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Forecasting Spot and Futures Price Volatility of Agricultural Commodities: The Role of Climate-Related Migration Uncertainty

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Abstract

We evaluate the predictive ability of the newly developed climate-related migration uncertainty index (CMUI) and its two components, the climate uncertainty index (CUI) and the migration uncertainty index (MUI), for the return volatility of agricultural commodity prices in both futures and spot markets. Employing a GARCH-MIDAS model, based on mixed data frequencies covering the period from 1977Q4 (with the earliest daily observation on October 3, 1977) to 2024Q1 (with the latest daily observation on March 29, 2024), we conduct both statistical and economic evaluations, including the Modified Diebold-Mariano test, Model Confidence Set procedure, and risk-adjusted performance metrics. The results demonstrate that integrating CUI, MUI, and CMUI into the predictive model of the return volatility of agricultural commodity prices significantly improves forecast accuracy relative to the conventional GARCH-MIDAS-RV benchmark. These findings suggest that the climate and migration related uncertainty indices are both statistically significant and economically relevant, offering enhanced predictive power and investment performance.

Keywords: Climate-related Migration Uncertainty Index, Climate Uncertainty Index, Migration Uncertainty Index, Agricultural commodity prices, GARCH-MIDAS, Forecast evaluation, Economic Significance

JEL Codes: C53; D8; F22; Q02; Q13

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1. Introduction

Global migration patterns have been progressively impacted by climate change, with major population displacements resulting from catastrophic weather events and long-term environmental changes. According to the UN Refugee Agency (UNHCR), their rescue and support works revolving around climate-driven crises cover devastating floods in nearly four out of ten climate-driven emergencies, while earthquakes account for about a quarter of their emergencies.. Notably, the World Bank's 2021 Groundswell Report indicates that climate change could lead to the internal displacement of up to 216 million people by 2050, with 66% of this population coming from Sub-Saharan Africa, South Asia, and Latin America[1]. This phenomenon has significant economic implications, especially for agricultural commodity markets, which are naturally vulnerable to labor shifts brought on by migration and climate fluctuation.

Existing literature on climate change and migration uncertainty broadly explores displacement patterns, economic adaptation, and labour market effects, with the notable work of Salisu and Salisu (2025) which measures climate-induced migration uncertainty using news-based indices. Furthermore, Carling and Schewel (2018) emphasize the role of structural constraints in shaping migration outcomes, while McLeman (2018) suggests that migration shocks disrupt agricultural labour supply, indirectly affecting productivity and market volatility of agricultural commodities. However, research explicitly linking climate-related migration uncertainty to the volatility of agricultural commodity is very limited. Most studies on commodity volatility have traditionally focused on supply shocks, including climate change, speculation, and macroeconomic fluctuations (Faccini et al., 2021; Lasisi et al., 2025), largely overlooking the role of migration uncertainty.

In this study, we pursue two specific objectives. Firstly, we evaluate the out-of-sample predictive power of three uncertainty indices newly developed by Salisu and Salisu (2025), namely the climate-related migration uncertainty index (CMUI) and its two sub-indexes, the climate uncertainty index (CUI) and migration uncertainty index (MUI), relative to the benchmark model that excludes these indices. Secondly, we assess the economic significance of accommodating the

[1] See (https://www.worldbank.org/en/news/press-release/2021/09/13/climate-change-could-force-216-million-people-to-migrate-within-their-own-countries-by-2050)

three uncertainty indices in the utility function of spot and futures prices of agricultural commodities. The second objective is particularly important as it strengthens the statistical results obtained from the first objective by providing practical and economically relevant insights about the relationship between climate-related migration uncertainty and agricultural commodities. For robustness purposes, we conduct additional analyses that consider alternative measures of out-of-sample forecast performance and economic significance as well as multiple forecast horizons.

The theoretical linkage between climate-related migration uncertainty and agricultural commodity volatility can be interpreted in two ways. On one hand, migration from climate-vulnerable regions to relatively safer environments – often as an adaptation or coping mechanism – can reduce the labour supply in agriculture, a sector that is typically labour-intensive. This may lead to lower output and higher wages in the climate-affected areas. On the other hand, the resulting increase in production costs and labour shortages could trigger a rise in global agricultural commodity prices, thereby contributing to heightened agricultural commodity volatility. This type of volatility – arising from climate-induced migration – can be seen as a manifestation of a 'Climate Minsky Moment' (see Carney, 2015; Campiglio et al., 2023; Lasisi et al., 2025). Thus, the theoretical framework is based on the intersection of migration uncertainty, climate uncertainty, and economic fundamentals. It builds upon previous attempts to quantify migration uncertainty (Fraser and Ungor, 2019; IOM, 2023) and climate uncertainty (Faccini et al., 2021; Gavriilidis, 2021), but extends these concepts by utilising a new index (namely, the climate-related migration uncertainty of Salisu and Salisu (2025) that directly links climate change to migration uncertainty. This framework recognizes migration as a response to climate change, occurring either as forced displacement or as an adaptive strategy. It further integrates migration-related studies with broader economic considerations, emphasizing the importance of a global index that connects climate-induced migration uncertainty with agricultural commodity price dynamics.

The study contributes, via the use of a new index developed by Salisu and Salisu (2025) to quantify climate-related migration uncertainty, to the understudied research between climate-related migration uncertainty and the volatility of agricultural commodities, reflecting the impact both climate change and labour shift on the agricultural markets. We propose a predictive model for forecasting the return volatility of agricultural commodity prices where the CMUI serves as a predictor. Notwithstanding, the predictive ability of the distinct sub-indexes involving the CUI and MUI are also evaluated for completeness. These uncertainty indices are integrated into the GARCH-MIDAS [Generalized Autoregressive Conditional Heteroscedasticity-Mixed Data Frequency sampling] framework, based on the available data frequencies for the variables in question. The uncertainty indices are available quarterly while agricultural commodity prices (both spot and futures) are daily. The GARCH-MIDAS framework circumvents information loss due aggregation, while preserving the natural frequencies of the variables under study. Therefore, besides being the first to evaluate the predictive value of climate-related migration uncertainty for the return volatility of agricultural commodity prices on the spot and futures markets, this study employs a unique framework that accommodates the peculiarities of the climate-related and migration uncertainty indexes and commodity return volatility series.

The main findings highlight that climate and migration uncertainties contain valuable predictive information beyond the benchmark model, improving the accuracy of agricultural commodity volatility forecasts. Notably, the macroeconomic uncertainty indices are both statistically significant and economically relevant, offering enhanced predictive power and investment performance.

The process of financialization has caused institutional investors to increase their holdings in agricultural commodities relative to traditional assets (Aït-Youcef, 2019; Bonato 2019), thus accurate forecasting of the volatility of agricultural commodity prices is of paramount importance to investors. This is because volatility is a key input in investment and portfolio allocation decisions, risk management, derivatives pricing, and assessments of hedging performance (Poon and Granger, 2003). Moreover, agricultural price volatility is likely to have substantial consequences for food security, especially as far as the economically vulnerable groups of a population are concerned, for whom agricultural commodities are an important proportion of their consumption (Ordu, et al., 2018). Naturally, from the perspective of policy authorities, it is important to obtain accurate predictions of agricultural commodity price volatility, so that policies can be developed to shelter vulnerable groups of a population from large and adverse food price fluctuations (Greb and Prakash, 2015, 2017). Furthermore, academically speaking, while there exist studies that have predicted or forecasted the volatility of agricultural commodity prices due to climate risks (see, for example, Bonato et al., 2023; Gupta and Pierdzioch, 2023; Luo and Zhang, 2024; Nel et al., 2024) to the best of our knowledge, this is the first paper to forecast the same based on an index of climate related migration uncertainty, and its associated sub-indexes involving climate and migration. Hence, our study offers a unique perspective into analyzing climate-related migration risks, and underscores the need for researchers to incorporate such fundamentals when modelling volatility dynamics of agricultural commodity prices, which, thus far has primarily relied on macroeconomic, financial and behavioral predictors (Tian et al., 2017a, 2017b; Yang et al., 2017; Luo and Chen, 2019; Luo et al., 2019; Chatziantoniou et al., 2021; Degiannakis et al., 2022; Marfatia et al., 2022; Shiba et al., 2022; Bonato et al., 2024a; b).

Following this section, the remainders are as structured follows: While section 2 deals with data collection, and methodology, Section 3 shows the empirical results covering both the statistical and economic significance of the volatility forecasts. Section 4 concludes the paper.

2. Data and Methodology

2.1. Data and Preliminary Analyses

This study is set out to evaluate the in-sample and out-of-sample predictability of daily agricultural commodity return volatility, driven by the quarterly climate uncertainty index (CUI), migration uncertainty index (MUI), and a composite index (CMUI) combining both uncertainties. The uncertainty indices are novel, text-based measures developed by Salisu and Salisu (2025) to capture global uncertainty arising from climate change, migration, and their intersection. Drawing on term sets inspired by Baker, Bloom, and Davis (2016) Fraser and Ungor (2019) and Gavriilidis (2021), Salisu and Salisu (2025) refine and expand the keyword lists across three themes climate, migration, and uncertainty to ensure comprehensive coverage. Following ProQuest TDM Studio search guidelines (2022), Salisu and Salisu (2025) use the following search terms for the composite index (CMUI) we utilized the following keywords (full text) ("carbon dioxide" // “climate” // "climate risk" // "greenhouse gas emissions" // “greenhouse” // “co2” // “emission” // "global warming" // "climate change" // "green energy" // "renewable energy" // “environment” // “environmental” // "carbon footprint" // "climate adaptation" // "climate mitigation" // "extreme weather event" // "adaptation strategies" // "mitigation effort" // “drought” // “desertification” // “flood” // "sea level rise") and ("border control" // “Schengen” // "open borders" // “migrant” //

“migration” // “asylum” // “refugee” // “immigrant” // “immigration” // “immigration” // "human trafficking" // “emigration” // “displacement” // “resettlement” // “integration” // "migrant workers" // "border crossing" // "displaced persons" // “deportation” // “visa”) and (“uncertainty” // “uncertainty” // “uncertain” // “unstable” // “fluctuation” // “speculation” // “complexity” // “inconsistency” // “unpredictability” // “volatility”).

