2022), it is a factor, derived using the expectation maximization (EM) algorithm, based on 16 indicators associated with economic activity, commodity (copper) prices, financial indicators, transportation, uncertainty and expectation measures, weather and energy-related indicators. [2] Additionally, we derive a synthetic variable (denoted as PCA), which is the first principal component of GSCPI and GECON, to integrate information from these predictors, and see how this combination performs in the context of our VaR predictions.

The sample consists of 6,605 daily observations involving the log-returns of the Total Return indexes of the commodities, and 317 monthly observations of the levels of GSCPI and GECON, spanning from January 1, 1998, to May 31, 2024, based on data availability at the time of writing this paper. Observations from January 1, 1998, to October 24, 2017, are employed for model estimation, while data from October 25, 2017, to May 31, 2024, are reserved for out-of-sample forecasting.

Table 1 presents descriptive statistics—including mean, standard deviation, minimum, maximum, skewness, and kurtosis. The mean returns of most commodities is negative, with only precious metals and industrial metals exhibiting a positive values. Regarding volatility, the energy market has the highest standard deviation and the largest fluctuation range. Moreover, nearly all commodities, particularly those in the energy sector, show negative skewness, indicating a higher probability of extreme negative returns. Finally, most variables have a kurtosis greater than 3, showing a leptokurtic distribution. Notably, energy commodities and GECON display particularly prominent extreme volatility characteristics, with the presence of a fat-tailed phenomenon. The non-normality of the commodity returns provides preliminary motivation to adopt a quantiles-based modeling approach.

[1] The data can be accessed from: :https://www.newyorkfed.org/research/policy/gscpi#/overview.
[2] The data is available for download from: https://sites.google.com/site/cjsbaumeister/datasets?authuser=0.

Table 1: **Descriptive statistics of variables**

Column	Mean	Std	Min	Max	Skew	Kurt
Commodity	-0.001	0.018	-12.522	7.617	-0.470	4.472
Precious Metal	0.029	0.014	-10.105	8.763	-0.257	6.026
Energy	-0.004	0.026	-30.169	15.983	-0.807	11.980
Non-Energy	-0.001	0.010	-5.829	5.870	-0.310	3.620
Industrial Metals	0.016	0.016	-9.015	7.588	-0.209	3.021
Agriculture	-0.014	0.015	-7.475	7.157	-0.057	2.505
Livestock	-0.011	0.012	-6.237	5.302	-0.234	1.794
Softs	-0.007	0.016	-8.886	6.379	-0.168	1.850
Grains	-0.017	0.018	-8.413	7.689	0.035	2.244
GSCPI	0.006	0.012	-1.330	4.290	2.092	4.571
GECON	-0.055	0.006	-4.458	1.390	-3.447	23.014
PCA	-0.001	0.013	-1.720	8.296	3.127	17.225

Note: Commodities are in log-returns; GSCPI and GECON are in levels; PCA being the first principal component of GSCPI and GECON.

3 Methodology

3.1 The QR-GARCH-MIDAS Model

Given that our time series data are of mixed frequencies, we let $i = 1, \dots, N_t$ and $t = 1, \dots, T$ denote daily and monthly frequency respectively, with N_t representing the number of trading days in a given month t. Letting the log-returns of indexes $P_{i,t}$ be $r_{i,t} := \ln P_{i,t} - \ln P_{i-1,t}$, we model the time series of $\{r_{i,t}\}$ as the following:

$$r_{i,t} = \mu_{i,t} + a_{i,t}, \tag{1}$$

where $\mu_{i,t} := E[r_{i,t}|F_{i-1,t}]$ is the conditional expectation of $r_{i,t}$ based on the information set $F_{i-1,t}$ and $\mathrm{Var}(r_{i,t}|F_{i-1,t}) = \mathrm{Var}(a_{i,t}|F_{i-1,t})$. For a given $\xi \in (0, 1/2]$, our main focus is the time-series model of the conditional ξ-th quantile of $r_{i,t}$, $Q_\xi(r_{i,t}|F_{i-1,t})$, and the suitable choice of the information set $F_{i-1,t}$. For this purpose, we adopt the symmetric threshold GARCH(1,1) model proposed by Zakoian (1994), and modify the univariate GARCH-MIDAS model proposed by Engle et al. (2013) as follows:

$$a_{i,t} = \sigma_{i,t}\tau_t\epsilon_{i,t}, \quad \epsilon_{i,t} \overset{\text{i.i.d.}}{\sim} F_\epsilon(x), \tag{2}$$

$$\sigma_{i,t} = \alpha_0 + \alpha_1\frac{|a_{i-1,t}|}{\tau_t} + \beta\sigma_{i-1,t}, \tag{3}$$

$$\log(\tau_t) = m + \theta\sum_{k=1}^{K}\phi_k(\omega)X_{t-k}. \tag{4}$$

where $F_\epsilon(x)$ is some distribution satisfying mean 0 and variance 1. The parameter θ measures the influence of a low-frequency variable, X_{t-k}, on the low-frequency volatility, τ_t. When $\theta = 0$, τ_t becomes a constant, and the modified univariate GARCH-MIDAS model becomes the symmetric threshold GARCH(1,1) model. Here, X_{t-k} and θ can be negative, so we take the logarithm of τ_t to keep it positive. Regarding the weighting function, $\phi_k(\omega)$, of the lag-terms of the low-frequency variable, we adopt the Beta-weighting scheme proposed by Conrad et al. (2014):

$$\phi_k(\omega) = \frac{(1-k/K)^{\omega-1}}{\sum_{l=1}^{K}(1-l/K)^{\omega-1}}. \tag{5}$$

Here, k represents the lag order of the low-frequency variable, K is the maximum number of lag-terms considered, and ω is a shape parameter, which determines how the weights decay or distribute across different lag-terms.

Let the ξ-th quantile of the i.i.d. random variable $\epsilon_{i,t}$ be ϵ_ξ, then we have:

$$\begin{aligned} Q_\xi\left(r_{i,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i,t} &= \sigma_{i,t}\tau_t\epsilon_\xi \\ &= \left[\alpha_0 + \alpha_1\frac{|a_{i-1,t}|}{\tau_t} + \beta\sigma_{i-1,t}\right]\tau_t\epsilon_\xi \\ &= \epsilon_\xi\left[\alpha_0\exp\left(m + \theta\sum_{k=1}^{K}\phi_k(\omega)X_{t-k}\right) + \alpha_1|a_{i-1,t}|\right] + \beta\left[Q_\xi\left(r_{i-1,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i-1,t}\right] \\ &= \gamma_0\exp\left(m + \theta\sum_{k=1}^{K}\phi_k(\omega)X_{t-k}\right) + \gamma_1|a_{i-1,t}| + \beta\left[Q_\xi\left(r_{i-1,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i-1,t}\right]. \end{aligned} \tag{6}$$

where $\gamma_0 = \epsilon_\xi\alpha_0$ and $\gamma_1 = \epsilon_\xi\alpha_1$. Note that we are focusing on the left tail of the log-returns $r_{i,t}$, therefore $Q_\xi(r_{i,t}|F_{i-1,t})$ and ϵ_ξ are assumed to be negative.

