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Double Asymmetric Impacts, Dynamic Correlations, and Risk Management Amidst Market Risks: A Comparative Study between the US and China

Poshan Yu ^{1,*} , Haoran Xu ² and Jianing Chen ²

¹ Business School, Soochow University, Suzhou 215006, China

² Independent Researcher, Suzhou 215006, China; xhr0316@outlook.com (H.X.); chenjn0929@outlook.com (J.C.)

* Correspondence: samyu@suda.edu.cn

Abstract: Extreme shocks, including climate change, economic sanctions, geopolitical conflicts, etc., are significant and complex issues currently confronting the global world. From the US–China perspective, this paper employs the DCC-DAGM model to investigate how diverse market risks asymmetrically affect return volatility, and extract correlations between stock indices and hedging assets. Then, diversified and hedging portfolios, constructed by optimal weight and hedge ratio, are investigated using multiple risk reduction measures. The empirical results highlight that, first, diverse risks exhibit an asymmetric effect on the return volatility in the long term, while in the short term, the US stock market is more sensitive to negative return shocks than the Chinese market. Second, risks impact correlations differently across time horizons and countries. Short-term correlations are stronger than long-term ones for the US market, with the Chinese stock market displaying more stable correlations. Third, the hedging strategy is more effective in reducing volatility and risk for US stocks, while the diversification strategy proves more effective for Chinese stocks. These findings have implications for market participants striving to make their portfolios robust during turbulent times.

Keywords: hedging asset; risk and uncertainty; emerging market; risk management strategy; double asymmetric GARCH-MIDAS



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1. Introduction

Over the last few decades, worldwide financial markets have been subjected to a slew of extreme shocks, including trade wars (Xu and Lien 2020; Chen et al. 2023), the COVID-19 pandemic (Zaremba et al. 2020; Yu and Xiao 2023), geopolitical conflicts (Saâdaoui et al. 2022; Umar et al. 2023), economic sanctions (Korotin et al. 2019; Meyer et al. 2023), and climate change (Bellard et al. 2012; Xu et al. 2022), all of which have posed significant obstacles and hazards to the growth of global financial markets. With elevated risks, equity investors confront hurdles and typically employ portfolio diversification and hedging strategies to manage these risks.

Previous research demonstrates the efficacy of assets, like green bonds (Dong et al. 2023), crude oil (Lin et al. 2021), gold (Akhtaruzzaman et al. 2021), and Bitcoin (Garcia-Jorcano and Benito 2020), etc., as hedges against stock market fluctuations. However, these studies often overlook the nuanced impact of distinct risks and treat them uniformly without acknowledging their asymmetric characteristics. Furthermore, certain studies have addressed market risks, albeit limited to one or several types (Kamal et al. 2022; Cheng et al. 2022; Xia et al. 2023). Risks stemming from diverse sources demand a comprehensive assessment, as prior research has not collectively considered these variables (Hasan et al. 2023). Moreover, most scholarly research focuses on stock markets in developed economies (Guo and Zhou 2021), with limited attention given to emerging markets. However, as globalization progresses, international investors are increasingly turning their focus to emerging markets (Butt et al. 2022; Boufounou and Tinos 2023). Hence, it remains a

relatively unexplored research problem about whether various risks asymmetrically impact asset return volatility and what distinctions are in correlation and risk management between developed and emerging countries' stock markets and these assets.

China is undeniably the main trading partner of the emerging stock markets. Therefore, the Chinese stock market is highly integrated with emerging stock markets (Yousaf and Hassan 2019; Yousaf and Ali 2021). Mensi et al. (2023) find strong dependence on the US stock market and other markets in developed countries. Inspired by the above, this study aims to provide updated evidence for asymmetric impacts that various risks have on different assets and dynamic correlations, as well as risk management of these assets with stock indices, using a comparative study of representative developed economies (US) and emerging economies (China).

This study contributes to the literature in at least two dimensions. First, it delves into the leverage effect stemming from negative return shocks while also addressing the distinct impact of positive and negative uncertainty variations on return volatility. In contrast to the prevailing focus on the overall changes in macro uncertainty, this decomposition provides more precise insights. Second, this study extends the existing literature by simultaneously examining five different risks and discerning distinctions in risk management strategies within stock markets of developed and emerging countries. To the best of our knowledge, such a comprehensive investigation has not been conducted previously.

This study reveals intriguing findings. Firstly, various risks exhibit asymmetric impacts on asset return volatility, with oil and S&P 500 displaying significant short-term leverage effects. Negative shocks impact the US stock market more than the Chinese market. In the long run, risk fluctuations lead to either symmetric or asymmetric consequences. Secondly, risks influence the relationships between US and Chinese stocks and other assets differently across short and long timeframes, with stronger and more volatile short-term correlations for the S&P 500. The Chinese stock market displays more stable correlations, intensifying during extreme events. Thirdly, hedging is more effective at mitigating the volatility and risk of US stocks, while diversification proves more effective for Chinese stocks. Diversified Chinese portfolios allocate more to green bonds and gold, whereas US portfolios favor a higher exposure to oil and Bitcoin. Hedging Chinese stocks is notably cost-effective, except when involving green bonds in hedging portfolios.

The remainder of this paper is organized as follows: Section 2 reviews related literature, Section 3 presents the methodology and data, Section 4 discusses the empirical results, and Section 5 concludes the findings.

2. Literature Review

After the 2008 GFC, multiple policy risk factors emerged and have been proven to be very informative in describing or forecasting the fluctuations of various markets in current research. Particularly, the Economic Policy Uncertainty (EPU) and Trade Policy Uncertainty (TPU) of Baker et al. (2016), the Climate Policy Uncertainty (CPU) of Gavrilidis (2021), the Equity Market Volatility (EMV) of Baker et al. (2019), and the Geopolitical Risk (GPR) of Caldara and Iacoviello (2022) recently attracted the most attention from scholars. This section provides a concise review of prior research examining the impact on asset returns and their correlation with developed and emerging stock markets.