For completeness, our empirical analysis also examines sub-indices related to climate-induced and migration-induced uncertainty indexes of Salisu and Salisu (2025). The following keywords (Full text) are used for the Climate-related Uncertainty Index: ("carbon dioxide" // “climate” // "climate risk" // "greenhouse gas emissions" // “greenhouse” // “co2” // “emission” // "global warming" // "climate change" // "green energy" // "renewable energy" // “environment” // “environmental” // "carbon footprint" // "climate adaptation" // "climate mitigation" // "extreme weather event" // "adaptation strategies" // "mitigation effort" // “drought” // “desertification” // “flood” // "sea level rise") AND (“uncertainty” // “uncertainty” // “uncertain” // “unstable” // “fluctuation” // “speculation” // “complexity” // “inconsistency” // “unpredictability” // “volatility”)).

Regarding the Migration Induced-Uncertainty index, the following keywords (Full text) are used: ((“border control" // “Schengen” // "open borders" // “migrant” // “migration” // “asylum” // “refugee” // “immigrant” // “immigration” // "human trafficking" // “emigration” // “displacement” // “resettlement” // “integration” // "migrant workers" // "border crossing" // "displaced persons" // “deportation” // “visa”) AND (“uncertainty” // “uncertainty” // “uncertain” // “unstable” // “fluctuation” // “speculation” // “complexity” // “inconsistency” // “unpredictability” // “volatility”)).

The analysis is constrained by the availability of climate and migration data, covering the period from 1977Q4 (with the earliest daily observation on October 3 1977) to 2024Q1 (with the latest daily observation on March 29, 2024); however, the data series have varying start dates. The uncertainty indices can be obtained from: https://epuindexng.com/climate-induced-migration-uncertainty/.

Concerning the daily closing prices of agricultural commodities, they are collected from DataStream. They include the futures prices of 11 major agricultural commodities, traded on the CME Group, namely Cocoa, Coffee ‘C’, Corn, Feeder Cattle, Lean Hogs, Oats, Orange Juice, Rough Rice, Soybean Meal, Soybean Oil, Soybeans, Sugar #11, and Wheat. Given that these agricultural commodities can be categorized into Grains, Livestock, and Softs, we also use the S&P GSCI sub-indexes covering these three categories of agricultural commodities (S&P GSCI Grains, S&P GSCI Livestock, and S&P GSCI Softs) along with the aggregated GSCI agriculture commodity index. Notably, these sub-indexes reflect spot prices, making them a nice complement to the use of futures prices of individual agricultural commodities. All commodity futures prices and spot indexes are expressed in USD.

Table 1 presents some preliminary results, outlining the key features of agricultural commodity spot and futures price returns, along with the different measures of uncertainty - CUI, MUI, and CMUI. On average, all agricultural commodities, except for grain spot returns, exhibit positive returns. Among them, feeder cattle (Livestock) has the lowest variability, while Coffee (Softs) displays the highest in both futures and spot markets. Approximately 53% of the distributions are positively skewed, while the remaining 47% exhibit negative skewness. All the agriculture commodity returns show leptokurtic behaviour. Conditional heteroscedasticity and serial correlation are detected in most cases, except for lean hogs and rough rice. The uncertainty indices (CUI, MUI, and CMUI) show positive mean values, rightly skewed, and leptokurtic distributions, with indication of conditional heteroscedasticity and serial correlation. Given these characteristics and the mixed-frequency nature of the data series, the GARCH-MIDAS model emerges as a suitable framework for examining the predictability of agricultural commodity volatility based on cimate-related migration uncertainty indexes.

The returns are graphically displayed in Figure 1, showing the volatility inherent in the prices of the agriculture commodities. Figure 2 plots the global trends in the climate-related migration uncertainty. Figure 3 shows the trend in the climate-related uncertainty, while Figure 4 displays the evolution of the migration uncertainty index.

[INSERT TABLE 1]

From Figure 1, we notice a mixed trend in price volatility among the various agricultural commodities. While Figure 1 depicts a concentration of price (volatility) movements around the mean for some agricultural commodities including livestock, grains and wheat, most other commodity products show instances of negative trends. This suggests that rising climate-induced migration uncertainty, in particular, and other forms of uncertainty measures (including climate and migration-related factors) more generally, may have varying impacts on agricultural price volatility (see also Figures 2, 3, and 4). These observations are properly discussed in Section 3.

[INSERT FIGURES 1, 2, 3 AND 4]

2.2 Methodology

As previously noted, we employ the GARCH-MIDAS model framework owing to the mixed frequencies of the variables under study, where the dependent variable (the volatility of agriculture commodity returns) is observed daily, while the predictors (climate uncertainty, migration uncertainty and the composite of both indexes) are measured quarterly. This framework effectively preserves critical information by incorporating mixed-frequency variables within a single model, avoiding the loss of essential details that could occur if the data were aggregated into a uniform frequency.

The GARCH-MIDAS model, originally proposed by Engle et al. (2013), incorporates an unconditional mean and models the conditional variance as a product of high and low-frequency components. The formal structure of the model is specified in Equations (1) to (5) as:

$$r_{i,t} = \mu + \sqrt{h_{i,t} \times \tau_t} \times \varepsilon_{i,t}, \qquad \forall\ i = 1,2,...,N_t \tag{1}$$

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

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \phi_k\left(\omega\right) X_{i-k}^{(rw)} \tag{3}$$

$$\phi_k\left(w\right) = \frac{\left[1-k/\left(K+1\right)\right]^{w-1}}{\sum_{j=1}^{K}\left[1-j/\left(K+1\right)\right]^{w-1}} \tag{4}$$

$$\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1) \tag{5}$$

where $r_{i,t} = ln(P_{i,t}) - ln(P_{i-1,t})$ is the i^{th} day of the month t returns for the different agriculture commodities (based on futures and spot prices), with N_t indicating days in a month t; μ is the unconditional mean of the agriculture commodity returns; $h_{i,t}$ and τ_t are accordingly the short-run and long-run components of the conditional variance $\left(\sqrt{h_{i,t} \times \tau_t}\right)$ part of Equation (1).

In Equation (2), α and β account for the ARCH and GARCH terms, respectively, that are restricted by conditions: $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$;

In Equation (3), m is the long-run constant; θ is the slope coefficient that reflects the realized volatility (RV) of the agricultural commodity (index) returns or the incorporated exogenous variable (CUI, MUI and CMUI); $\phi_k(w)$ is a flexible (Colacito et al., 2011) one parameter beta polynomial weighting scheme[2], such that $\phi_k(w) \geq 0,\ k = 1, 2, \ldots, K$ and $\sum_{k=1}^{K} \phi_k(w) = 1$, for the model identification condition to be satisfied; the imposed constraint $(w > 1)$ is used to assign greater weight to more recent lag observations compared to distant ones; X_{i-k} stand for exogenous predictor (CUI, MUI and CMUI); the superscript "*rw*" indicates that the estimation is done using a rolling window to implicitly account for plausible time varying parameter stances that could be occasioned by some historical significant events, say for example, COVID-19; $\varepsilon_{i,t} \mid \Phi_{i-1,t}$ is the information set that is available at the $(i-1)^{th}$ day of the month t is normally distributed. The adjustment of the long-run component from τ_t to τ_i is a reflection of the transformation of the lower (monthly) frequency long-run component to the higher (daily) frequency, in consonance with the frequency of the stock volatility, without loss of generality (Engle et al., 2013).

[2] This is obtained from the two-parameter beta weighting scheme $\phi_k(w_1, w_2) = \left[k/(K+1)\right]^{w_1-1} \times \left[1 - k/(K+1)\right]^{w_2-1} \Big/ \sum_{j=1}^{K} \left[j/(K+1)\right]^{w_1-1} \times \left[1 - j/(K+1)\right]^{w_2-1}$ by constraining w_1 to 1 and setting $w = w_2$.

The predictive accuracy of our GARCH-MIDAS-uncertainty variants is evaluated by comparing their out-of-sample forecast performance against the benchmark GARCH-MIDAS-RV model; and the CMUI-based GARCH-MIDAS against the CUI and MUI variants separately. We achieve this using the modified Diebold-Mariano test proposed by Harvey et al. (1997; DM^c), as specified in Equation (6). This test extends the conventional Diebold and Mariano (1995; DM) framework, formulated in Equation (7), making it more suitable for comparing paired non-nested models. The statistical formulations for these tests are provided in Equations (6) and (7).

$$DM^* = \left(\sqrt{\frac{T + 1 - 2h + T^{-1} h(h-1)}{T}} \right) DM \tag{6}$$

$$DM = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{7}$$

where DM^* denotes the modified DM statistic; T represents the number of the out-of-sample periods of the forecast errors and h represents the forecast horizon; $\bar{d} = 1/T\left[\sum_{t=1}^{T} d_t\right]$ indicates the average of the loss differential, $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$; $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ are loss functions (squares of the forecast errors (ε_{it} and ε_{jt}, respectively) from the paired competing models); while $V(d_t)$ is the unconditional variance of the loss differential d_t. The DM^c test null hypothesis asserts equality in the forecast precision of the paired non-nested contending models $(H_0 : d = 0)$ against a mutually exclusive alternative, $(H_1 : d \neq 0)$. The null would be preferred if the forecast accuracy of the both models is statistically equivalent, whereas rejecting it indicate otherwise. The sign of the DM^c statistic reveals a preferred model, such that a negative value suggests that the GARCH-MIDAS model incorporating uncertainty outperforms the GARCH-MIDAS model based on RV, while a positive value indicates the opposite. For the analysis, 75% of the total dataset is used for in-sample estimation, and the remaining 25%, for out-of-sample forecast assessment across three forecast horizons – 20, 60, and 120 days ahead.