It is well known in the literature that "good" and "bad news" have asymmetric influence on future volatility, which is the so-called leverage effect (Black, 1976). In order to capture this feature in our model, we call the former model symmetric-MIDAS (S-MIDAS), and propose the following asymmetric-MIDAS (A-MIDAS) set-up:

$$\begin{aligned} Q_\xi\left(r_{i,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i,t} = \gamma_0\exp\left(m + \theta\sum_{k=1}^{K}\phi_k(\omega)X_{t-k}\right) + \gamma_1\left(a_{i-1,t}\right)^{+} + \gamma_2\left(a_{i-1,t}\right)^{-} \\ + \beta\left[Q_\xi\left(r_{i-1,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i-1,t}\right]. \end{aligned} \tag{7}$$

When $\theta = 0$, which means the low-frequency explanatory variable has no influence on the conditional quantile of $r_{i,t}$, our models become:

$$Q_\xi\left(r_{i,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i,t} = \gamma_0 + \gamma_1|a_{i-1,t}| + \beta\left[Q_\xi\left(r_{i-1,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i-1,t}\right]. \tag{8}$$

for the symmetric set-up, and

$$Q_\xi\left(r_{i,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i,t} = \gamma_0 + \gamma_1\left(a_{i-1,t}\right)^{+} + \gamma_2\left(a_{i-1,t}\right)^{-} + \beta\left[Q_\xi\left(r_{i-1,t}|\mathcal{F}_{i-1,t}\right) - \mu_{i-1,t}\right], \tag{9}$$

for the asymmetric case. Therefore, we call them the symmetric (S) and asymmetric (A) set-ups, respectively. We use these two models as benchmarks to compare the performance of adding a low-frequency explanatory variable (GSCPI, GECON, or PCA) in predicting daily VaR.

3.2 Model Estimation

In our empirical analyses, we estimate the four cases of S-MIDAS, A-MIDAS, S-CAViaR, and A-CAViaR, corresponding to equations (6), (7), (8), and (9) respectively. For simplicity, we assume $\mu_{i,t} = \mu$ does not vary over time.

Model parameters are estimated by minimizing the following objective function:

$$\min_{\Theta} \sum_{t=1}^{T} \sum_{i=1}^{N_t} \rho_{\xi} \left(r_{i,t} - Q_{\xi} \left(r_{i,t} | \mathcal{F}_{i-1,t} \right) \right), \tag{10}$$

where the parameters are encapsulated by $\Theta = (\mu, \beta, m, \theta, \omega, \gamma')'$, $\rho_{\xi}(z) = (\xi - I\{z < 0\})z$, with $I\{\cdot\}$ being an indicator function. The estimation involves a nonlinear quantile regression, due to the nonlinearity of the function: $Q_{\xi}(r_{i,t}|F_{i-1,t})$.

For the S-CAViaR model, we adopt the quantile regression results of Engle & Manganelli (2004) to serve as its initial values. Subsequently, the initial values for the A-CAViaR model are set through a multi-start optimization process, which combines the regression results of the S-CAViaR model with initial values generated by random perturbations. As for the MIDAS models, the initial values for the S-MIDAS model are specified based on both the aforementioned regression results and the regression results of the GARCH-MIDAS model reported in Engle et al. (2013). Similarly, the initial values for the A-MIDAS model are set following the same logic. Furthermore, drawing on the findings of Hahn (1995) and Buchinsky (1995) regarding the effectiveness of the bootstrap method in quantile regression estimations, we employ the error bootstrap approach to obtain the p-values of the parameters.

3.3 Backtesting VaR

Backtesting is important for validating the accuracy and reliability of VaR models. It involves comparing the predicted VaR, $\hat{r}_{i,t,\xi} := \hat{Q}_{\xi}(r_{i,t}|F_{i-1,t})$, against actual outcomes, $r_{i,t}$, to ensure the effectiveness of the model in real-world scenarios. Several key aspects are essential when conducting backtesting for VaR, and includes coverage, independence, and the choice of a scoring function (or loss function). These factors help assess how well the model captures risk and its predictive power.

3.3.1 Coverage

Coverage refers to the proportion of times the actual losses exceed the VaR estimates. A well-calibrated VaR model should exhibit a coverage rate that is close to the confidence level used in the VaR calculation. For instance, if a 95% confidence level is used, the model should produce exceptions (i.e., instances where losses exceed the VaR estimate) approximately 5% of the time. The coverage test, often implemented using the Kupiec's Proportion of Failures (POF) test (Kupiec et al., 1995), evaluates whether the observed exception rate is statistically consistent with the expected rate. If the model fails this test, it suggests that the VaR estimates are either too conservative or too lenient.

3.3.2 Independence

Independence tests assess whether the exceptions are independently distributed over time. A good VaR model should not exhibit clustering of exceptions, as this would indicate that the model fails to capture certain dependencies or volatility clustering in the data. The Wald statistic test is commonly used to evaluate this aspect (Engle & Manganelli, 2004). If the exceptions are found to be serially correlated, it may suggest that the model needs to be adjusted to better account for time-varying volatility or other dependencies in the data.

3.3.3 Scoring Function (Loss Function)

Scoring functions, or loss functions, provide a quantitative measure of the accuracy of VaR estimates. These functions assign a penalty based on the magnitude of the deviation between the actual losses and the VaR estimates. A commonly used scoring function is the Quantile Loss Function (Koenker & Hallock, 2001), which penalizes exceptions more heavily than non-exceptions. The loss function can be defined as:

$$\text{Quantile Loss}\left(r_{i,t}, \hat{r}_{i,t,\xi}; \xi\right) = \begin{cases} \xi \cdot \left(r_{i,t} - \hat{r}_{i,t,\xi}\right), & \text{if } r_{i,t} \geq \hat{r}_{i,t,\xi} \\ (1-\xi) \cdot \left(\hat{r}_{i,t,\xi} - r_{i,t}\right), & \text{if } r_{i,t} < \hat{r}_{i,t,\xi} \end{cases} \tag{11}$$

In our empirical study, we provide the results of Kupiec's Proportion of Failures test, Wald statistic independence test, and the average quantile loss at 95% and 99% level for each model under consideration.

4 Empirical Findings

We present the in-sample estimation and out-of-sample backtesting results for nine MIDAS models. The reported parameters include the unconditional mean returns (μ), the ARCH term (γ_1 and γ_2), the GARCH term (β_1), the adjusted beta weights (ω), and the low-frequency coefficient term (θ) for the contending GARCH-MIDAS model variants. The models are estimated with GSCPI, GECON, and PCA as the low-frequency variable. Considering the impact of economic cycles, we set K as 12.

Additionally, we performed three backtesting tests on the out-of-sample VaR, including the Coverage Test (Kupiec-POF), Independence Test (Wald Test), Multiple Levels of Backtesting, and calculated the Scoring Function (Loss Function). All results from model estimation and tests are listed in Tables 2 to 10.

4.1 Estimation and Backtests of MIDAS and CAViaR

The results pertaining to the Commodity Total Return index, corresponding to the overall commodity sector, are presented in Table 2. With regards to the in-sample estimation performance, only the coefficients of the S-MIDAS model are statistically significant at the 1% quantile level. Regarding the out-of-sample VaR backtesting results, all models failed the Kupiec-POF test at the 1% quantile level. In contrast, only the S-CAViaR model failed the Kupiec-POF test at the 5% quantile level. These findings suggest that the MIDAS framework tends to outperform the CAViaR model.

As indicated by the results for the Precious Metal Total Return index in Table 3, when compared with the MIDAS model, the CAViaR model exhibits relatively weaker performance in the out-of-sample tests. Across the two quantile levels, only the S-CAViaR model failed all the tests.

The results for the Energy Total Return Index in Table 4 reveal that the A-MIDAS model demonstrates the best in-sample fitting performance. All A-MIDAS models successfully passed the out-of-sample tests, whereas only the GECON case did so under the S-MIDAS model. Conversely, the CAViaR models failed to pass the Kupiec-POF test at the 5% significance level.