Due to the vast and fragmented literature in the field, this paper collates relevant studies to our best knowledge in Table 1 and lists some important ones in Table 2 for a brief illustration. Specifically, we can summarize the following points. Firstly, in terms of risk, the literature is predominantly focused on EPU, while studies concerning other factors are relatively rare. One explanation is that EPU daily data is available, unlike other factors that are merely at a monthly frequency, imposing limitations on methods. Besides EPU, CPU and GPR also receive considerable attention. Nonetheless, numerous current studies fail to consider the asymmetric effects, which is a crucial aspect of understanding impact patterns. Secondly, as for methodology, the related research extensively involves wavelet-based (Cao et al. 2023) and copula-based (Reboredo 2018) approaches, and the

most prevalent GARCH models. However, methodological limitations pose barriers to conducting asymmetric analysis, as few approaches effectively handle asymmetry and data at varying frequencies simultaneously. Limited studies often rely on ARDL models for asymmetry using consistent low-frequency data, which also lacks support from alternative methods (Xiang et al. 2023; Simran and Sharma 2023). The literature on the dynamic relationship between assets and stock markets bifurcates into two main streams. One stream explores risk spillovers and connectedness using methods such as quantile regression and the TVP-VAR model, which, however, face challenges in data frequencies (Chen et al. 2022; Zhang et al. 2021b), while the other regularly utilizes the DCC model to evaluate correlation. Hence, to address these issues, we adopt the double asymmetry GARCH-MIDAS model proposed by Amendola et al. (2019), which can be combined with the DCC model and is ideal for our investigation to fill the research gap. Third, from a national perspective, research on the disparities between emerging and developed countries on the impact of risk on assets, or the relationship between assets and stock markets, is insufficient, necessitating a more thorough investigation. Additionally, the current literature falls short in practical examinations, such as establishing investment portfolios (Zhao and Wang 2022; Salisu et al. 2022). Some studies predominantly emphasize hedging strategies, overlooking a simultaneous evaluation of alternative risk management approaches like diversification, especially in the context of both developed and emerging nations.

Table 1. Summary of relevant literature.

	Stock		Green Bond		Gold		Oil		Bitcoin	
	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging
EPU	✓✓	✓✓	✓✓*	✓*	✓✓*	✓*	✓*	✓*	✓✓*	✓✓*
CPU	✓✓	✓✓	✓✓*	✓✓	✓	×	✓*	✓*	✓	×
TPU	✓✓	✓✓	×	✓*	✓	✓	✓	✓	✓	✓
EMV	✓	✓	✓✓	✓✓	✓*	✓	✓✓	✓	✓	×
GPR	✓✓	✓✓	✓✓*	✓✓	✓✓*	✓	✓*	✓	✓*	✓*

Notes: A ✓ means the impact of specific risk on such asset from the perspective of developed or emerging countries has been studied, and × represents not, and a double ✓ means asymmetry is considered. A * means the correlation between such assets and developed or emerging stock markets has been explored under certain risks.

Table 2. Summary of some important research.

Author	Risk	Asset	Country	Main Findings
Dong et al. (2023)	EPU, CPU, GPR	GB, stock	US	Both conventional and green bonds have a safe-haven feature when the GPR is high. However, green bonds provide a safer haven than conventional bonds as EPU and CPU increase.
Xu et al. (2023)	CPU	stock	US, China	High CPU in China decreases stock market return and increases volatility, while in the US, it decreases short-term return but increases long-term returns, increasing the correlation between China and US stock markets.
Ben Nour and Ben Haj Hamida (2023)	EPU, GPR	BTC, oil, stock, currency	US, China	The relationship between uncertainty and Bitcoin volatility varies, with US uncertainty having short-term effects and China's long-term effects. Bitcoin responds similarly to US EPU and GPR but oppositely when combined.
Chen et al. (2022)	TPU	precious metals	US, China	Chinese and American TPU spillover effects on precious metal markets are asymmetrical, with American TPUs dominating. Gold and silver's self-adjustment makes them suitable for hedging investments amid TPU.
Salisu et al. (2022)	GPR	stock	Emerging countries	Emerging stock market volatility responds more positively to GPR than developed ones.

Table 2. Cont.

Author	Risk	Asset	Country	Main Findings
Ding et al. (2022)	CPU	GB, stock, oil	US	High CPU decreases the effectiveness of low-carbon assets as a hedge of carbon-intensive assets while improving the performance of carbon-intensive portfolios diversified by low-carbon assets.
Zhao and Wang (2022)	EPU	gold, oil, stock	US, China	EPU has homogeneous negative effects on gold-stock correlations and stronger positive impacts on oil-stock correlations in medium and high regimes, suggesting gold offers better diversification during economic uncertainty.
Ma et al. (2021)	EMV	GB, stock	US	EMV significantly and asymmetrically affects stock-bond and stock-gold correlations in different ways. Bonds are more effective than gold in hedging volatility during market turbulence.
Al Mamun et al. (2020)	GPR	bonds, stock, gold, dollar	US	GPR and EPU charge a risk premium in distress markets, with geopolitical risk and global and US EPU more significant during unfavorable economic conditions.
Cheng and Yen (2020)	EPU	cryptocurrencies	US, China, Japan, Korea	China's EPU can predict Bitcoin monthly returns, unlike the US or other Asian countries. But it has no predictive power for other major cryptocurrencies, and its ban on crypto-trading affects Bitcoin returns.

3. Data and Methodology

3.1. Data and Descriptive Statistics

Data spanning from September 2013 to September 2023 is sourced from various channels due to availability. This period includes significant events such as the US–China trade conflict, the COVID-19 epidemic, and the Ukraine–Russia military engagement. These impactful events, with notable effects on financial markets, provide a comprehensive view of the dynamic correlations within the examined market. The dataset contains the daily time series of the S&P 500, S&P Green Bond Index, S&P GSCI Gold, CSI 300, WTI crude oil, and Bitcoin. S&P 500 and CSI 300 are proxies for the US and Chinese stock markets, respectively. Other indices represent corresponding global markets. Despite the existing Chinese ban on crypto-trading, this paper incorporates Bitcoin as a hedging asset to align with the perspective of international investors. Monthly uncertainty factors are provided by www.policyuncertainty.com (accessed on 11 September 2023). Details about variables are summarized in Table 3. All the daily data are converted into logarithmic percentage return series as $r_t = \ln(P_t/P_{t-1})$ and monthly data are converted into the difference in logarithms as $\Delta risk_t = \ln(risk_t/risk_{t-1})$.

Table 3. Summary of variables.

Variable	Abbr.	Market	Source
CSI 300 Index	CSI 300	Chinese stock market	www.csindex.com.cn (accessed on 11 September 2023)
S&P 500 Index	S&P 500	US stock market	S&P Dow Jones Indices (accessed on 11 September 2023)
S&P Green Bond Index	GB	Global green bonds market	S&P Dow Jones Indices (accessed on 11 September 2023)
S&P GSCI Gold Index	Gold	Global gold market	S&P Dow Jones Indices (accessed on 11 September 2023)
Crude Oil WTI Futures	Oil	Global oil market	www.investing.com (accessed on 11 September 2023)
Bitcoin Closing Prices	Bitcoin	Global bitcoin market	www.investing.com (accessed on 11 September 2023)
Economic Policy Uncertainty	EPU	Risk from global economy	www.policyuncertainty.com (accessed on 11 September 2023)
Climate Policy Uncertainty	CPU	Risk from global climate change	www.policyuncertainty.com (accessed on 11 September 2023)
Trade Policy Uncertainty	TPU	Risk from global trade wars	www.policyuncertainty.com (accessed on 11 September 2023)
Equity Market Volatility	EMV	Risk from US equity market volatility	www.policyuncertainty.com (accessed on 11 September 2023)
Geopolitical Risk	GPR	Risk from global geopolitical conflicts	www.policyuncertainty.com (accessed on 11 September 2023)

The descriptive statistics listed in Table 4 show that the means of all six asset returns are close to 0. The skewness deviates from 0 and the kurtosis is greater than 3, highlighting

the non-normality of the returns. Moreover, it is noteworthy that Bitcoin and GPR exhibit high positive skewness and kurtosis values, suggesting longer or fatter tails on the right side. The Jarque–Bera test formally confirms the non-normality of the return series except for TPU. The ADF test verifies that all return series are stationary. The Ljung–Box test indicates autocorrelation, and the ARCH test shows conditional heteroscedasticity.