3. Empirical Results

3.1. Statistical Significance

We present a comprehensive analysis of the out-of-sample forecasting performance related to the return volatility of agricultural commodities, utilizing the Realized Volatility (RV) framework alongside our integrated uncertainty indexes, CUI, MUI), and CMUI. Then, we assess the accuracy of our forecasts, we employ the Diebold-Mariano (DMc) test statistic, which is widely recognized for its effectiveness in comparing the predictive accuracy of different forecasting models that are non-nested.

Initially, we establish a comparative framework through which we evaluate each variant of the GARCH-MIDAS-uncertainty models—CUI, MUI, and CMUI—against a conventional benchmark: the GARCH-MIDAS-RV model. This model serves as a standard reference due to its established performance in capturing volatility dynamics in financial time series. Such a layered comparison allows us to discern the unique contributions of each uncertainty index to forecasting accuracy (refer to the detailed results presented in Table 2). In addition to our emphasis on out-of-sample performance, we recognize the importance of in-sample predictability. Therefore, we have included results that confirm the predictive potential of the various predictors employed in our analysis. These in-sample results can be found in Table A1, accompanied by a graphical representation in Figure A1 within the Appendix. This dual approach ensures a robust understanding of the models' effectiveness in forecasting agricultural commodity returns volatility.

The out-of-sample predictability results based on the *DMc* test indicate the relative performance of different GARCH-MIDAS models in forecasting agricultural commodity volatility. The negative and statistically significant *DMc* statistics in columns 3–5 suggest that the inclusion of climate and migration uncertainty indices in the GARCH-MIDAS framework enhances predictive accuracy compared to the conventional GARCH-MIDAS-RV model. Specifically, across various forecast horizons ($h = 20, 60, 120$), the climate uncertainty index (CUI) and migration uncertainty index (MUI) consistently improve forecast accuracy, as evidenced by their significant negative *DMc* values. This trend holds for spot agricultural indices, including the S&P GSCI Agriculture Index, S&P GSCI Livestock Index, and S&P GSCI Softs Index, as well as some agriculture commodity futures such as wheat, corn, soybeans, and feeder cattle. The stronger predictability of uncertainty-based models over the realized volatility (RV) benchmark suggests that climate and migration factors contribute valuable information for explaining and forecasting volatility in agricultural markets. Similar results in terms of climate risks have also been discussed in Bonato et al. (2023), Gupta and Pierdzioch (2023), Luo and Zhang (2024), Lasisi et al. (2025) and Salisu and Salisu (2025).

Further comparisons in columns 6 and 7 evaluate the performance of GARCH-MIDAS-CUI and GARCH-MIDAS-MUI relative to the GARCH-MIDAS-CMUI (benchmark), which is a composite of both climate and migration uncertainty indices. The mixed results indicate that while the GARCH-MIDAS-CMUI-based model generally underperformed in comparison with individual uncertainty-based models (CUI and MUI), there are some exceptions. For example, in agriculture commodities such as soybean oil, rough rice, lean hogs, and feeder cattle, the GARCH-MIDAS-CMUI model exhibits stronger predictive power than the GARCH-MIDAS-MUI and GARCH-MIDAS-CUI models, as indicated by the significantly positive *DMc* statistics. Imperatively, it appears that in some cases, climate and migration uncertainty independently capture volatility dynamics more effectively than their composite index - CMUI. Summarily, while both climate and migration uncertainties play critical roles in forecasting agricultural commodity returns volatility, their relative importance tend to vary across the agriculture commodities, possibly due to differences in supply chain exposure, production cycles, and/or market sensitivities to climate and migration shocks.

[INSERT TABLE 2]

3.2. Economic Significance

After confirming the statistical superiority of the CUI, MUI and CMUI over the RV, we proceed to assess the economic benefits of integrating each of these uncertainty measures (CUI, MUI and CMUI) as a predictor of agriculture commodity return volatility. This comparison against the GARCH-MIDAS-RV model is crucial for reinforcing the statistical findings from the DM^c test with economically meaningful insights.

We consider a typical investor that is guided by mean-variance utility and consistently optimizes portfolios compared to a risk-free asset[3]. The optimization involves the allocation of shares among investment options using optimal weight, w_t, defined as

$$w_t = \frac{1}{\gamma} \frac{\delta \hat{r}_{t+1} + (\delta - 1) \hat{r}^f_{t+1}}{\delta^2 \hat{\sigma}^2_{t+1}} \tag{8}$$

where γ represents the risk aversion coefficient co; δ is a leverage ratio initially set on the understanding that investors often maintain a 10% margin; $\hat{r}_{t+1}$ is the stocks returns forecast at time $t+1$; $\hat{r}^f_{t+1}$ is a risk-free asset (which we proxy through US 3-month Treasury bill rate[4]); and $\hat{\sigma}^2_{t+1}$ represents an estimate of return volatility, calculated using a 30-day rolling window of daily return observations. Thus, Equation (9) defines the certainty equivalent return (CER) associated with the investor's optimal portfolio allocation

$$CER = \bar{R}_p - 0.5(1/\gamma)\sigma^2_p \tag{9}$$

where $\bar{R}_p$ is the out-of-sample mean; and σ^2_p is the out-of-sample variance of the portfolio return, defined as $R_p = w\delta(r - r^f) + (1-w)r^f$. The economic significance is determined by maximizing an objective function of a utility as:

$$U(R_p) = E(R_p) - 0.5(1/\gamma)Var(R_p) = w\delta(r - r^f) + (1-w)r^f - 0.5(1/\gamma)w^2\delta^2\sigma^2 \tag{10}$$

where $Var(R_p) = w^2\delta^2\sigma^2$ is the variance of the portfolio return, and σ^2 represents excess return volatility. A model is considered to have a more advantageous economic gain if it produces the highest returns, CER, and Sharpe ratio (SR), defined by: $SR = (R_p - r^f)/\sqrt{Var(R_p)}$; and minimum volatility (see, Liu et al., 2019).

[3] We compare the stock with a risk-free asset (Treasury bills, which serves as a baseline for risk-free returns, reflecting time value without default risk) as a way to determine the agriculture commodity risk premium. This allows for investors assessment of justification of the volatility of a commodity's potential return relative to a guaranteed return. The approach aligns with modern portfolio theory, where rational investors demand compensation for taking on risk, ensuring efficient capital allocation.
[4] The data can be downloaded from: https://fred.stlouisfed.org/series/DTB3.

Table 3 presents the outcomes of integrating each of the uncertainty measures (CUI, MUI or CMUI) as predictors for the volatility of agriculture commodities. The economic significance results in Table 3 reveal key insights into the performance of the uncertainty-based GARCH-MIDAS models (CUI, MUI, and CMUI) relative to the realized volatility (RV)-based GARCH-MIDAS model across different agricultural commodities, considering returns, volatility, and Sharpe ratios under two parameter – risk aversion (($\gamma = 3$) and leverage ($\delta = 6$ and $\delta = 8$). Generally, for most commodities, the uncertainty-based GARCH-MIDAS models exhibit superior economic performance, as indicated by higher returns and Sharpe ratios compared to the RV-based model.

The results indicate that for several commodities; particularly livestock, grains, wheat, soybeans, soybean oil, rough rice, sugar, coffee, orange juice, lean hogs and feeder cattle; the uncertainty-based models yield higher economic gains than the RV-based variant, as highlighted in bold. For the S&P GSCI Livestock Index, the uncertainty-based models generally outperform the RV model, with MUI and CMUI achieving the highest Sharpe ratios (0.0693 and 0.0691, respectively) when the leverage is specified as 6, and maintaining the stance under leverage set at 8. The stances of clear outperformance of the uncertainty-based GARCH-MIDAS model over the GARCH-MIDAS-RV model is indicative that incorporating external uncertainty measures improves risk-adjusted returns. However, for the agriculture commodities where the RV appears to have upper hand in comparison to uncertainty-based variants, it is indicative that the economic gains associated with the incorporation of uncertainty-based models are less comparable with those of the own (i.e., agricultural commodity) market volatility.

We also observe that the economic gains for some of the agriculture commodities increase when the leverage is changed from 6 to 8. The results generally seem sensitive to the agriculture commodities, but not to the choice of leverage parameter specification. In other words, the varying performance across commodities suggests that while uncertainty-based models can enhance risk-adjusted returns for certain assets, their effectiveness is commodity-dependent. In summary, the findings highlight that integrating macroeconomic uncertainty provide some economic gains that could be useful in enhancing investment decisions. Our result confirms the statistical stance obtained in the modified Diebold and Mariano test.

[INSERT TABLE 3]

3.3. Model Confidence Set

We evaluate the performance of our exogenous predictor-based GARCH-MIDAS model variants relative to the GARCH-MIDAS-RV model to determine their suitability as potential models for forecasting agricultural commodity return volatility. This assessment is conducted using the Model Confidence Set (MCS) approach proposed by Hansen et al. (2011). The MCS identifies the best-performing models from an initial set M_0 using an equivalence test (δ_M) and an elimination rule (e_M). If the models differ significantly, the underperforming ones are iteratively removed until (δ_M) is accepted. The final MCS comprises surviving models, ensuring $P(M^* \subseteq M_{1-\alpha}) \geq 1-\alpha$ asymptotically. MCS assigns p-values to each model; a model is included in the MCS if its p-values are greater or equal to the stated level of significance α. Consequently, models with small p-values are less likely to be among the best-performing models in the set.