From the results of the Non-Energy Total Return index in Table 5, it can be observed that the coefficients of both the A-MIDAS (GECON) and A-MIDAS (PCA) models are significant at the 1% level, indicating that these two models possess excellent in-sample fitting performance. In terms of out-of-sample backtesting results, the CAViaR models failed the tests, while all MIDAS models passed them. In general, the A-MIDAS model exhibits the best performance.

The findings for the Industrial Metals Total Return index in Table 6 show that all MIDAS models passed the tests, and the differences among the models are negligible. In contrast, the S-CAViaR model failed the out-of-sample backtesting. On the whole, the MIDAS models demonstrate stronger performance in the out-of-sample tests.

Regarding the results for the Agriculture Total Return index in Table 7, the coefficients of the A-MIDAS (PCA) model are significant at the 5% level, indicating that this model provides a good fit for the in-sample data. In terms of out-of-sample backtesting results, there is little variation among the MIDAS models, but a substantial gap exists between the MIDAS and CAViaR models. Overall, the MIDAS model outperforms the CAViaR model, and the A-MIDAS model performs better than the S-MIDAS model.

The results for the Livestock Total Return index in Table 8 demonstrate that the A-MIDAS (PCA) model depicts the best in-sample fitting performance. Additionally, all asymmetric (A) models passed the out-of-sample backtesting, indicating that the asymmetric (A) models outperform the symmetric (S) models.

The results for the Softs Total Return index in Table 9 reveal that both the S-MIDAS model and the S-CAViaR model failed the Kupiec-POF test at the 1% level, while the A-MIDAS model passed the test at both significance levels. This implies that, in the context of soft commodities , the asymmetric (A) models outperform their symmetric (S) counterparts.

The results for the Grains Total Return index in Table 10 indicate that all CAViaR models failed the out-of-sample backtesting, while all MIDAS models passed. This shows that, in the context of grains, the MIDAS model outperforms the CAViaR model.

In summary, in terms of models, the asymmetric MIDAS models (A-MIDAS) outperform the symmetric MIDAS models (S-MIDAS), which in turn outperform the CAViaR models. In terms of variable selection, incorporating low-frequency economic indicators (especially, GECON and PCA) into the models can significantly enhance their ability to capture long-term risks.

Table 2: Estimation Results: Commodity Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	-0.104^{**}	-0.097^{**}	-0.098^{**}	-0.031	-0.101^{**}	-0.098^{**}
p values	-	-	0.000	0.000	0.000	0.688	0.000	0.000
γ_0	-0.122^{**}	-0.102^{**}	-0.005	-0.087	-0.100^{**}	-0.072	-0.002	-0.077
p values	0.000	0.000	0.480	0.200	0.000	0.239	0.440	0.169
γ_1	-0.171^{**}	-0.184^{**}	-0.120	-0.030	0.284^{**}	-0.004	-0.124	-0.003
p values	0.000	0.000	0.360	0.200	0.000	0.369	0.326	0.232
γ_2	-	0.264^{**}	-	-0.456^{**}	-	-0.293^{**}	-	-0.473^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.924^{**}	0.913^{**}	0.917^{**}	0.854^{**}	0.885^{**}	0.902^{**}	0.917^{**}	0.847^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	-0.001^{**}	-0.001^{**}	-0.004^{**}	-0.010^{**}	-0.010^{**}	-0.008^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.460^{**}	1.000^{**}	1.000^{**}	1.580^{**}	1.980^{**}	1.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.030^{*}	0.018^{*}	0.005^{**}	0.005^{**}	0.001^{**}	0.010^{*}	0.003^{**}	0.018^{*}
Wald Test p values	0.340	0.125	0.588	0.410	0.431	0.588	0.588	0.431
Average quantile loss	0.059	0.058	0.059	0.059	0.059	0.058	0.059	0.058
5%VaR								
μ	-	-	-0.105^{**}	-0.093^{**}	-0.069^{**}	-0.077^{**}	-0.105^{**}	-0.108^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.069^{**}	-0.051^{**}	-0.060	-0.082	-0.030	-0.067	-0.017	-0.079
p values	0.000	0.000	0.158	0.102	0.749	0.306	0.680	0.136
γ_1	-0.256^{**}	0.158^{**}	-0.107	-0.009^{**}	-0.270	-0.013^{**}	-0.143	-0.013^{*}
p values	0.000	0.000	0.480	0.000	0.421	0.008	0.213	0.020
γ_2	-	-0.199^{**}	-	-0.176^{**}	-	-0.248^{**}	-	-0.209^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.857^{**}	0.897^{**}	0.853^{**}	0.891^{**}	0.686^{**}	0.858^{**}	0.807^{**}	0.863^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	-0.001^{**}	-0.003^{**}	-0.006^{**}	-0.009^{**}	-0.001^{**}	-0.008^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	2.240^{**}	10.000^{**}	2.090^{**}	4.260^{**}	2.370^{**}	2.460^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.046^{*}	0.062	0.546	0.222	0.475	0.703	0.787	0.622
Wald Test p values	0.807	0.768	0.610	0.164	0.245	0.263	0.328	0.450
Average quantile loss	0.187	0.181	0.176	0.175	0.180	0.175	0.175	0.176

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 3: Estimation Results: Precious Metals Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	0.065	0.100^{**}	0.086^{**}	0.098^{**}	0.098^{**}	0.095^{**}
p values	-	-	0.447	0.000	0.000	0.000	0.000	0.000
γ_0	-0.085^{**}	-0.091^{**}	-0.013	-0.067	-0.016	-0.046	-0.005	-0.072
p values	0.000	0.000	0.640	0.306	0.680	0.238	0.480	0.238
γ_1	-0.209^{**}	-0.180^{**}	-0.114	-0.054	-0.182	-0.001^{**}	-0.155	-0.025
p values	0.000	0.000	0.068	0.520	0.520	0.008	0.360	0.440
γ_2	-	-0.219^{**}	-	-0.750^{**}	-	-0.269^{**}	-	-0.378^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.924^{**}	0.921^{**}	0.901^{**}	0.796^{**}	0.897^{**}	0.912^{**}	0.856^{**}	0.831^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.001^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	4.690^{**}	10.000^{**}	4.670^{**}	10.000^{**}	10.000^{**}	10.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.041^{*}	0.055	0.240	0.906	0.240	0.522	0.240	0.549
Wald Test p values	0.217	0.214	0.214	0.691	0.781	0.297	0.214	0.498
Average quantile loss	0.045	0.037	0.037	0.037	0.037	0.036	0.037	0.036
5%VaR								
μ	-	-	0.039	0.106^{**}	0.107^{**}	0.105^{**}	0.096^{**}	0.120^{**}
p values	-	-	0.878	0.000	0.000	0.000	0.000	0.000
γ_0	-0.038^{**}	-0.051^{**}	-0.015	-0.054	-0.027	-0.065	-0.008	-0.072
p values	0.000	0.000	0.640	0.265	0.764	0.200	0.600	0.238
γ_1	-0.198^{**}	-0.228^{**}	-0.205	-0.002^{**}	-0.086	-0.008	-0.264^{**}	-0.004
p values	0.000	0.000	0.520	0.000	0.335	0.480	0.000	0.096
γ_2	-	-0.274^{**}	-	-0.143^{**}	-	-0.167^{**}	-	-0.210^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.896^{**}	0.863^{**}	0.762^{**}	0.897^{**}	0.870^{*}	0.877^{**}	0.732^{*}	0.857^{*}
p values	0.000	0.000	0.004	0.000	0.010	0.009	0.010	0.010
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.009^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	6.480^{**}	1.000^{**}	1.000^{**}	10.000^{**}	10.000^{**}	1.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.055	0.088	-0.323^{**}	0.523	0.269	0.180	0.600	0.222
Wald Test p values	0.047^{*}	0.072	0.504	0.420	0.746	0.769	0.400	0.629
Average quantile loss	0.138	0.118	0.117	0.116	0.116	0.116	0.117	0.116