Table 4. Descriptive statistics.

	Mean	Max.	Min.	St. Dev.	Skew.	Kurt.	J-B	ADF	L-B(10)	ARCH(10)
CSI 300	0.000	0.065	−0.092	0.014	−0.799	5.982	3901.893 ***	−8.692 ***	38.783 ***	327.588 ***
S&P 500	0.000	0.090	−0.128	0.011	−0.837	17.465	31,335.996 ***	−12.922 ***	211.11 ***	953.819 ***
GB	0.000	0.023	−0.024	0.004	−0.243	4.495	2080.953 ***	−32.013 ***	43.444 ***	279.257 ***
Gold	0.000	0.056	−0.051	0.009	−0.093	3.895	1548.091 ***	−11.117 ***	11.595 ***	125.426 ***
Oil	0.000	0.320	−0.282	0.030	0.301	23.643	56,938.933 ***	−9.848 ***	73.766 ***	660.549 ***
Bitcoin	0.002	1.474	−0.849	0.062	4.285	148.051	2,238,660.052 ***	−18.544 ***	80.568 ***	235.490 ***
EPU	0.005	0.743	−0.495	0.182	0.676	1.707	53.642 ***	−13.167 ***		
CPU	0.004	1.233	−1.701	0.374	−0.248	1.170	17.894 ***	−7.083 ***		
TPU	−0.011	2.027	−1.988	0.740	−0.026	−0.143	0.339	−9.586 ***		
EMV	0.000	1.090	−0.824	0.273	0.444	1.392	30.601 ***	−8.625 ***		
GPR	0.001	2.051	−0.600	0.229	2.653	22.376	6015.617 ***	−8.020 ***		

Notes: *** denotes statistical significance at 1% level.

Table 5 displays a correlation matrix of the variables. S&P 500 and CSI 300 demonstrate significant correlations with green bonds and oil while exhibiting non-significant correlations with gold. Moreover, the S&P 500 displays stronger correlations with these assets compared to the CSI 300, except for gold.

Table 5. Correlation matrix of returns.

	CSI 300	S&P 500	Green Bond	Gold	Oil	Bitcoin
CSI 300	1.0000	0.1591 ***	0.0452 **	0.0138	0.1025 ***	0.0223
S&P 500	0.1591 ***	1.0000	0.0950 ***	0.0113	0.2430 ***	0.1394 ***
Green bond	0.0452 **	0.0950 ***	1.0000	0.4478 ***	−0.0092	0.0537 ***
Gold	0.0138	0.0113	0.4478 ***	1.0000	0.0750 ***	0.0277
Oil	0.1025 ***	0.2430 ***	−0.0092	0.0750 ***	1.0000	0.0431 **
Bitcoin	0.0223	0.1394 ***	0.0537 ***	0.0277	0.0431 **	1.0000

Notes: *** and ** denote statistical significance at 1% and 5% levels, respectively.

3.2. Methodology

Engle et al. (2013) extend the GARCH model by Bollerslev (1986) into the GARCH-MIDAS model, which can deal with variations in different frequencies. To investigate the asymmetry in the volatility dynamics, Amendola et al. (2019) adopt the Double Asymmetric GARCH-MIDAS (DAGM) model; an asymmetric GJR-GARCH model by Glosten et al. (1993) describes the daily dynamics (first asymmetry) and a variable available at a lower frequency drives the slow-moving level of volatility (MIDAS) but produces differentiated effects according to its sign (second asymmetry). The DCC-MIDAS model (Colacito et al. 2011) improves on the DCC model by allowing time-varying short- and long-term correlations to be distinguished. Similar to Conrad et al. (2014) and Ding et al. (2022), this paper extends the DCC-MIDAS model by including CPU, EMV, EPU, GPR, and TPU into the correlation component, respectively, which can capture the influences of these different exogenous risks on the asset return volatility and correlations.

Following Amendola et al. (2019, 2020, 2021), initially, this paper employs the DAGM model to assess return volatility across diverse assets amid uncertainties. Subsequently, it estimates dynamic conditional correlations using the return volatility derived from the first step through the DCC-MIDAS model.

In the first step, consider a set of n assets and let the vector of returns be denoted as $r_t = [r_{1,t}, r_{2,t} \dots r_{n,t}]'$. Then, all the asset returns $r_{i,t} (i = 1 \dots n)$ follow the process $r_{i,t} = \sqrt{\tau_t} \times g_{i,t} \varepsilon_{i,t}$, with $\varepsilon_{i,t} | \Phi_{i,t-1} \sim N(0, 1)$ in which τ_t and $g_{i,t}$ indicate the long-term and short-term component of variance, respectively.

In the DAGM model, $g_{i,t}$ follows a unit-mean reverting GJR-GARCH(1,1) process specified by

$$g_{i,t} = (1 - \alpha - \gamma/2 - \beta) + \left(\alpha + \gamma \cdot \mathcal{I}_{(r_{i-1,t} < 0)} \right) \frac{(r_{i-1,t})^2}{\tau_t} + \beta g_{i-1,t} \quad (1)$$

where $\mathcal{I}_{(\cdot)}$ is an indicator function. As is customary in a GARCH model, the short-run parameters are subject to $\alpha > 0$; $\beta \geq 0$; $\gamma \geq 0$; $\alpha + \beta + \gamma/2 < 1$. Meanwhile, τ_t delivers the long-run component of the local level of volatility defined as

$$\log(\tau_t) = m + \theta^+ \sum_{k=1}^K \delta_k(\omega)^+ X_{t-k} \mathcal{I}_{(X_{t-k} \geq 0)} + \theta^- \sum_{k=1}^K \delta_k(\omega)^- X_{t-k} \mathcal{I}_{(X_{t-k} < 0)} \quad (2)$$

where m plays the role of an intercept, θ^+ and θ^- appear for the asymmetric responses to the one-sided filter, and $\delta_k(\omega)^+$ and $\delta_k(\omega)^-$ are suitable functions weighing the past K realizations of the exogenous stationary predetermined variable, which is labeled X_{t-k} . Throughout this work, the Beta function will be used as a weighting function of all the GM models, which is expressed as

$$\delta_k(\omega)^+ = \frac{(k/K)^{\omega_1^+ - 1} (1 - k/K)^{\omega_2^+ - 1}}{\sum_{j=1}^K (j/K)^{\omega_1^+ - 1} (1 - j/K)^{\omega_2^+ - 1}} \quad (3)$$

$$\delta_k(\omega)^- = \frac{(k/K)^{\omega_1^- - 1} (1 - k/K)^{\omega_2^- - 1}}{\sum_{j=1}^K (j/K)^{\omega_1^- - 1} (1 - j/K)^{\omega_2^- - 1}} \quad (4)$$

with $\omega_1^+ = \omega_1^- = 1$, which enables more weighting of the most recent observations (monotonically decreasing weighting scheme). The Beta functions ensure that $\sum_{k=1}^K \delta_k(\omega_2^+) = \sum_{k=1}^K \delta_k(\omega_2^-) = 1$.