The Model Confidence Set (MCS) results in Table 4 evaluate the predictive performance of four GARCH-MIDAS variants—RV, CUI, MUI, and CMUI—across different forecast horizons (20-, 60-, and 120-day) for various agricultural commodities. The table reports mean squared errors (MSE) alongside MCS p-values, where models with p-values above 10% are adjudged as candidate models to be within the confidence set. The results reveal that CUI (47.06%) is the most frequently selected candidate model, followed closely by MUI (41.18%) and CMUI (41.18%), while RV, the benchmark model, qualifies in only 5.88% of cases. The exogenous predictor-based models (CUI, MUI, and CMUI) more frequently outperformed the RV model, judging by their lower MSE values. Notably, for commodities like wheat, corn, and coffee, CUI consistently provides superior forecasts across the different horizons. These findings suggest that incorporating macroeconomic uncertainty indices enhances forecast accuracy, emphasizing the relevance of exogenous predictors in modeling agricultural commodity volatility. The superior performance of CUI, MUI, and CMUI underscores the limitations of the RV-based model, highlighting the need to integrate broader economic indicators for improved predictive power in the agriculture commodity price volatility modeling. Summarily, this result further confirms the out-of-sample predictability of CUI, MUI and CMUI for agriculture commodities' returns volatility, and subsequently, the statistical relevance of CUI, MUI and CMUI as predictors.

[INSERT TABLE 4]

4. Conclusion

This study examines the predictive power of the climate-related migration uncertainty and its sub-indices involving climate uncertainty and migration uncertainty for the out-of-sample return volatility forecast of agricultural commodities. To this end, the GARCH-MIDAS framework is used, which accommodates mixed-frequency data occasioned by the available data frequencies of the variables being examined. The analysis considers both the statistical and economic significance of the uncertainty indices. The statistical significance involves evaluating the out-of-sample predictability of the uncertainty indices relative to the benchmark model of the GARCH-MIDAS-RV. The economic significance relates to assessing the significance of the uncertainty indices in the utility function of the spot and futures of agricultural commodity prices. The empirical analyses are carried out for alternative measures of both statistical and economic significance for robustness purposes.

The results from our analysis show that climate-related migration factors contribute valuable information for explaining and forecasting the volatility of agricultural commodities. This evidence is valid for both statistical and economic significance. This suggests that the macroeconomic uncertainty indices are not only statistically significant but also economically meaningful, offering enhanced predictive power and investment performance. Notwithstanding, the relative importance of the uncertainty indices tends to vary across the agriculture commodities, possibly due to differences in supply chain exposure, production cycles, and/or market sensitivities to climate and migration shocks. Given the importance of food price stability from a policy perspective, and forecasts of agricultural commodity prices from an investor's portfolio allocation decision, this study carries critical implications for both policymakers and traders in the context of rising agricultural commodity volatility associated with climate related migration risks.

Besides agricultural commodities, various other sectors – including housing, hospitality, tourism, and others – are exposed to climate-induced migration uncertainty, but are not covered in the present study. Future research could address this by exploring the impact of such uncertainty on these sectors. Additionally, examining how climate-related migration uncertainty can alter the interconnectedness among these sectors represents an interesting avenue for further research.

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Table 1: Summary and Preliminary Analyses

	Mean	Std. Dev.	Skewness	Kurtosis	Nobs	$ARCH(5)$	$ARCH(10)$	$Q(5)$	$Q(10)$	$Q^2(5)$	$Q^2(10)$
DAILY AGRICULTURAL COMMODITY RETURNS											
FUTURES											
COCOA	7.95E-03	1.87	0.05	6.07	11803	27.09[a]	19.71[a]	1.91	7.31	160.24[a]	277.29[a]
COFFEE	2.85E-03	2.20	0.18	9.58	11803	104.42[a]	93.82[a]	18.33[a]	24.73[a]	728.09[a]	1463.10[a]
CORN	6.42E-03	1.57	-0.81	18.45	12130	20.21[a]	14.88[a]	11.47[b]	22.47[b]	117.27[a]	197.33[a]
FEEDER CATTLE	1.14E-02	1.00	0.25	8.10	11919	78.42[a]	48.84[a]	4.14	43.84[a]	515.74[a]	813.96[a]
LEAN HOGS	6.63E-03	2.09	0.16	26.56	12130	0.33	0.67	5.09	10.15	1.69	7.00
OATS	1.55E-02	2.14	-0.68	12.07	4696	7.74[a]	4.14[a]	18.54[a]	24.11[a]	41.86[a]	45.66[a]
ORANGE JUICE	9.32E-03	1.92	0.23	10.68	11803	25.76[a]	13.85[a]	14.66[b]	17.94[c]	151.45[a]	173.84[a]
ROUGH_RICE	1.40E-02	8.45	2.80	2938.28	6323	0.0004	0.0005	0.98	2.33	0.002	0.005
SOYBEAN MEAL	1.35E-02	1.76	-1.21	17.14	4696	6.79[a]	5.00[a]	9.79[c]	10.25	37.27[a]	63.28[a]
SOYBEAN OIL	9.49E-03	1.47	-0.02	5.92	7325	85.97[a]	61.31[a]	5.25	9.34	612.08[a]	1213.80[a]
SOYBEANS	6.61E-03	1.44	-0.62	8.90	12130	63.85[a]	48.59[a]	15.64[a]	36.32[a]	411.55[a]	808.10[a]
SUGAR 11	8.38E-03	2.58	0.37	21.72	11803	86.76[a]	50.72[a]	56.29[a]	61.70[a]	520.26[a]	708.88[a]
WHEAT	6.58E-03	1.76	0.11	7.51	12130	110.65[a]	65.56[a]	15.58[a]	18.26[c]	773.49[a]	1157.30[a]
S&P GSCI INDEXES (***SPOT***)											
AGRIC TOTAL	2.76E-03	1.08	-0.07	6.06	12130	242.40[a]	144.06[a]	6.02	10.65	1789.00[a]	3056.20[a]
GRAINS	-1.45E-03	1.28	0.03	5.74	12130	196.86[a]	120.53[a]	6.10	12.88	1423.70[a]	2479.90[a]
LIVESTOCK	1.57E-02	0.94	-0.17	4.40	12130	376.51[a]	214.82[a]	16.22[a]	37.34[a]	3068.00[a]	5153.60[a]
SOFTS	5.57E-04	1.21	-0.18	5.08	7618	72.08[a]	44.59[a]	15.31[a]	20.49[b]	507.51[a]	822.90[a]
QUARTERLY FREQUENCY UNCERTAINTY MEASURES											
CMUI	3.22E+01	21.32	1.23	3.81	186	4.13[a]	2.50[a]	19.88[a]	26.30[a]	18.09[a]	19.93[b]
CUI	3.79E+01	19.96	1.07	4.03	186	2.37[b]	2.72[a]	21.40[a]	27.93[a]	8.49	28.95[a]
MUI	3.57E+01	16.59	1.18	4.89	186	5.04[a]	2.79[a]	10.41[c]	18.03[c]	29.37[a]	30.62[a]

Note: The daily agriculture commodity returns summary statistics generally cover the overall sample period of October 3 1977 to March 29 2024, while CUI, MUI and CMUI run from 1977Q4 to 2024Q1. [a], [b], and [c] respectively indicate significance at the 1, 5, and 10 per cent levels.