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 4: Estimation Results: Energy Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	-0.107^{**}	-0.096^{**}	-0.052	-0.097^{**}	-0.115^{**}	-0.023
p values	-	-	0.000	0.000	0.466	0.000	0.000	0.596
γ_0	-0.105^{**}	-0.138^{**}	-0.014	-0.087^{*}	-0.101^{**}	-0.072	-0.025	-0.082
p values	0.000	0.000	0.600	0.043	0.002	0.238	0.800	0.101
γ_1	-0.111^{**}	-0.221^{**}	-0.078^{*}	-0.031	-0.216	-0.008^{**}	-0.065	-0.011^{*}
p values	0.000	0.000	0.280	0.135	0.36	0.000	0.561	0.048
γ_2	-	-0.346^{**}	-	-0.413^{**}	-	-0.238^{**}	-	-0.308^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.947^{**}	0.894^{**}	0.940^{**}	0.872^{**}	0.836^{**}	0.918^{**}	0.943^{**}	0.898^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	-0.010^{**}	-0.009^{**}	-0.010^{**}	-0.009^{**}	-0.010^{**}	-0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.000^{**}	1.000^{**}	1.000^{**}	1.200^{**}	1.510^{**}	1.050^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.010^{*}	0.008^{**}	0.018^{*}	0.083	0.051	0.051	0.018^{*}	0.051
Wald Test p values	0.383	0.207	0.506	0.207	0.317	0.541	0.529	0.371
Average quantile loss	0.205	0.096	0.105	0.095	0.097	0.098	0.106	0.096
5%VaR								
μ	-	-	-0.101^{**}	-0.080^{**}	-0.040	-0.080^{**}	-0.028	-0.016
p values	-	-	0.000	0.000	0.497	0.000	0.588	0.634
γ_0	-0.039^{**}	-0.102^{**}	-0.021	-0.082	-0.032	-0.077	-0.028	-0.077
p values	0.000	0.000	0.788	0.102	0.729	0.169	0.771	0.169
γ_1	-0.099^{**}	-0.150^{**}	-0.127	-0.013^{**}	-0.067^{**}	-0.007^{**}	-0.064^{**}	-0.005
p values	0.000	0.000	0.360	0.006	0.001	0.004	0.001	0.204
γ_2	-	-0.166^{**}	-	-0.222^{**}	-	-0.199^{**}	-	-0.218^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.944^{**}	0.895^{**}	0.860^{**}	0.878^{**}	0.912^{**}	0.878^{**}	0.910^{**}	0.882^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	9.860^{**}	10.000^{**}	4.420^{**}	2.320^{**}	2.040^{**}	2.290^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.017^{*}	0.020^{*}	0.020^{*}	0.091	0.171	0.113	0.171	0.113
Wald Test p values	0.379	0.331	0.949	0.431	0.075	0.228	0.075	0.337
Average quantile loss	0.301	0.298	0.278	0.275	0.280	0.278	0.280	0.275

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 5: Estimation Results: Non-Energy Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	-0.038	-0.107^{**}	-0.096^{**}	-0.119^{**}	0.056	-0.112^{**}
p values	-	-	0.454	0.000	0.000	0.000	0.397	0.000
γ_0	-0.002^{**}	-0.006^{**}	-0.001	-0.003^{**}	-0.002	-0.023^{**}	-0.005	-0.001^{**}
p values	0.000	0.000	0.560	0.000	0.363	0.000	0.647	0.000
γ_1	-0.389^{**}	-0.450^{**}	-0.229	-0.015	-0.200^{**}	-0.001^{**}	-0.351	-0.009^{**}
p values	0.000	0.000	0.400	0.200	0.000	0.000	0.320	0.001
γ_2	-	-0.382^{**}	-	-0.283^{**}	-	-0.446^{**}	-	-0.310^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.900^{**}	0.891^{**}	0.826^{**}	0.924^{**}	0.829^{**}	0.887^{**}	0.812^{**}	0.916^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.007^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	10.000^{**}	10.000^{**}	1.030^{**}	10.000^{**}	1.980^{**}	1.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.004^{**}	0.005^{**}	0.522	0.906	0.718	0.366	0.240	0.897
Wald Test p values	0.000^{**}	0.000^{**}	0.637	0.688	0.081	0.637	0.612	0.663
Average quantile loss	0.234	0.221	0.024	0.022	0.022	0.022	0.023	0.022
5%VaR								
μ	-	-	-0.019	-0.099^{**}	-0.106^{**}	-0.013	-0.103^{**}	-0.039
p values	-	-	0.702	0.000	0.000	0.776	0.000	0.450
γ_0	-0.006^{**}	-0.007^{**}	-0.008	-0.004	-0.007	-0.046	-0.016	-0.003
p values	0.000	0.000	0.520	0.440	0.720	0.283	0.680	0.360
γ_1	-0.130^{**}	-0.412^{**}	-0.298	-0.004^{*}	-0.148	-0.003^{**}	-0.188	-0.005^{**}
p values	0.000	0.000	0.427	0.022	0.318	0.000	0.479	0.000
γ_2	-	-0.525^{**}	-	-0.300^{**}	-	-0.293^{**}	-	-0.229^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.936^{**}	0.787^{**}	0.714^{**}	0.844^{**}	0.843^{*}	0.849^{**}	0.768^{*}	0.892^{**}
p values	0.000	0.000	0.000	0.000	0.040	0.000	0.040	0.000
θ	-	-	0.009^{**}	0.009^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	2.940^{**}	1.290^{**}	1.020^{**}	4.100^{**}	4.030^{**}	1.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.005^{**}	0.005^{**}	0.269	0.450	0.222	0.768	0.090	0.222
Wald Test p values	0.623	0.142	0.296	0.768	0.489	0.284	0.398	0.404
Average quantile loss	0.279	0.272	0.082	0.080	0.080	0.081	0.081	0.080

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 6: Estimation Results: Industrial Metals Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	0.105^{**}	0.097^{**}	0.101^{**}	0.102^{**}	0.099^{**}	0.095^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.117^{**}	-0.197^{**}	-0.001	-0.072	-0.009	-0.066	-0.005	-0.092^{**}
p values	0.000	0.000	0.440	0.238	0.680	0.353	0.480	0.006
γ_1	-0.207^{**}	-0.327^{**}	-0.133	-0.017	-0.136	-0.030	-0.181	-0.065
p values	0.000	0.000	0.400	0.440	0.400	0.480	0.320	0.120
γ_2	-	-0.408^{**}	-	-0.605^{**}	-	-0.485^{**}	-	-0.620^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.918^{**}	0.853^{**}	0.924^{**}	0.813^{**}	0.829^{**}	0.840^{**}	0.825^{**}	0.809^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.007^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	3.210^{**}	10.000^{**}	1.000^{**}	5.980^{**}	1.000^{**}	1.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.007^{**}	0.548	0.897	0.897	0.549	0.522	0.522	0.703
Wald Test p values	0.000^{**}	0.506	0.144	0.124	0.719	0.106	0.106	0.124
Average quantile loss	0.134	0.036	0.034	0.035	0.034	0.034	0.034	0.034
5%VaR								
μ	-	-	0.062^{**}	0.045^{**}	0.105^{**}	0.091^{**}	0.107^{**}	0.097^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.061^{**}	-0.059^{**}	-0.012	-0.028	-0.014	-0.053	-0.012	-0.034
p values	0.000	0.000	0.600	0.268	0.880	0.132	0.640	0.336
γ_1	-0.248^{**}	-0.189^{**}	-0.167	-0.010	-0.114	-0.017	-0.116	-0.003
p values	0.000	0.000	0.217	0.293	0.524	0.280	0.110	0.056
γ_2	-	-0.266^{**}	-	-0.279^{**}	-	-0.261^{**}	-	-0.258^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.859^{**}	0.870^{**}	0.815^{**}	0.871^{**}	0.822	0.856^{**}	0.868^{**}	0.863^{**}
p values	0.000	0.000	0.000	0.000	0.080	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.780^{**}	1.010^{**}	10.000^{**}	10.000^{**}	10.000^{**}	1.020^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.036^{*}	0.472	0.875	0.546	0.208	0.682	0.768	0.787
Wald Test p values	0.061	0.317	0.427	0.526	0.656	0.427	0.948	0.640
Average quantile loss	0.163	0.124	0.123	0.123	0.124	0.123	0.123	0.123