In the second step, following Colacito et al. (2011), this paper assumes that the short-term correlations fluctuate around the long-term correlations. Specifically, the time-varying correlations can be constituted as follows:

$$q_{ij,t} = (1 - a_{ij} - b_{ij}) \bar{\rho}_{ij,\tau} + a_{ij} \varepsilon_{i,t-1} \varepsilon_{j,t-1} + b_{ij} q_{ij,t-1} \quad (5)$$

where the $q_{ij,t}$ is the short-term correlation at the time t . $\varepsilon_{i,t-1}$ and $\varepsilon_{j,t-1}$ are standard residuals of the returns obtained from the first step. $\bar{\rho}_{ij,\tau}$ is the long-term correlation driven by the exogenous risks. To ensure that the long-term correlations lie within the $[-1, +1]$ interval, this paper uses the following Fisher-Z transformation of correlation coefficients:

$$\bar{\rho}_{ij,\tau} = \frac{e^{2z_{ij,t}} - 1}{e^{2z_{ij,t}} + 1} \quad (6)$$

with

$$z_{ij,t} = m_{ij} + \theta_{ij}^+ \sum_{k=1}^K \varphi_k(\omega_{ij})^+ X_{t-k} \mathcal{I}_{(X_{t-k} \geq 0)} + \theta_{ij}^- \sum_{k=1}^K \varphi_k(\omega_{ij})^- X_{t-k} \mathcal{I}_{(X_{t-k} < 0)} \quad (7)$$

where θ_{ij}^+ and θ_{ij}^- capture the effect of the uncertainties on the long-term correlations between stock indices and hedging assets. The weighting scheme in Equation (7) is also a restricted Beta weighting scheme with similar definitions in Equations (3) and (4). Eventually, the time-varying conditional correlations can be obtained by the specification as follows:

$$\rho_{ij,k} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} \cdot q_{jj,t}}} \quad (8)$$

4. Empirical Results

4.1. Double Asymmetric GARCH-MIDAS Model Analysis

The empirical results of the DAGM model are presented in Tables 6–11. Lags are selected based on the BIC. Large and significant β values specify the persistence of volatility. The sum of the parameters $\alpha + \beta + 0.5\gamma$ is close to 1, suggesting the stability of the model. Most coefficients γ , which measure the leverage effect, are positive but insignificant, implying that negative shocks are likely to have a larger influence on volatility than the positive shocks on these assets in the short term. It is worth noting that all γ values of the S&P 500 and crude oil are significant, demonstrating that their volatility is obviously more vulnerable to negative shocks. Compared to the S&P 500, the CSI 300 has an insignificant and weaker leverage effect. Further, gold with weak positive γ and green bonds with weak negative γ are basically symmetrically impacted by fluctuations in returns.

Table 6. Empirical results for DAGM-CSI 300.

	α	γ	β	m	θ^+	ω^+	θ^-	ω^-	LL	AIC	BIC
EPU	0.0653 *** (0.0142)	0.0135 (0.0218)	0.9156 ** (0.0194)	−7.4691 *** (0.3898)	−16.4764 *** (1.6917)	1.2010 *** (0.2998)	−1.7339 (1.9715)	10.3759 *** (0.6942)	7240.110	−14,468.221	−14,433.493
CPU	0.0727 *** (0.0135)	0.0150 (0.0247)	0.9106 *** (0.0200)	−9.4810 *** (0.3989)	−5.2046 *** (1.3442)	1.2217 *** (0.4195)	−12.4170 *** (0.8298)	1.0011 ** (0.4122)	7240.591	−14,469.183	−14,434.450
TPU	0.0706 *** (0.0135)	0.0144 (0.0223)	0.9147 *** (0.0184)	−7.2056 *** (0.4786)	−3.0898 *** (0.6131)	1.5283 *** (0.4208)	0.7828 ** (0.3146)	9.5406 *** (1.6572)	7236.748	−14,461.507	−14,426.774
EMV	0.0680 *** (0.0128)	0.0119 (0.0202)	0.9202 *** (0.0169)	−7.9784 *** (0.3904)	−2.4064 *** (0.8221)	3.8693 *** (0.4812)	0.8805 *** (0.3290)	12.3706 *** (3.5888)	7236.887	−14,461.772	−14,427.051
GPR	0.0725 *** (0.0137)	0.0113 (0.0223)	0.9156 *** (0.0188)	−7.9365 *** (0.3672)	−2.0526 *** (0.3374)	1.0148 *** (0.3286)	2.6474 *** (0.9877)	3.1484 *** (0.4721)	7237.728	−14,463.463	−14,428.737
Baseline	α 0.0748 *** (0.0134)	γ 0.0104 (0.0131)	β 0.9155 *** (0.0139)	ω 0.0000 *** (0.0000)					7225.612	−14,443.224	−14,420.073

Notes: The standard deviations are reported in parentheses. *** and ** denote statistical significance at 1% and 5% levels, respectively. The baseline item is from a basic DCC-GJR-GARCH model without any exogenous variable.

Table 7. Empirical results for DAGM-S&P 500.

	α	γ	β	m	θ^+	ω^+	θ^-	ω^-	LL	AIC	BIC
EPU	0.0664 ** (0.0331)	0.2463 *** (0.0555)	0.7830 *** (0.0356)	−7.9223 *** (0.4211)	−14.6334 *** (1.2851)	1.0012 *** (0.3176)	−2.5615 *** (0.7827)	46.2344 *** (0.1190)	8119.283	−16,226.578	−16,191.844
CPU	0.0607 * (0.0342)	0.2584 *** (0.0566)	0.7801 *** (0.0373)	−8.8367 *** (0.4055)	0.0363 (0.9213)	6.6176 *** (2.0584)	0.1277 *** (0.0110)	9.2463 *** (0.0468)	8108.501	−16,205.001	−16,170.286
TPU	0.0407 (0.0280)	0.2699 *** (0.0546)	0.7903 *** (0.0351)	−7.3164 *** (0.7442)	−4.1877 ** (1.8823)	1.1048 *** (0.2520)	1.3571 *** (0.4784)	1.0010 ** (0.5043)	8111.394	−16,210.790	−16,176.064
EMV	0.0467 * (0.0283)	0.2689 *** (0.0546)	0.7976 *** (0.0343)	−9.5042 *** (0.4351)	−1.4126 *** (0.4511)	15.9402 *** (0.9630)	−8.4054 *** (0.2842)	1.0311 *** (0.3464)	8115.182	−16,218.365	−16,183.648
GPR	0.0452 (0.0318)	0.2894 *** (0.0612)	0.7661 *** (0.0409)	−11.6180 *** (0.3418)	6.8752 *** (2.3687)	2.1555 *** (0.5459)	−26.9655 *** (0.7132)	1.5874 *** (0.5999)	8107.974	−16,203.954	−16,169.223
Baseline	α 0.0633 *** (0.0193)	γ 0.2721 *** (0.0618)	β 0.7784 *** (0.0227)	ω 0.0000 *** (0.0000)					8100.115	−16,192.231	−16,169.080