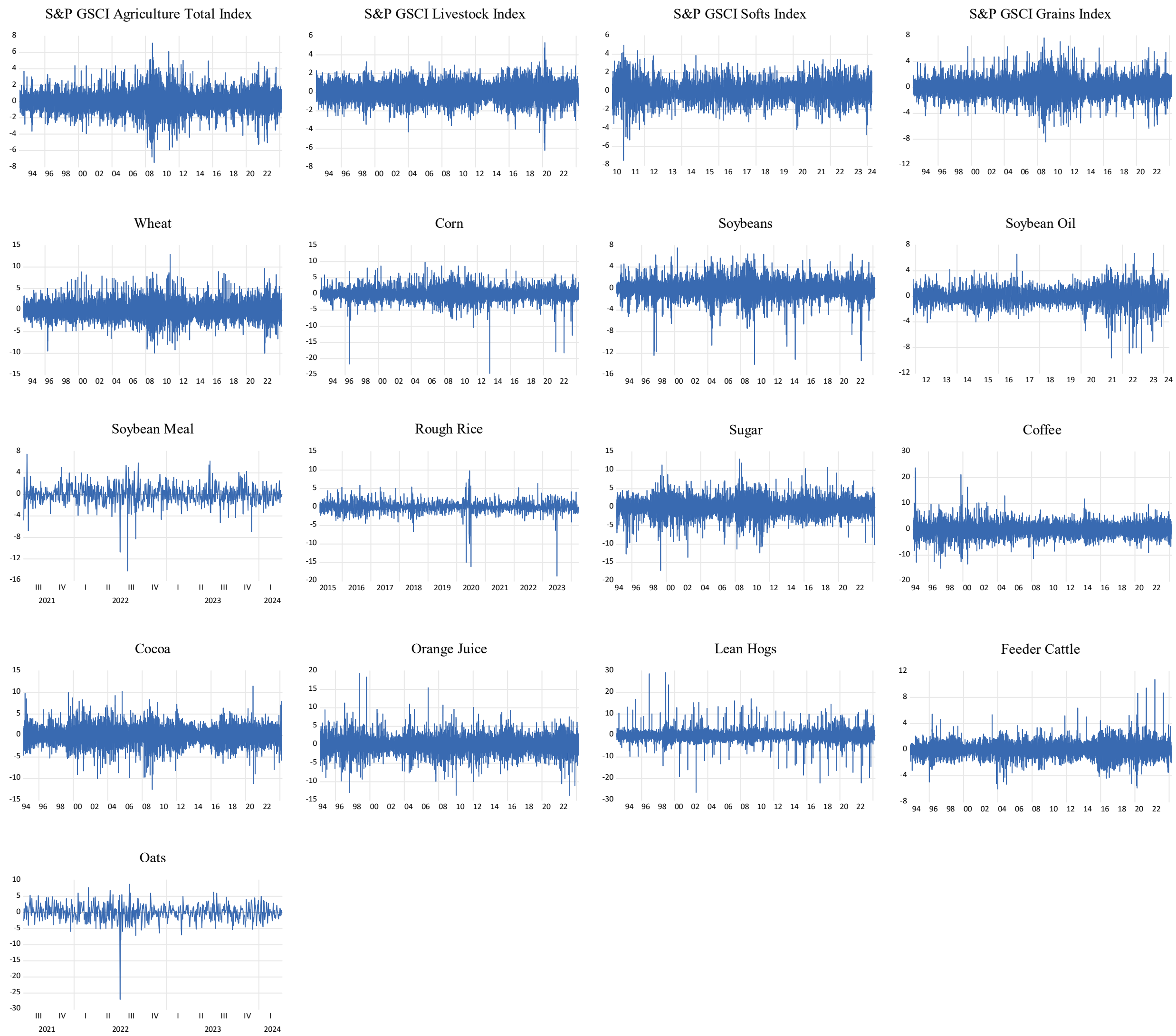


Figure 1: Time plot of the Agriculture Commodity Returns

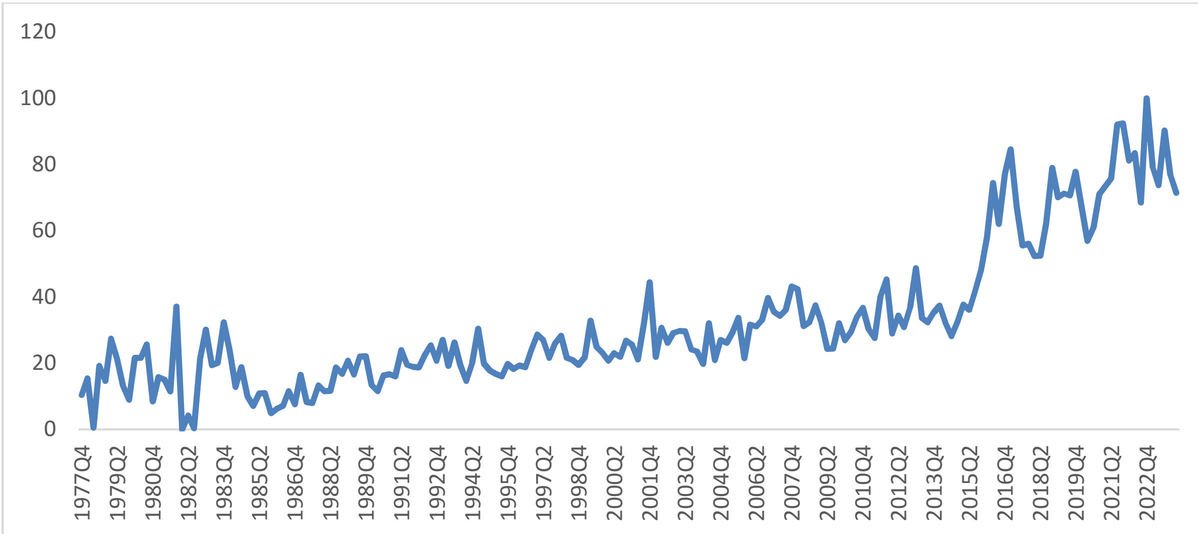


Figure 2: Quarterly Composite Index (Climate-Related Migration Uncertainty

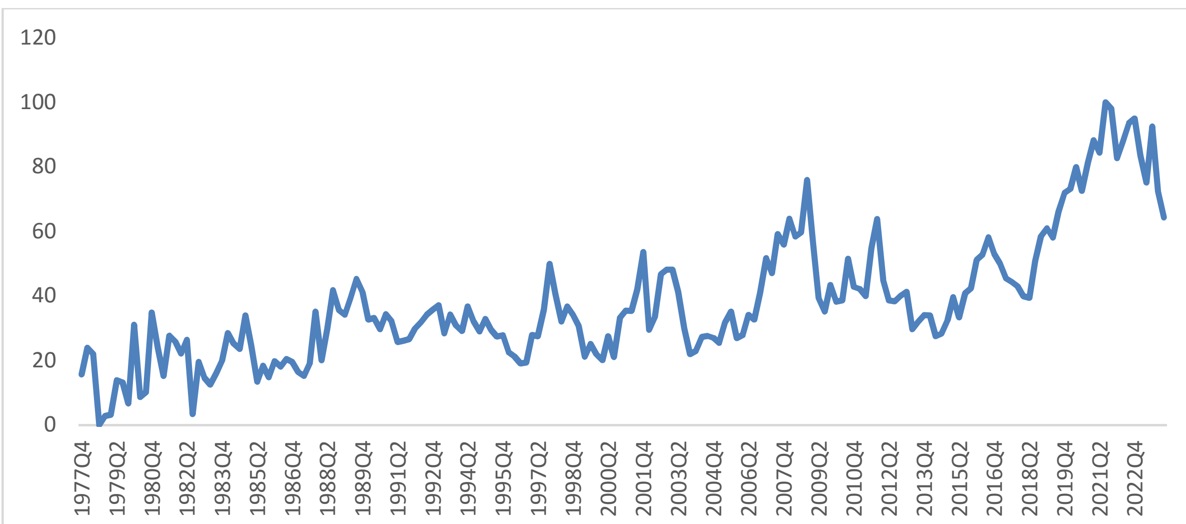


Figure 3: Quarterly Climate-Related Uncertainty Index

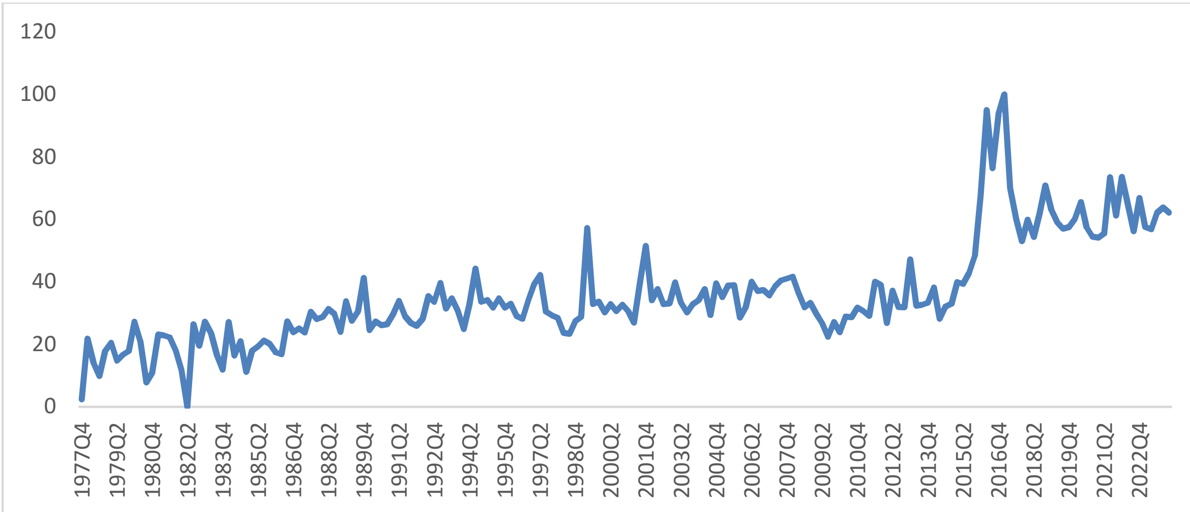


Figure 4: Quarterly Migration-Induced Uncertainty Index

Table 2: Out-of-Sample Predictability Results using modified Diebold and Mariano Test