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 7: Estimation Results: Agriculture Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	-0.007^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.013^{**}	-0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.059^{**}	-0.052^{**}	-0.014	-0.058^{**}	-0.011	-0.072	-0.015	-0.046
p values	0.000	0.000	0.410	0.000	0.400	0.238	0.480	0.320
γ_1	-0.226^{**}	-0.276^{**}	-0.134^{*}	-0.016	-0.268	-0.012^{**}	-0.248	-0.011
p values	0.000	0.000	0.040	0.440	0.280	-0.440	0.400	0.320
γ_2	-	-0.313^{**}	-	-0.604^{**}	-	-0.479^{**}	-	-0.489^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.922^{**}	0.905^{**}	0.878^{**}	0.802^{**}	0.836^{**}	0.842^{**}	0.850^{**}	0.846^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.000^{**}	10.000^{**}	1.550^{**}	2.050^{**}	10.000^{**}	1.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.024^{*}	0.024^{*}	0.366	0.703	0.522	0.522	0.366	0.366
Wald Test p values	0.000^{**}	0.007^{**}	0.081	0.663	0.097	0.688	0.081	0.852
Average quantile loss	0.163	0.163	0.035	0.034	0.035	0.034	0.035	0.034
5%VaR								
μ	-	-	-0.025^{**}	-0.040^{**}	-0.009^{**}	-0.044^{**}	-0.010^{**}	-0.009^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.009^{*}	-0.026^{**}	-0.018	-0.073	-0.008	-0.089	-0.001	-0.008^{**}
p values	0.040	0.000	0.160	0.399	0.060	0.680	0.177	0.000
γ_1	-0.123^{**}	-0.191^{**}	-0.105	-0.006	-0.208	-0.045	-0.061^{**}	-0.010^{*}
p values	0.000	0.000	0.056	0.252	0.233	0.160	0.000	0.045
γ_2	-	-0.250^{**}	-	-0.317^{**}	-	-0.310^{**}	-	-0.228^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.938^{**}	0.883^{**}	0.865^{**}	0.835^{**}	0.783^{**}	0.813^{**}	0.944^{**}	0.888^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.008^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.020^{**}	1.000^{**}	10.000^{**}	10.000^{**}	10.000^{**}	10.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.008^{**}	0.007^{**}	0.384	0.772	0.768	0.053	0.180	0.090
Wald Test p values	0.000^{**}	0.053	0.723	0.582	0.927	0.260	0.968	0.115
Average quantile loss	0.286	0.284	0.120	0.118	0.121	0.120	0.120	0.119

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 8: Estimation Results: Livestock Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	-0.110^{**}	-0.099^{**}	-0.106^{**}	-0.100^{**}	-0.108^{**}	-0.097^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.133^{**}	-0.101^{**}	-0.021	-0.059	-0.005	-0.062	-0.013	-0.069
p values	0.000	0.000	0.720	0.403	0.480	0.372	0.600	0.480
γ_1	-0.446^{**}	-0.171^{**}	-0.111	-0.038	-0.189	-0.022	-0.141	-0.004^{**}
p values	0.000	0.000	0.401	0.264	0.363	0.438	0.152	0.000
γ_2	-	-0.303^{**}	-	-0.370^{**}	-	-0.263^{**}	-	-0.261^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.818^{**}	0.887^{**}	0.896^{**}	0.857^{**}	0.856^{**}	0.885^{**}	0.888^{**}	0.897^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.000^{**}	1.280^{**}	2.070^{**}	1.330^{**}	5.220^{**}	1.060^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.548	0.196	0.240	0.718	0.522	0.130	0.366	0.897
Wald Test p values	0.000^{**}	0.441	0.688	0.541	0.637	0.435	0.663	0.588
Average quantile loss	0.030	0.029	0.025	0.025	0.025	0.024	0.025	0.024
5%VaR								
μ	-	-	-0.126^{**}	-0.091^{**}	-0.081^{**}	-0.099^{**}	-0.106^{**}	-0.067^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.077^{**}	-0.099^{**}	-0.035	-0.072	-0.015	-0.057	-0.020	-0.064
p values	0.000	0.000	0.675	0.238	0.640	0.435	0.720	0.530
γ_1	-0.246^{**}	-0.082^{**}	-0.087	-0.002^{**}	-0.187	-0.011^{*}	-0.164	-0.009^{**}
p values	0.000	0.000	0.219	0.000	0.519	0.024	0.460	0.000
γ_2	-	-0.217^{**}	-	-0.272^{**}	-	-0.328^{**}	-	-0.302^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.838^{**}	0.866^{**}	0.867^{**}	0.849^{**}	0.789^{*}	0.841^{**}	0.807^{**}	0.847^{**}
p values	0.000	0.000	0.000	0.000	0.040	0.000	0.000	0.000
θ	-	-	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.009^{**}	-0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	10.000^{**}	1.000^{**}	4.950^{**}	4.000^{**}	3.540^{**}	1.990^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.560	0.699	0.964	0.875	0.703	0.703	0.787	0.856
Wald Test p values	0.041^{*}	0.800	0.171	0.516	0.828	0.450	0.480	0.610
Average quantile loss	0.110	0.108	0.096	0.094	0.096	0.094	0.096	0.093

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 9: Estimation Results: Softs Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	-0.097^{**}	-0.097^{**}	-0.060^{**}	-0.080^{**}	-0.095^{**}	-0.095^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.143^{**}	-0.114^{**}	-0.002	-0.069	-0.023	-0.072	-0.024	-0.082
p values	0.000	0.000	0.480	0.271	0.438	0.238	0.440	0.102
γ_1	-0.447^{**}	-0.375^{**}	-0.118^{**}	-0.023	-0.167^{*}	-0.013	-0.142^{**}	-0.023
p values	0.000	0.000	0.002	0.219	0.013	0.440	0.005	0.280
γ_2	-	-0.399^{**}	-	-0.458^{**}	-	-0.363^{**}	-	-0.461^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.839^{**}	0.857^{**}	0.900^{**}	0.834^{*}	0.830^{*}	0.865^{*}	0.891^{*}	0.834^{*}
p values	0.000	0.000	0.000	0.010	0.010	0.010	0.010	0.010
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	10.000^{**}	9.960^{**}	1.220^{**}	10.000^{**}	10.000^{**}	10.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.042^{*}	0.008^{**}	0.019^{*}	0.718	0.008^{**}	0.366	0.019^{*}	0.897
Wald Test p values	0.373	0.807	0.223	0.540	0.959	0.663	0.794	0.588
Average quantile loss	0.035	0.035	0.035	0.033	0.034	0.033	0.035	0.033
5%VaR								
μ	-	-	-0.126^{**}	-0.100^{**}	-0.107^{**}	-0.036^{**}	-0.104^{**}	-0.096^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.102^{**}	-0.065^{**}	-0.034	-0.055	-0.076^{*}	-0.063	-0.012	-0.065
p values	0.000	0.000	0.670	0.293	0.011	0.141	0.600	0.114
γ_1	-0.268^{**}	-0.134^{**}	-0.080^{**}	-0.006^{**}	-0.077^{**}	-0.012^{*}	-0.187	-0.015
p values	0.000	0.000	0.000	0.000	0.006	0.013	0.199	0.280
γ_2	-	-0.207^{**}	-	-0.240^{**}	-	-0.183^{**}	-	-0.243^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.827^{**}	0.890^{**}	0.892^{**}	0.870^{**}	0.915^{**}	0.876^{**}	0.806^{**}	0.859^{**}
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	2.770^{**}	1.000^{**}	10.000^{**}	10.000^{**}	2.580^{**}	10.000^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.048^{*}	0.272	0.145	0.946	0.222	0.946	0.145	0.875
Wald Test p values	0.532	0.892	0.444	0.620	0.811	0.153	0.586	0.389
Average quantile loss	0.129	0.122	0.122	0.121	0.122	0.120	0.123	0.121