Notes: The standard deviations are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively. The baseline item is from a basic DCC-GJR-GARCH model without any exogenous variable.

Table 8. Empirical results for DAGM-Green bonds.

	α	γ	β	m	θ^+	ω^+	θ^-	ω^-	LL	AIC	BIC
EPU	0.0455 ** (0.0197)	0.0059 (0.0143)	0.9429 *** (0.0168)	−9.2103 *** (0.3122)	−4.2379 *** (0.2550)	6.8120 *** (0.3712)	24.5674 *** (0.8011)	1.0610 *** (0.2435)	10,376.302	−20,740.597	−20,705.868
CPU	0.0495 *** (0.0192)	0.0033 (0.0138)	0.9411 *** (0.0170)	−11.2935 *** (0.3058)	−1.9713 *** (0.5894)	2.9533 *** (0.7364)	−2.7888 *** (0.6578)	1.2821 *** (0.4465)	10,376.190	−20,740.375	−20,705.647
TPU	0.0522 *** (0.0199)	0.0023 (0.0145)	0.9368 *** (0.0180)	−11.8987 *** (0.2690)	−0.1421 (0.3127)	4.5700 *** (1.6498)	−2.4891 *** (0.4066)	1.0014 * (0.5491)	10,377.387	−20,742.764	−20,708.045
EMV	0.0457 ** (0.0191)	0.0056 (0.0135)	0.9446 *** (0.0165)	−10.8240 *** (0.2980)	−1.4717 * (0.7973)	2.5090 *** (0.4240)	1.7426 *** (0.2399)	6.3158 *** (0.6943)	10,375.991	−20,739.994	−20,705.267
GPR	0.0399 ** (0.0163)	0.0037 (0.0123)	0.9559 *** (0.0133)	−12.5270 *** (0.8003)	20.8786 *** (1.1303)	1.0530 *** (0.2122)	−2.6946 *** (0.9804)	18.5130 *** (0.4037)	10,377.676	−20,743.330	−20,708.601
Baseline	α 0.0473 *** 0.0127	γ 0.0026 0.0075	β 0.9451 *** 0.0106	ω 0.0000 *** (0.0000)					10,368.521	−20,729.042	−20,705.891

Notes: See notes in Table 7.

Table 9. Empirical results for DAGM-Gold.

	α	γ	β	m	θ^+	ω^+	θ^-	ω^-	LL	AIC	BIC
EPU	0.0296 ** (0.0143)	−0.0090 (0.0133)	0.9669 *** (0.0167)	−9.0975 *** (0.2652)	−4.7658 *** (1.6599)	1.8806 *** (0.7137)	−1.7873 *** (0.6530)	2.0060 *** (0.4594)	7951.780	−15,891.564	−15,856.837
CPU	0.0342 (0.0333)	−0.0124 (0.0267)	0.9504 *** (0.0551)	−10.3858 *** (0.3496)	2.7739 *** (1.0750)	1.0106 * (0.5301)	−6.6116 *** (1.0466)	1.0843 ** (0.4856)	7943.342	−15,874.682	−15,839.967
TPU	0.0265 * (0.0153)	−0.0067 (0.0120)	0.9718 *** (0.0193)	−8.3297 *** (0.5269)	−1.3332 * (0.7700)	1.2394 *** (0.4395)	1.7577 (1.6742)	1.0929 *** (0.3720)	7945.316	−15,878.636	−15,843.902
EMV	0.0294 * (0.0151)	−0.0118 (0.0230)	0.9581 *** (0.0346)	−9.3918 *** (0.2768)	−5.2368 *** (0.9759)	1.4385 *** (0.4774)	−2.2391 *** (0.7178)	1.0189 *** (0.3354)	7950.389	−15,888.783	−15,854.056
GPR	0.0226 *** (0.0074)	−0.0104 (0.0092)	0.9801 *** (0.0096)	−9.4123 *** (0.4833)	1.3817 *** (0.3845)	13.1424 *** (3.4870)	−1.8816 *** (0.5801)	9.7280 *** (2.3670)	7942.874	−15,873.753	−15,839.029
Baseline	α 0.0242 *** (0.0052)	γ −0.0038 (0.0072)	β 0.9701 *** (0.0034)	ω 0.0000 *** (0.0000)					7928.191	−15,848.382	−15,825.230

Notes: See notes in Table 7.

Table 10. Empirical results for DAGM-Crude oil.

	α	γ	β	m	θ^+	ω^+	θ^-	ω^-	LL	AIC	BIC
EPU	0.0462 *** (0.0161)	0.1000 *** (0.0275)	0.8907 *** (0.0201)	−7.2201 *** (0.3638)	−2.5525 *** (0.8494)	2.8434 *** (0.8786)	−2.2820 *** (0.5607)	7.7948 *** (1.5683)	5695.399	−11,378.806	−11,344.075
CPU	0.0496 *** (0.0170)	0.1015 *** (0.0304)	0.8831 *** (0.0226)	−6.3627 *** (0.4393)	−3.4080 *** (1.1698)	1.7708 ** (0.8841)	2.5159 ** (1.1124)	2.0011 *** (0.3778)	5691.184	−11,370.377	−11,335.645
TPU	0.0513 *** (0.0182)	0.1023 *** (0.0304)	0.8808 *** (0.0232)	−6.4930 *** (0.3370)	−2.4409 *** (0.0951)	1.4060 *** (0.3791)	0.1343 (0.5116)	8.3515 *** (1.5795)	5691.479	−11,370.962	−11,370.960
EMV	0.0467 ** (0.0188)	0.0965 *** (0.0315)	0.8789 *** (0.0270)	−8.8777 *** (0.2426)	8.4530 *** (0.5133)	1.5193 *** (0.3808)	−4.7007 *** (0.4959)	1.0011 *** (0.3255)	5697.315	−11,382.632	−11,347.906
GPR	0.0469 *** (0.0178)	0.1093 *** (0.0349)	0.8622 *** (0.0305)	−11.3574 *** (0.2339)	32.2203 *** (0.6012)	1.0419 *** (0.1228)	−18.7574 *** (0.3578)	1.0010 *** (0.3689)	5693.895	−11,375.796	−11,341.067
Baseline	α 0.0531 *** (0.0022)	γ 0.1050 *** (0.0151)	β 0.8826 *** (0.0072)	ω 0.0000 *** (0.0000)					5687.071	−11,366.159	−11,343.008

Notes: See notes in Table 6.