Agriculture Commodity	Forecast Horizon	Benchmark: Realized Volatility			Benchmark: Climate-Migration Uncertainty Index	
		Climate Uncertainty Index	Migration Uncertainty Index	Climate-Migration Uncertainty Index	Climate Uncertainty Index	Migration Uncertainty Index
S&P GSCI Agriculture Total Index	$h = 20$	-3.06E+01[a]	-3.10E+01[a]	-2.96E+01[a]	-4.45E+01[a]	-3.26E+01[a]
	$h = 60$	-3.04E+01[a]	-3.07E+01[a]	-2.94E+01[a]	-4.47E+01[a]	-3.23E+01[a]
	$h = 120$	-3.00E+01[a]	-3.04E+01[a]	-2.90E+01[a]	-4.48E+01[a]	-3.24E+01[a]
S&P GSCI Livestock Index	$h = 20$	-3.13E+01[a]	-3.01E+01[a]	-3.16E+01[a]	3.55E+01[a]	2.06E+01[a]
	$h = 60$	-3.11E+01[a]	-3.00E+01[a]	-3.15E+01[a]	3.57E+01[a]	2.02E+01[a]
	$h = 120$	-3.09E+01[a]	-2.98E+01[a]	-3.13E+01[a]	3.61E+01[a]	1.98E+01[a]
S&P GSCI Softs Index	$h = 20$	-3.95E+01[a]	-3.91E+01[a]	-3.93E+01[a]	-1.29E+01[a]	-1.46E+01[a]
	$h = 60$	-3.93E+01[a]	-3.89E+01[a]	-3.91E+01[a]	-1.23E+01[a]	-1.53E+01[a]
	$h = 120$	-3.90E+01[a]	-3.87E+01[a]	-3.88E+01[a]	-1.14E+01[a]	-1.71E+01[a]
S&P GSCI Grains Index	$h = 20$	-3.01E+01[a]	-3.06E+01[a]	-2.90E+01[a]	-4.43E+01[a]	-3.28E+01[a]
	$h = 60$	-2.98E+01[a]	-3.03E+01[a]	-2.87E+01[a]	-4.45E+01[a]	-3.26E+01[a]
	$h = 120$	-2.94E+01[a]	-2.99E+01[a]	-2.83E+01[a]	-4.45E+01[a]	-3.26E+01[a]
WHEAT	$h = 20$	-4.33E+01[a]	-4.32E+01[a]	-4.20E+01[a]	-4.89E+01[a]	-2.70E+01[a]
	$h = 60$	-4.33E+01[a]	-4.32E+01[a]	-4.20E+01[a]	-4.92E+01[a]	-2.68E+01[a]
	$h = 120$	-4.29E+01[a]	-4.29E+01[a]	-4.16E+01[a]	-4.94E+01[a]	-2.68E+01[a]
CORN	$h = 20$	-2.01E+01[a]	-2.03E+01[a]	-1.92E+01[a]	-4.10E+01[a]	-3.24E+01[a]
	$h = 60$	-1.96E+01[a]	-1.98E+01[a]	-1.87E+01[a]	-4.10E+01[a]	-3.22E+01[a]
	$h = 120$	-1.93E+01[a]	-1.95E+01[a]	-1.84E+01[a]	-4.10E+01[a]	-3.22E+01[a]
SOYBEANS	$h = 20$	-4.53E+01[a]	-4.50E+01[a]	-4.61E+01[a]	2.60E+01[a]	3.00E+01[a]
	$h = 60$	-4.51E+01[a]	-4.48E+01[a]	-4.59E+01[a]	2.64E+01[a]	3.01E+01[a]
	$h = 120$	-4.48E+01[a]	-4.45E+01[a]	-4.56E+01[a]	2.70E+01[a]	3.02E+01[a]
SOYBEAN OIL	$h = 20$	-13.8934[a]	-13.9265[a]	-13.9370[a]	36.8898[a]	11.2917[a]
	$h = 60$	-13.9156[a]	-13.9483[a]	-13.9590[a]	36.8503[a]	11.4756[a]
	$h = 120$	-13.9558[a]	-13.9873[a]	-13.9986[a]	36.4913[a]	11.8779[a]
SOYBEAN MEAL	$h = 20$	-4.76E+01[a]	-4.76E+01[a]	-4.76E+01[a]	-9.11E+00[a]	-1.73E+01[a]
	$h = 60$	-4.65E+01[a]	-4.65E+01[a]	-4.65E+01[a]	-9.16E+00[a]	-1.74E+01[a]
	$h = 120$	-4.41E+01[a]	-4.41E+01[a]	-4.41E+01[a]	-9.24E+00[a]	-1.76E+01[a]
ROUGH RICE	$h = 20$	-3.20E+01[a]	-3.20E+01[a]	-3.20E+01[a]	2.24E+01[a]	1.90E+01[a]
	$h = 60$	-3.18E+01[a]	-3.18E+01[a]	-3.18E+01[a]	2.20E+01[a]	1.93E+01[a]
	$h = 120$	-3.16E+01[a]	-3.16E+01[a]	-3.16E+01[a]	2.13E+01[a]	1.95E+01[a]
SUGAR #11	$h = 20$	-1.48E+01[a]	-1.35E+01[a]	-1.47E+01[a]	-2.95E+01[a]	5.00E+01[a]
	$h = 60$	-1.44E+01[a]	-1.32E+01[a]	-1.44E+01[a]	-2.92E+01[a]	4.95E+01[a]
	$h = 120$	-1.42E+01[a]	-1.30E+01[a]	-1.41E+01[a]	-2.87E+01[a]	4.89E+01[a]
COFFEE 'C'	$h = 20$	-3.42E+01[a]	-2.83E+01[a]	-2.47E+01[a]	-4.82E+01[a]	-2.86E+01[a]
	$h = 60$	-3.41E+01[a]	-2.82E+01[a]	-2.47E+01[a]	-4.84E+01[a]	-2.83E+01[a]
	$h = 120$	-3.39E+01[a]	-2.79E+01[a]	-2.44E+01[a]	-4.84E+01[a]	-2.80E+01[a]
COCOA	$h = 20$	6.92E+00[a]	7.12E+00[a]	1.13E+01[a]	-2.89E+01[a]	-3.05E+01[a]
	$h = 60$	7.07E+00[a]	7.31E+00[a]	1.15E+01[a]	-2.89E+01[a]	-3.03E+01[a]
	$h = 120$	6.89E+00[a]	7.20E+00[a]	1.13E+01[a]	-2.90E+01[a]	-2.98E+01[a]
ORANGE JUICE	$h = 20$	-1.28	-1.27	-1.28	-0.226	8.73E+00[a]
	$h = 60$	-1.84E+00[c]	-1.82E+00[c]	-1.84E+00[c]	0.593	9.06E+00[a]
	$h = 120$	-1.73E+00[c]	-1.71E+00[c]	-1.73E+00[c]	2.08E+00[b]	9.88E+00[a]
LEAN HOGS	$h = 20$	-8.74E+00[a]	-6.52E+00[a]	-1.04E+01[a]	3.09E+01[a]	4.40E+01[a]
	$h = 60$	-8.53E+00[a]	-6.32E+00[a]	-1.02E+01[a]	3.08E+01[a]	4.40E+01[a]
	$h = 120$	-8.15E+00[a]	-5.95E+00[a]	-9.82E+00[a]	3.08E+01[a]	4.38E+01[a]
FEEDER CATTLE	$h = 20$	-2.65E+01[a]	-2.61E+01[a]	-2.65E+01[a]	2.30E+01[a]	1.27E+01[a]
	$h = 60$	-2.65E+01[a]	-2.62E+01[a]	-2.66E+01[a]	2.36E+01[a]	1.19E+01[a]
	$h = 120$	-2.69E+01[a]	-2.66E+01[a]	-2.70E+01[a]	2.46E+01[a]	1.10E+01[a]
OATS	$h = 20$	-4.71E+01[a]	-4.71E+01[a]	-4.71E+01[a]	-8.01E+00[a]	-1.66E+01[a]
	$h = 60$	-4.62E+01[a]	-4.62E+01[a]	-4.62E+01[a]	-8.07E+00[a]	-1.68E+01[a]

	$h = 120$	-4.48E+01^{a}	-4.48E+01^{a}	-4.48E+01^{a}	-8.16E+00^{a}	-1.69E+01^{a}

Note: The figures in each cell are the modified Diebold and Mariano statistics with ^{a}, ^{b}, and ^{c} indicating statistical significance at 1%, 5%, and 10%, respectively. Columns 3 - 5 on the tables compare the exogeneous variable-based GARCH-MIDAS model with the conventional GARCH-MIDAS-RV (benchmark) model; while columns 6 and 7 compares respectively GARCH-MIDAS-CUI and GARCH-MIDAS-MUI with GARCH-MIDAS-CMUI (benchmark) model. Significant negative DMc estimates imply the outperformance of the exogeneous variable-based GARCH-MIDAS model over the benchmark model, as the case may be given the afore-described comparisons; while significant positive estimates denote the outperformance of the latter (the benchmark model) over the former.