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

Table 10: Estimation Results: Grains Total Return

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%VaR								
μ	-	-	-0.106^{**}	-0.097^{**}	-0.061^{**}	-0.098^{**}	-0.097^{**}	-0.094^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
γ_0	-0.030^{**}	-0.113^{**}	-0.042^{**}	-0.072	-0.022	-0.077	-0.012	-0.086^{*}
p values	0.000	0.000	0.000	0.238	0.320	0.170	0.400	0.043
γ_1	-0.265^{**}	-0.266^{**}	-0.248	-0.011	-0.266	-0.011	-0.162	-0.033
p values	0.000	0.000	0.240	0.230	0.160	0.112	0.320	0.150
γ_2	-	-0.248^{**}	-	-0.462^{**}	-	-0.326^{**}	-	-0.377^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.920^{**}	0.902^{**}	0.827^{**}	0.852^{**}	0.820^{*}	0.879^{**}	0.886^{*}	0.862^{**}
p values	0.000	0.000	0.000	0.000	0.040	0.000	0.040	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.009^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.000^{**}	1.000^{**}	1.280^{**}	2.300^{**}	2.140^{**}	1.020^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.007^{**}	0.037^{*}	0.906	0.366	0.522	0.366	0.703	0.522
Wald Test p values	0.013^{*}	0.565	0.155	0.852	0.097	0.081	0.115	0.097
Average quantile loss	0.285	0.058	0.043	0.043	0.043	0.043	0.044	0.043
5%VaR								
μ	-	-	-0.097^{**}	-0.072^{**}	-0.014	-0.094^{**}	-0.003	-0.094^{**}
p values	-	-	0.000	0.000	0.720	0.000	0.863	0.000
γ_0	-0.036^{**}	-0.040^{**}	-0.020	-0.047	-0.053^{**}	-0.017	-0.015	-0.020
p values	0.000	0.000	0.720	0.247	0.000	0.200	0.640	0.320
γ_1	-0.239^{**}	-0.225^{**}	-0.163	-0.015^{*}	-0.082	-0.017^{**}	-0.209	-0.014
p values	0.000	0.000	0.386	0.036	0.149	0.003	0.600	0.079
γ_2	-	-0.242^{**}	-	-0.189^{**}	-	-0.175^{**}	-	-0.267^{**}
p values	-	0.000	-	0.000	-	0.000	-	0.000
β	0.875^{**}	0.873^{**}	0.800	0.886^{**}	0.908^{**}	0.904^{**}	0.774^{**}	0.867^{**}
p values	0.000	0.000	0.080	0.000	0.000	0.000	0.000	0.000
θ	-	-	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}	0.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
ω	-	-	1.000^{**}	1.010^{**}	10.000^{**}	10.000^{**}	10.000^{**}	1.010^{**}
p values	-	-	0.000	0.000	0.000	0.000	0.000	0.000
Kupiec-POF p values	0.008^{**}	0.041^{*}	0.946	0.856	0.249	0.787	0.351	0.703
Wald Test p values	0.799	0.666	0.576	0.610	0.274	0.480	0.638	0.828
Average quantile loss	0.463	0.156	0.148	0.146	0.149	0.146	0.149	0.148

Note: For coefficients, ** indicates p-value below 0.01, * indicates p-value between 0.01 and 0.05.

4.2 Out-of-Sample Predictability: Further Insights

To further compare the predictive abilities among different models for the various commodity indexes, we calculated the normalized average quantile loss (NAQL) for all the models. The normalization process involves that for any index, we set the best model, i.e., the one smallest quantile loss, normalized to 1, and the other models have their normalized quantile loss equal to their original quantile loss divided by the quantile loss of the best model. Then, for each model, we take average among the nine indexes, and the results are listed in Table 11. It can be seen that the minimum average quantile loss of each group occurs most frequently in the A-MIDAS(PCA) model. Moreover, the A-MIDAS(PCA) model has the smallest NAQL 1.004 at the 1% VaR level, while there is no significant differences among A-MIDAS models at the 5% VaR level. This verifies the conclusion from Section 4.1 that the asymmetric MIDAS model (A-MIDAS) outperforms the symmetric MIDAS version (S-MIDAS), with the latter outperforming the CAViaR model, and the differences within A-MIDAS models are very small.

Comparisons between GSCPI and GECON reveals that the A-MIDAS(GECON) performs slightly better in 1% VaR forecast (the NAQL for A-MIDAS(GECON) is 1.010, and the other is 1.011), while A-MIDAS(GSCPI) performs slightly better in 5% VaR forecast (the NAQL for A-MIDAS(GSCPI) is 1.002, and the other is 1.004). Since the difference is marginal, we find the information of the two indexes are both useful in predicting the VaR of commodity indexes.

In addition, the out-of-sample prediction results of all A-MIDAS (PCA) models are plotted in Figures 1, 2 and 3. Given these figures, the predicted curves from the model show a high overall degree of fit with the actual volatility curves of the commodity market. Particularly at critical junctures with intense market fluctuations, the predicted values can effectively capture changes in actual volatility, demonstrating sensitivity to extreme risks. A comparison of the sub-figures across the different commodity categories reveals that the model exhibits more stable prediction performance for commodities such as precious metals and energy, with a small degree of deviation between the predicted and actual curves. For short-term predictions of agriculture, slight lags occasionally occur, yet the consistency in long-term trends remains evident. Overall, the A-MIDAS(PCA) model demonstrates strong risk-capturing ability in out-of-sample predictions and achieves a good fitting and forecasting effect on the dynamic changes in long-term volatility of the commodities.