Table 11. Empirical results for DAGM-Bitcoin.

	α	γ	β	m	θ^+	ω^+	θ^-	ω^-	LL	AIC	BIC
EPU	0.1305 *** (0.0416)	0.0548 (0.0578)	0.8106 *** (0.0482)	−6.6769 *** (0.3549)	−2.1320 *** (0.7899)	51.5974 *** (13.7116)	−19.8560 *** (2.1900)	1.0010 *** (0.3391)	3977.126	−7942.253	−7942.253
CPU	0.1330 *** (0.0392)	0.0630 (0.0569)	0.8072 *** (0.0402)	−6.1580 *** (0.7298)	0.6138 (2.0383)	4.1925 *** (1.1631)	−4.6819 *** (1.4809)	4.8364 *** (1.5650)	3968.787	−7925.575	−7890.848
TPU	0.1092 ** (0.0479)	0.0528 (0.0471)	0.8464 *** (0.0601)	−2.2624 ** (0.9802)	−5.6732 *** (1.2666)	1.7470 *** (0.5610)	4.6839 * (2.5807)	1.0010 *** (0.2126)	3972.689	−7933.379	−7898.652
EMV	0.1464 *** (0.0337)	0.0651 (0.0628)	0.7714 *** (0.0408)	−3.3111 *** (0.5452)	−8.3550 *** (2.6867)	1.0011 ** (0.3973)	11.7066 *** (1.4611)	2.0892 *** (0.7169)	3976.444	−7940.888	−7906.161
GPR	0.1300 ** (0.0539)	0.0325 (0.0440)	0.8250 *** (0.0660)	−6.4442 *** (0.5105)	3.6586 ** (1.4807)	2.9418 *** (0.5998)	−7.9705 *** (2.0216)	1.2903 *** (0.4546)	3971.420	−7930.840	−7896.113
Baseline	α 0.1302 *** (0.0182)	γ 0.0506 *** (0.0186)	β 0.8298 *** (0.0171)	ω 0.0001 *** (0.0000)					3965.494	−7922.989	−7899.838

Notes: See notes in Table 7.

All coefficients ω^+ and ω^- are larger than 1, which means the weight function is monotonically decreasing so that market information can be efficiently transmitted in these markets. The coefficients θ^+ and θ^- depict the response of long-term volatility to positive and negative uncertainty changes, respectively. A negative sign for θ^+ means positive variation in a certain risk has a negative influence on the long-term volatility of the return and vice versa. In other words, if, from one month to the next, the sum of positive changes in uncertainties increases, the long-run volatility will decrease. The same logic applies to θ^- . The net effect on long-run volatility from one month to the next depends on the two sources of asymmetry. Concordant parameter signs signify uniform impacts of both positive and negative fluctuations on the asset, while countervailing effects arise when signs diverge. Table 12 lists the asymmetry of impact and the net effect that different uncertainties have on the volatility of returns. In summary, the impact of diverse risk variations on return volatility exhibits symmetry or asymmetry across different assets, with varying net effects. This discrepancy stems from distinct weighting functions and parameters related to sign-specific uncertainties, highlighting an additional form of volatility asymmetry alongside that caused by negative returns. To check robustness, this paper employs GJR-GARCH-MIDAS models and reports the outcomes in Table A1.

Table 12. Asymmetry and net effect from exogenous risks.

	CSI 300		S&P 500		Green Bond		Gold		Oil		Bitcoin	
	A	NE	A	NE	A	NE	A	NE	A	NE	A	NE
EPU	×	—	×	—	✓	—	×	—	×	—	×	—
CPU	×	—	×	+	×	—	✓	—	✓	+	✓	—
TPU	✓	+	✓	—	×	—	✓	—	✓	—	✓	—
EMV	✓	—	×	—	✓	+	×	—	✓	+	✓	+
GPR	✓	+	✓	—	✓	—	✓	+	✓	+	✓	—

Notes: A is asymmetry, and NE is the net effect. ✓ stands for the uncertainty has an asymmetric impact on the asset, and × represents not. + means the uncertainty has a positive net effect on the volatility of the asset, and — means not.

The inspection of residuals in Table A2 confirms that they are well approximated by white noise processes. The standardized residual series, excluding Bitcoin, displays a negative skewness and negative excess kurtosis, suggesting decreased heavy-tailed features. As evidenced by Table 4, it is discernible that the skewness and kurtosis of Bitcoin markedly surpass those of other assets, which is a unique feature of Bitcoin. The Jarque–Bera test consistently rejects normality, which is a common pattern in financial time series modeling. Since our subsequent study does not concentrate on the tails, and the Ljung–Box test proves no autocorrelation, non-normality does not affect the results. Additionally, all standardized residuals derived from the estimated GARCH models demonstrate homoscedasticity, indicating the efficacy of our model in capturing volatility clustering.

Comparatively, as delineated by information criteria (including log-likelihood, AIC, and BIC), DAGM-X models with uncertainty measures are superior to benchmark GJR-GARCH models without exogenous variables, which underscores the effectiveness of uncertainty measures as robust predictors of volatility.

4.2. DCC-MIDAS Model Analysis

The estimates in Table 13 for DCC-MIDAS models are all statistically significant. Values of estimate a exceeding 0.1 suggest fluctuating correlation coefficients in response to varying uncertainties. Values of estimate b indicate robust and stable correlations between stock indices and hedging assets. Figures 1–5 manifest short-term and long-term correlations between two stock indices and four other assets considering different risks and uncertainties. Statistics of correlations are presented in Table A3. Additionally, akin to the estimated GARCH models, the information criteria reveal that the DCC models, when estimated using five uncertainty measures, exhibit superior performance compared to the baseline model. The dynamic correlations derived from the baseline model also exhibit substantial disparities when compared with those utilizing predictors.

Table 13. Empirical results for DCC-MIDAS models.

	a	b	ω	$a + b$	LL	AIC	BIC
EPU	0.0188 *** (0.0044)	0.9474 *** (0.0232)	1.0010 *** (0.3020)	0.9662 *** (0.0230)	−12,366.036	24,738.072	24,755.435
CPU	0.0195 *** (0.0039)	0.9437 *** (0.0196)	1.0010 *** (0.2552)	0.9632 *** (0.0193)	−12,432.210	24,870.420	24,887.783
TPU	0.0194 *** (0.0041)	0.9431 *** (0.0213)	1.0010 *** (0.2676)	0.9625 *** (0.0211)	−12,531.151	25,068.302	25,085.665
EMV	0.0183 *** (0.0040)	0.9470 *** (0.0213)	1.0018 *** (0.2983)	0.9653 *** (0.0211)	−12,502.973	25,011.946	25,029.309
GPR	0.0194 *** (0.0046)	0.9466 *** (0.0245)	1.0013 *** (0.3238)	0.9660 *** (0.0243)	−12,304.928	24,615.856	24,633.219
Baseline	0.0138 *** (0.0033)	0.9608 *** (0.0116)		0.9746 *** (0.0116)	−13,387.111	26,778.222	26,789.798

Notes: See notes in Table 4.