Table 3: Economic Significance Result

Agriculture Commodity	Predictor	Returns	Volatility	Sharpe Ratio	Returns	Volatility	Sharpe Ratio
		$\gamma = 3$ *and* $\theta = 6$			$\gamma = 3$ *and* $\theta = 8$		
S&P GSCI Agriculture Total Index	RV	2.2106	2260.4771	0.0213	1.9840	4015.8021	0.0124
	CUI	1.6853	2409.5576	0.0099	1.2987	4279.5401	0.0016
	MUI	1.7233	2413.2483	0.0107	1.3488	4286.1192	0.0023
	CMUI	1.7037	2405.9627	0.0103	1.3229	4273.1963	0.0019
S&P GSCI Livestock Index	RV	3.2813	1386.8078	0.0560	3.5180	2466.8908	0.0467
	CUI	3.7446	1370.8752	**0.0688**	4.1383	2438.9057	**0.0596**
	MUI	3.7584	1366.8918	**0.0693**	4.1559	2431.8179	**0.0600**
	CMUI	3.7578	1373.4147	**0.0691**	4.1562	2443.4372	**0.0599**
S&P GSCI Softs Index	RV	6.4444	367.9071	0.2407	7.3618	654.7864	0.2163
	CUI	6.3437	479.1848	0.2063	7.2763	853.1040	0.1866
	MUI	6.3370	479.1802	0.2060	7.2683	853.1043	0.1863
	CMUI	6.3327	478.5496	0.2060	7.2622	851.9744	0.1862
S&P GSCI Grains Index	RV	-0.2346	3939.5521	-0.0228	-1.1393	7010.4329	-0.0279
	CUI	-0.0738	4175.9053	**-0.0197**	-0.9184	7431.4754	**-0.0245**
	MUI	-0.0758	4180.1699	**-0.0197**	-0.9208	7439.1118	**-0.0246**
	CMUI	-0.0881	4169.9382	**-0.0199**	-0.9374	7420.8475	**-0.0248**
WHEAT	RV	-4.8180	3884.6662	-0.0965	-7.3532	6900.5887	-0.1029
	CUI	-1.6899	3965.8674	**-0.0458**	-3.1350	7036.7054	**-0.0516**
	MUI	-1.6784	3977.0014	**-0.0456**	-3.1202	7056.4681	**-0.0514**
	CMUI	-1.6856	3968.2594	**-0.0458**	-3.1294	7040.9464	**-0.0516**
CORN	RV	-2.7398	19088.2087	-0.0285	-4.5710	33937.4263	-0.0313
	CUI	-2.6597	17665.9519	-0.0290	-4.4491	31409.7397	-0.0319
	MUI	-2.6428	17718.3220	-0.0288	-4.4280	31502.7924	-0.0317
	CMUI	-2.6677	17680.1831	-0.0291	-4.4606	31434.9745	-0.0319
SOYBEANS	RV	-0.5012	6789.0009	-0.0206	-1.5094	12076.3869	-0.0246
	CUI	0.2373	6829.7551	**-0.0116**	-0.5465	12147.8744	**-0.0158**
	MUI	0.2356	6821.9909	**-0.0116**	-0.5491	12134.0294	**-0.0159**
	CMUI	0.2418	6836.3970	**-0.0116**	-0.5401	12159.7438	**-0.0158**
SOYBEAN OIL	RV	5.3403	5450.1284	0.0468	5.6654	9689.3760	0.0384
	CUI	7.3460	1950.4880	**0.1237**	8.3467	3467.7841	**0.1098**
	MUI	7.3532	1952.4383	**0.1238**	8.3564	3471.2546	**0.1099**
	CMUI	7.3587	1953.5340	**0.1239**	8.3636	3473.2007	**0.1100**
SOYBEAN MEAL	RV	11.8151	1427.0714	0.2588	14.0179	2537.0158	0.2379
	CUI	11.7015	2879.7348	0.1801	14.0791	5119.5286	0.1683
	MUI	11.7044	2881.4231	0.1801	14.0829	5122.5299	0.1683
	CMUI	11.6997	2879.7022	0.1801	14.0766	5119.4705	0.1683
ROUGH RICE	RV	7.4161	7675.1744	0.0614	8.3921	13644.2684	0.0544
	CUI	9.4062	8215.9639	**0.0813**	11.0395	14605.4275	**0.0745**
	MUI	9.4019	8207.8736	**0.0813**	11.0338	14591.0503	**0.0745**
	CMUI	9.4089	8217.2171	**0.0813**	11.0434	14607.6576	**0.0745**
SUGAR #11	RV	-3.0713	11104.5132	-0.0408	-4.9919	19764.3395	-0.0442
	CUI	-2.0026	12838.6084	**-0.0285**	-3.6079	22843.2182	**-0.0320**
	MUI	-2.0679	12853.9870	**-0.0290**	-3.6948	22870.7418	**-0.0325**
	CMUI	-2.0067	12856.5110	**-0.0285**	-3.6134	22875.0911	**-0.0320**
COFFEE 'C'	RV	-5.0364	6581.1978	-0.0772	-7.5386	11731.1334	-0.0809
	CUI	-4.9892	6597.7020	**-0.0765**	-7.4750	11760.1848	**-0.0802**
	MUI	-4.9958	6581.3781	**-0.0767**	-7.4830	11731.2565	**-0.0804**
	CMUI	-5.0079	6581.8476	**-0.0768**	-7.4998	11731.9255	**-0.0806**
COCOA	RV	-2.0714	1895.0641	-0.0757	-3.5879	3377.7043	-0.0828
	CUI	-2.0049	1758.6069	-0.0770	-3.5152	3133.4869	-0.0847
	MUI	-1.9936	1764.1238	-0.0766	-3.5000	3143.3638	-0.0843
	CMUI	-2.0040	1761.4615	-0.0769	-3.5160	3138.5081	-0.0846
ORANGE JUICE	RV	-4.5589	7265.1411	-0.0679	-6.9377	12927.4091	-0.0718
	CUI	-4.2118	15641.0759	**-0.0435**	-6.4939	27847.1834	**-0.0463**
	MUI	-4.2134	15639.0347	**-0.0435**	-6.4959	27843.6130	**-0.0463**
	CMUI	-4.2116	15643.5573	**-0.0435**	-6.4937	27851.5869	**-0.0463**
LEAN HOGS	RV	-6.1371	173.9221	-0.5561	-9.1782	309.1940	-0.5901
	CUI	-5.0303	273.0962	**-0.3768**	-7.6838	485.4541	**-0.4031**
	MUI	-5.2987	265.0407	**-0.3990**	-8.0447	471.1930	**-0.4258**
	CMUI	-5.0087	264.1351	**-0.3818**	-7.6604	469.5823	**-0.4088**
FEEDER CATTLE	RV	2.4278	3463.9474	0.0206	2.3106	6159.6303	0.0140
	CUI	3.3383	2838.9493	**0.0399**	3.5040	5048.1808	**0.0322**

	MUI	3.3376	2839.0791	**0.0398**	3.5029	5048.4148	**0.0322**
	CMUI	3.3427	2838.0908	**0.0399**	3.5100	5046.6562	**0.0323**
OATS	RV	9.0082	4010.5231	0.1101	10.2406	7129.8189	0.0972
	CUI	9.7339	8044.9248	0.0858	11.4556	14302.0885	0.0788
	MUI	7.1125	6920.4412	0.0610	7.8443	12321.0551	0.0523
	CMUI	9.7325	8044.3890	0.0858	11.4538	14301.1359	0.0787

Note: Bold fonts indicate instances where the uncertainty-based GARCH-MIDAS model yields higher economic gains than the realized volatility (RV)-based variant.

Table 4: Model Confidence Set Result

Agriculture Commodity	Candidate Model	Estimate	Estimate	Estimate
		$h = 20$	$h = 60$	$h = 120$
S&P GSCI Agriculture Total Index	CUI	**2.394* [1.000]**	**8.127* [1.000]**	**5.311* [1.000]**
	MUI	**2.394* [0.925]**	**5.903* [1.000]**	**5.31* [1.000]**
S&P GSCI Livestock Index	CMUI	**2.374* [1.000]**	**5.904* [0.266]**	**8.299* [0.724]**
S&P GSCI Softs Index	CUI	**2.374* [0.883]**	**5.837* [1.000]**	**8.249* [1.000]**
	MUI	**2.333* [1.000]**	**5.838* [0.249]**	**8.249* [1.000]**
S&P GSCI Grains Index	CUI	**2.333* [0.93]**	**5.792* [1.000]**	**8.249* [1.000]**
	MUI	**1.763* [1.000]**	**5.794* [0.254]**	**8.177* [0.505]**
WHEAT	CUI	**1.77* [1.000]**	**3.765* [1.000]**	**8.082* [1.000]**
CORN	CUI	**1.777* [1.000]**	**3.764* [1.000]**	**8.083* [1.000]**
	MUI	**2.326* [0.376]**	**3.728* [1.000]**	**8.082* [1.000]**
SOYBEANS	CMUI	**2.325* [1.000]**	**4.232* [1.000]**	**8.146* [0.66]**
SOYBEAN OIL	CMUI	**4.588* [1.000]**	**4.620* [1.000]**	**4.653* [1.000]**
SOYBEAN MEAL	MUI	**2.329* [0.268]**	**4.296* [1.000]**	**8.088* [1.000]**
ROUGH RICE	CMUI	**2.328* [1.000]**	**4.409* [1.000]**	**8.089* [1.000]**
SUGAR #11	CUI	**2.329* [0.116]**	**4.228* [1.000]**	**8.088* [1.000]**
COFFEE 'C'	CUI	**2.328* [1.000]**	**4.251* [1.000]**	**10.427* [1.000]**
COCOA	RV	3.396* [1.000]	4.332* [1.000]	10.515* [1.000]
ORANGE JUICE	RV	3.396* [0.964]	5.977* [1.000]	10.519* [1.000]
	CUI	**3.37* [1.000]**	**5.98* [1.000]**	**2.579* [1.000]**
	MUI	**3.37* [0.925]**	**5.996* [1.000]**	**2.576* [1.000]**
	CMUI	**3.316* [1.000]**	**8.399* [1.000]**	**2.605* [1.000]**
LEAN HOGS	CMUI	**3.316* [0.963]**	**8.397* [1.000]**	**7.399* [1.000]**
FEEDER CATTLE	CMUI	**8.181* [1.000]**	**8.381* [1.000]**	**7.494* [1.000]**
OATS	MUI	**8.143* [1.000]**	**5.327* [1.000]**	**7.631* [1.000]**
The percentage number of qualifying as a candidate model				
	RV	**5.88%**		
	CUI	**47.06%**		
	MUI	**41.18%**		
	CMUI	**41.18%**		