Table 11: Original Quantile Loss and Normalized Average Quantile Loss Results

	CAViaR		MIDAS(GSCPI)		MIDAS(GECON)		MIDAS(PCA)	
	S	A	S	A	S	A	S	A
1%								
Commodity	0.059	0.058	0.059	0.059	0.059	0.058	0.059	0.058
Precious Metal	0.045	0.037	0.037	0.037	0.037	0.036	0.037	0.036
Energy	0.205	0.096	0.105	0.095	0.097	0.098	0.106	0.096
Non-Energy	0.234	0.221	0.238	0.219	0.220	0.224	0.227	0.219
Industrial Metals	0.134	0.036	0.034	0.035	0.034	0.034	0.034	0.034
Agriculture	0.163	0.163	0.035	0.034	0.035	0.034	0.035	0.034
Livestock	0.030	0.029	0.025	0.025	0.025	0.024	0.025	0.024
Softs	0.035	0.035	0.035	0.033	0.034	0.033	0.035	0.033
Grains	0.285	0.058	0.043	0.043	0.043	0.043	0.044	0.043
NAQL	3.663	2.518	1.041	1.011	1.019	1.010	1.038	1.004
5%								
Commodity	0.187	0.181	0.176	0.175	0.180	0.175	0.175	0.176
Precious Metal	0.138	0.118	0.117	0.116	0.116	0.116	0.117	0.116
Energy	0.301	0.298	0.278	0.275	0.280	0.278	0.280	0.275
Non-Energy	0.279	0.272	0.082	0.080	0.080	0.081	0.081	0.080
Industrial Metals	0.163	0.124	0.123	0.123	0.124	0.123	0.123	0.123
Agriculture	0.286	0.284	0.120	0.118	0.121	0.120	0.120	0.119
Livestock	0.110	0.108	0.096	0.094	0.096	0.094	0.096	0.093
Softs	0.129	0.122	0.122	0.121	0.122	0.120	0.123	0.121
Grains	0.463	0.156	0.148	0.146	0.149	0.146	0.149	0.148
NAQL	1.782	1.468	1.014	1.002	1.017	1.004	1.016	1.004

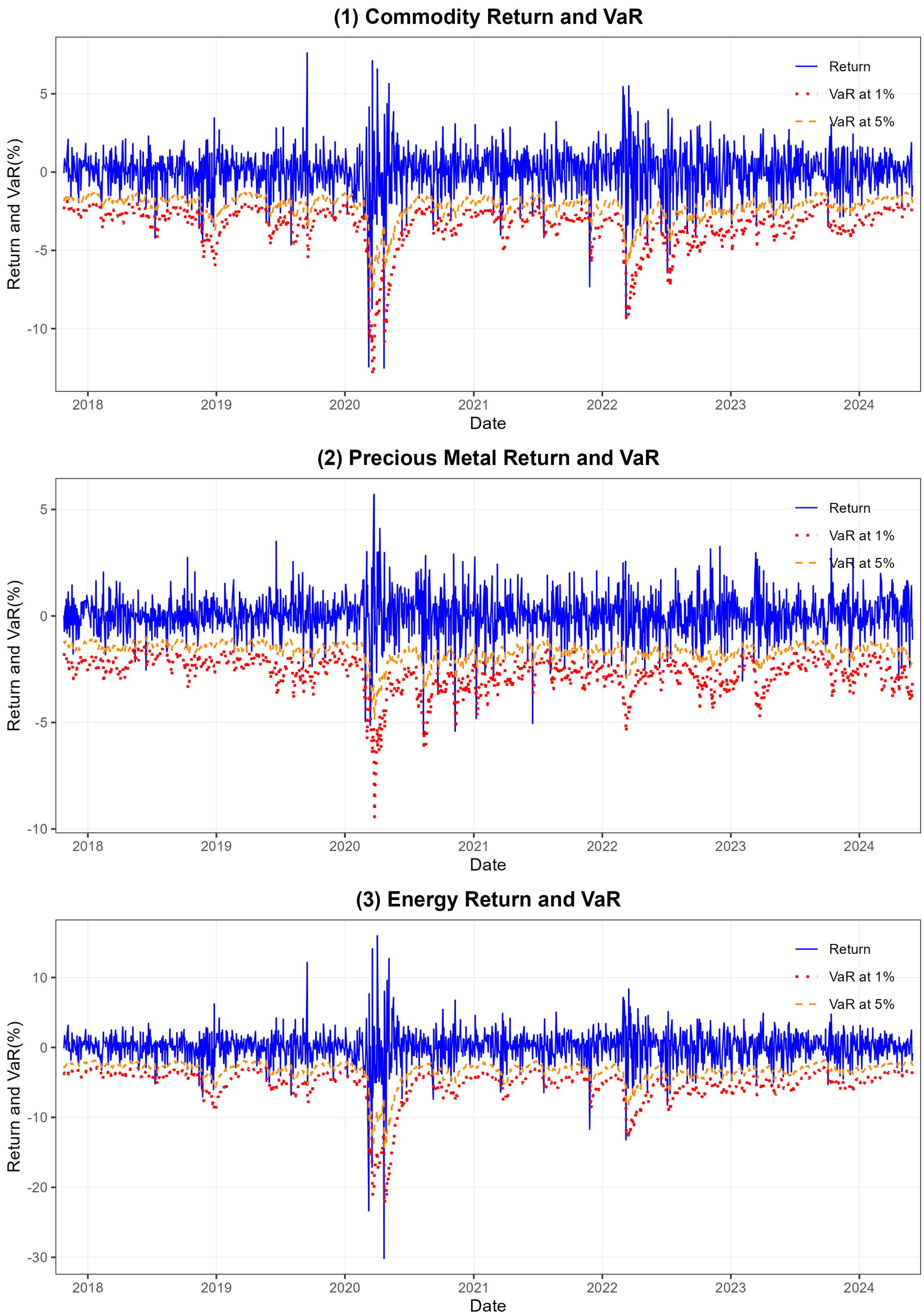

Figure 1: Overall Commodity & Precious Metal & Energy Total Return and VaRs at 1% and 5% under the A-MIDAS(PCA) model