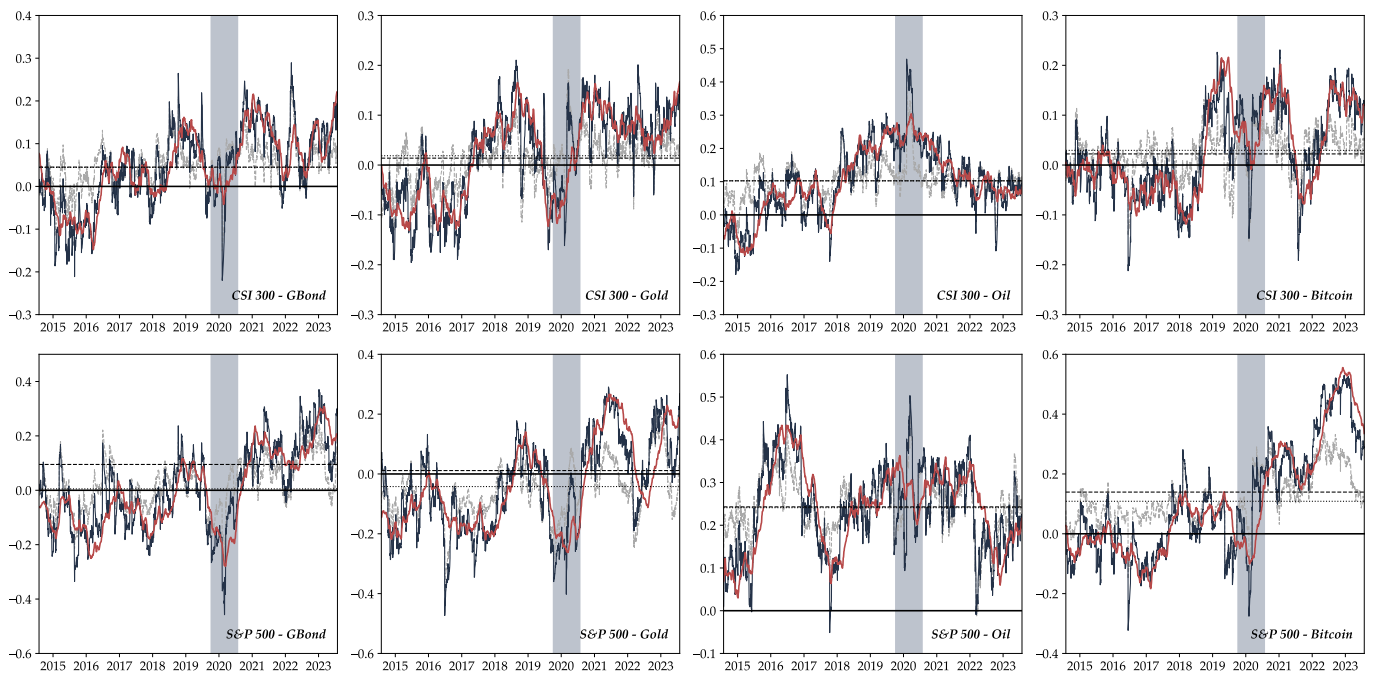


Figure 1. Dynamic short-run and long-run correlations under EPU. Notes: The dark blue line represents short-term correlations, and the dark red line represents long-term correlations. The grey dashed line indicates dynamic correlations estimated in baseline models. The black solid line indicates zero. The Black dashed line denotes unconditional correlation coefficients. The black dotted line stands for average dynamic correlations.

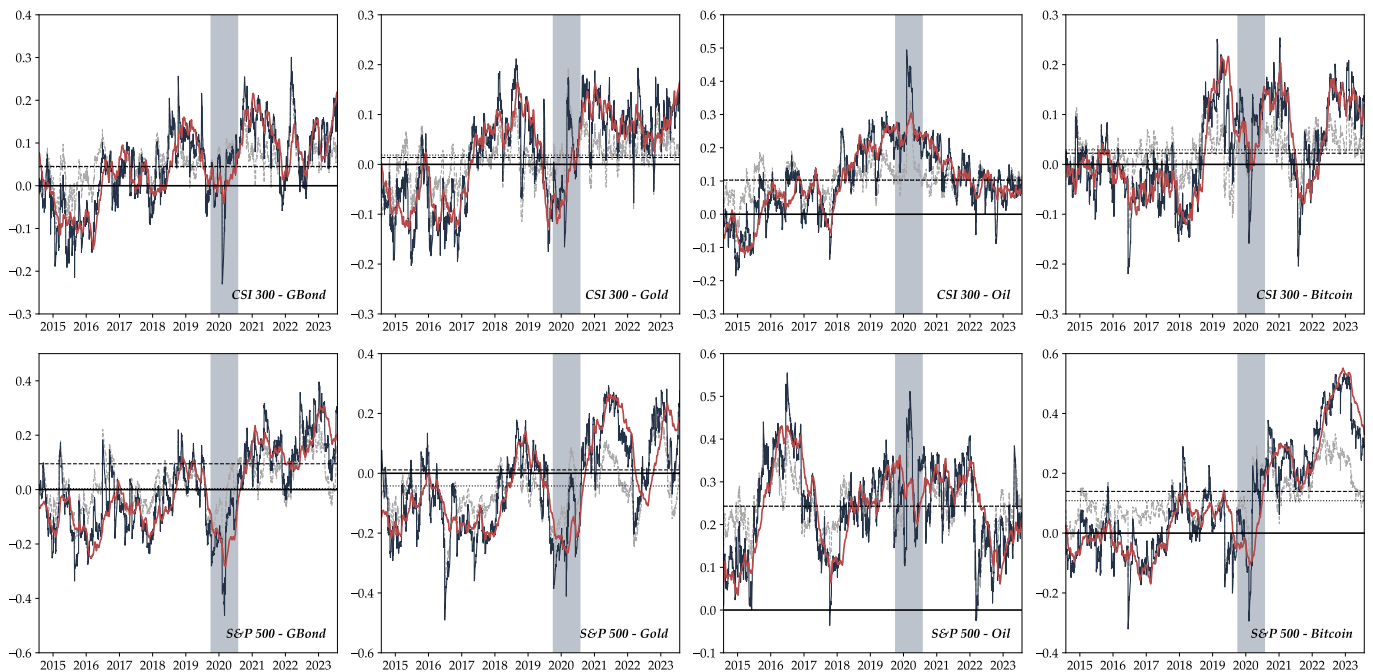


Figure 2. Dynamic short-run and long-run correlations under CPU. Notes: See notes in Figure 1.