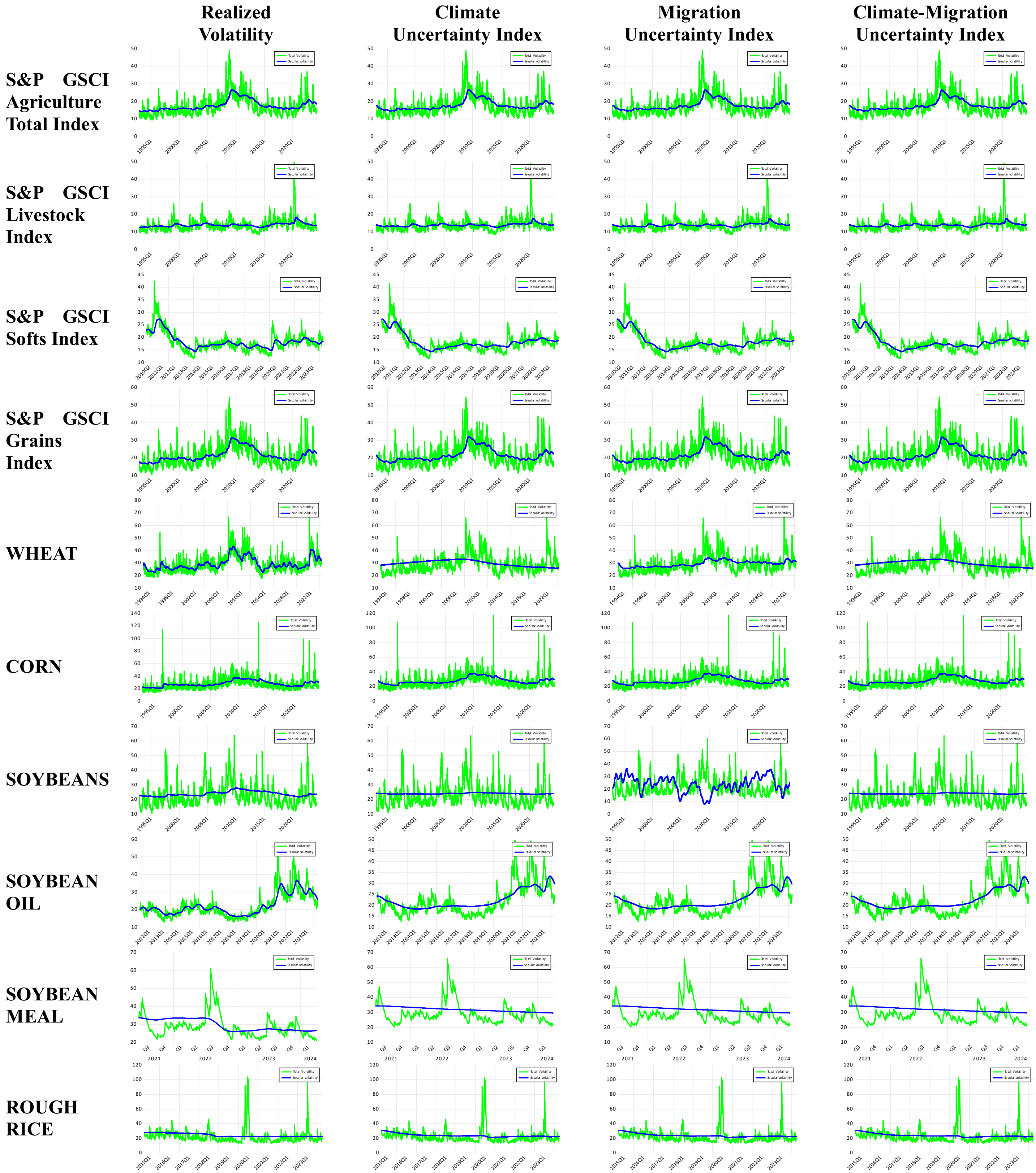
Note: The table shows the candidacy of four contending GARCH-MIDAS models, which are distinguished by the predictor (RV, CUI, MUI and CMUI) that is incorporated; under three different out-of-sample forecast horizons (20-, 60- and 120-day ahead). The figures in each cell are the mean squared error and the corresponding MCS p-value in square brackets. A model is considered to be among the 90% model confidence set if the observed MCS p-value is greater than 10% levels of significance; while the columns labelled "Candidate Model" indicate that the listed model(s) do(es) belong(s) to the 90% model confidence set for the corresponding agriculture commodity. The model with the least mean square error value is adjudged the most preferred. Figures in bold fonts indicate instances where the exogenous variable-based GARCH–MIDAS model variants are ranked above the GARCH–MIDAS–RV model. The asterisk "*" indicates that the corresponding model belongs to the model confidence set.

Appendix:

Table A1: In-Sample Predictability Result

	Climate Uncertainty Index	Migration Uncertainty Index	Climate-Migration Uncertainty Index
S&P GSCI Agriculture Total Index	6.60E-02[a] [1.01E-02]	6.63E-02[a] [1.03E-02]	6.56E-02[a] [1.02E-02]
S&P GSCI Livestock Index	5.72E-02[a] [2.18E-02]	5.90E-02[a] [2.26E-02]	5.75E-02[a] [2.18E-02]
S&P GSCI Softs Index	7.79E-02[a] [1.43E-02]	7.88E-02[a] [1.48E-02]	7.87E-02[a] [1.46E-02]
S&P GSCI Grains Index	6.55E-02[a] [8.29E-03]	6.61E-02[a] [8.48E-03]	6.54E-02[a] [8.42E-03]
WHEAT	-3.23E-02[a] [1.07E-02]	-3.25E-02[a] [1.08E-02]	-3.18E-02[a] [1.07E-02]
CORN	6.02E-02[a] [3.32E-03]	6.10E-02[a] [3.36E-03]	6.04E-02[a] [3.33E-03]
SOYBEANS	1.22E-02 [2.06E-02]	-1.37E-01[a] [2.93E-02]	1.09E-02 [2.09E-02]
SOYBEAN OIL	6.55E-02[a] [2.07E-02]	6.64E-02[a] [2.28E-02]	6.60E-02[a] [2.22E-02]
SOYBEAN MEAL	7.77E-02 [2.07E+00]	7.72E-02 [2.52E+00]	7.76E-02 [2.53E+00]
ROUGH RICE	-5.58E-02[a] [2.02E-02]	-5.81E-02[a] [2.03E-02]	-5.68E-02[a] [2.03E-02]
SUGAR #11	-1.87E-02 [1.25E-02]	-1.86E-02 [1.25E-02]	-1.93E-02 [1.26E-02]
COFFEE 'C'	8.48E-02 [1.81E-01]	9.08E-02 [1.80E-01]	8.15E-02 [1.80E-01]
COCOA	1.43E-01 [2.21E-01]	1.42E-01 [2.23E-01]	1.42E-01 [2.23E-01]
ORANGE JUICE	8.83E-02 [2.04E-01]	8.65E-02 [2.07E-01]	8.82E-02 [2.06E-01]
LEAN HOGS	-4.35E-01[a] [3.71E-02]	-4.52E-01[a] [3.98E-02]	-4.29E-01[a] [3.85E-02]
FEEDER CATTLE	1.13E-01[a] [6.24E-03]	1.23E-01[a] [6.84E-03]	1.14E-01[a] [6.20E-03]
OATS	6.53E-02 [1.87E+00]	6.52E-02 [1.87E+00]	6.64E-02 [1.89E+00]

Note: The figures in each cell are the estimates of the slope coefficients with their corresponding standard errors in square brackets, indicating the predictability or otherwise of the column-labelled predictors. The statistical significance of the estimates at 1%, 5% and 10% are indicated by a, b and c, respectively.


Realized Volatility
Climate Uncertainty Index
Migration Uncertainty Index
Climate-Migration Uncertainty Index
S&P GSCI Agriculture Total Index
S&P GSCI Livestock Index
S&P GSCI Softs Index
S&P GSCI Grains Index
WHEAT
CORN
SOYBEANS
SOYBEAN OIL
SOYBEAN MEAL
ROUGH RICE

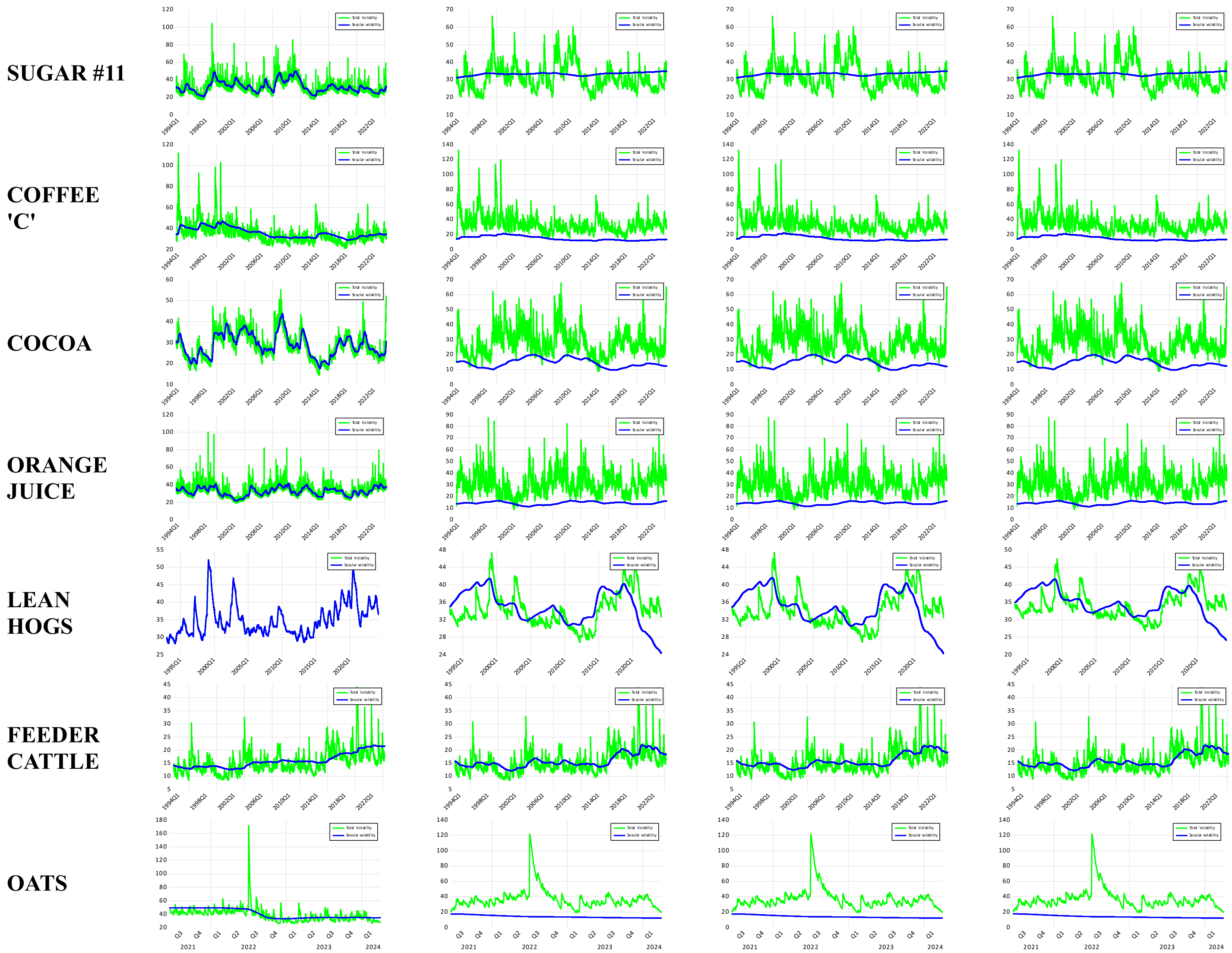


Figure A1: Predictability Graphs showing the Total Volatility (green line) and Secular volatility (Blur line)