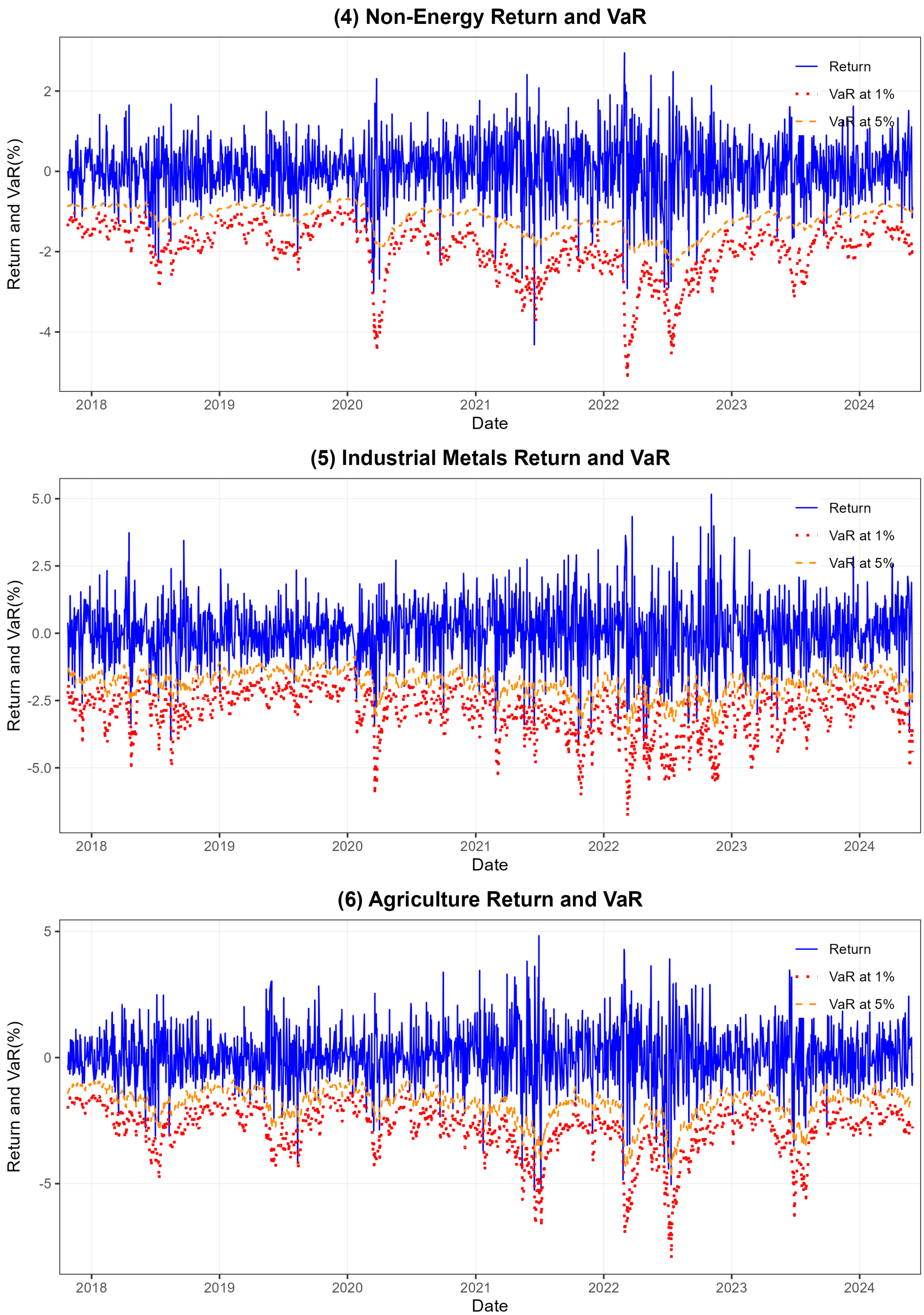

Figure 2: Non-Energy & Industrial Metals & Agriculture Total Return and VaRs at 1% and 5% under the A-MIDAS(PCA) model

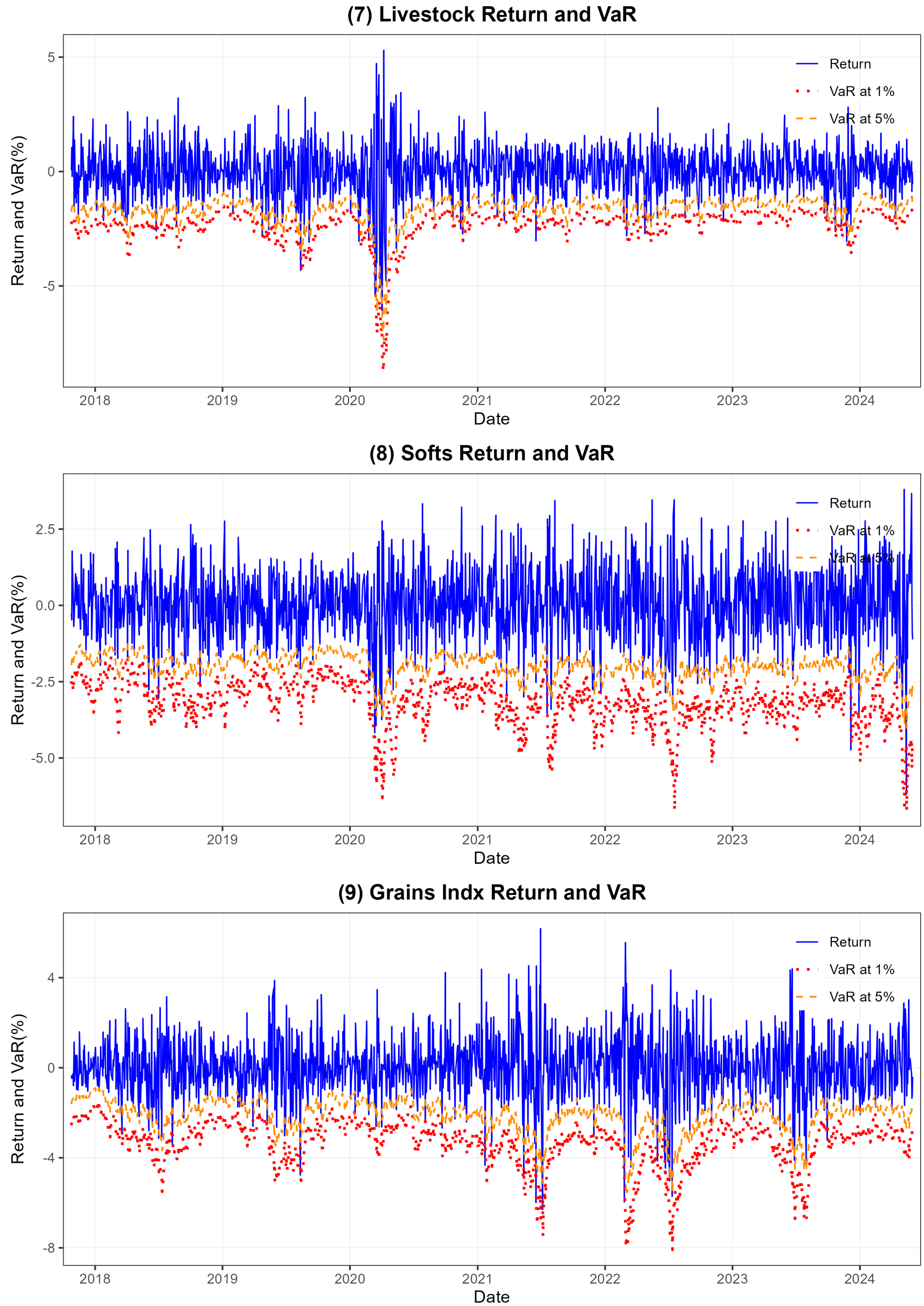

Figure 3: Non-Energy & Industrial Metals & Agriculture Total Return and VaRs at 1% and 5% under the A-MIDAS(PCA) model

5 Conclusion

In this paper, we have explored the ability of monthly indexes capturing the global macroeconomic and financial conditions to predict in the VaR of daily returns of the overall commodity sector and its various sub-sectors using a quantile regression (QR)-based GARCH-MIDAS framework, given the mismatch in data frequencies. We draw the following observations: First, the QR-GARCH-MIDAS model significantly outperforms the widely-used univariate conditional autoregressive VaR by regression quantiles (CAViaR) model, highlighting the critical role of incorporating low-frequency explanatory variables, capturing worldwide demand-supply situation, in model specifications. Second, asymmetric models exhibit superior performance compared to symmetric counterparts, underscoring the importance of integrating the leverage effect into VaR prediction frameworks. Notably, in asymmetric models, the impact of a decline in the previous day's return is substantially stronger than that of an increase. Third, both GSCPI and GECON, corresponding to metrics of global supply chain pressure and economic (demand) conditions respectively, demonstrate strong explanatory power in predicting VaR (at 1% and 5% quantiles) for all of the commodity returns, indicating their significant informational value in risk assessment. Overall, GSCPI has a more prominent impact on the long-term volatility of commodity markets. Finally, since the correlation between GSCPI and GECON is nearly zero, there remains a need to explore efficient methods for integrating information from these two variables. According to our empirical results, while the PCA-based MIDAS model exhibits the best performance, its predictive ability does not necessarily differ much from that of the standalone MIDAS models involving the GSCPI or the GECON. This, however, suggests that GSCPI and GECON carries unique information on their own, and is better to use them separately when predicting VaR of the commodity market. Overall, we demonstrate the significance of global indexes associated with both supply and demand conditions in influencing the future trajectory of VaR of commodities, and hence, the information content of GECON and GSCPI should be of tremendous value to investors operating in this market.

As part of future research, it would be interesting to extend our analyses to other asset classes, both at global and country-specific levels.

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