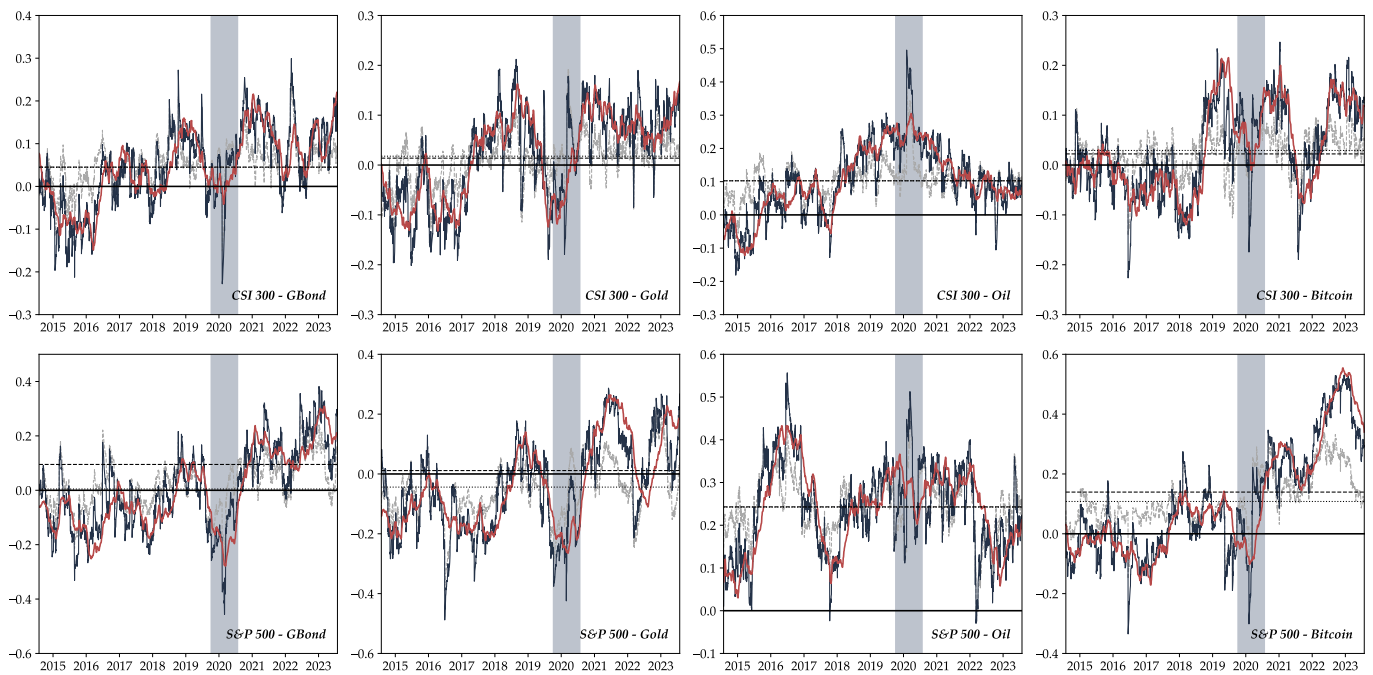


Figure 3. Dynamic short-run and long-run correlations under TPU. Notes: See notes in Figure 1.

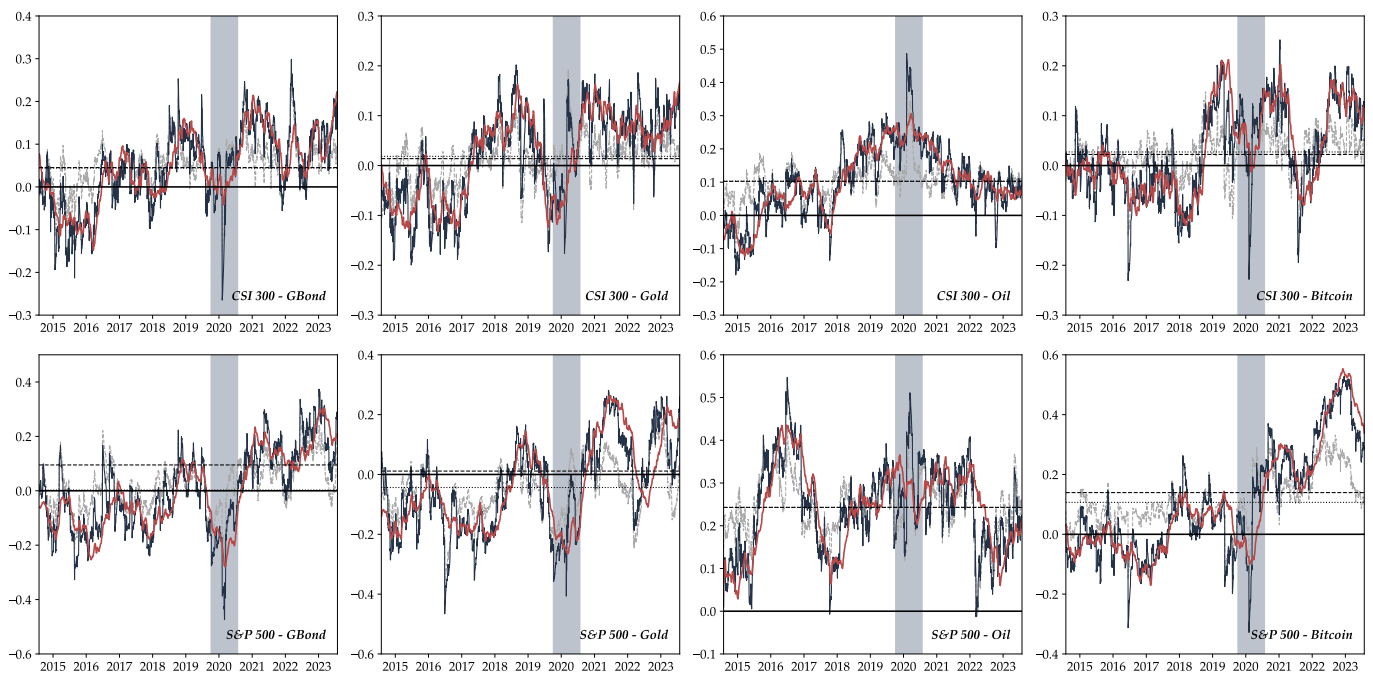


Figure 4. Dynamic short-run and long-run correlations under EMV. Notes: See notes in Figure 1.

The results underscore the nuanced impact of various uncertainties on correlations over different time horizons. Generally, average long-term correlations are weaker than short-term ones for the S&P 500, except for oil, and the opposite is true for the CSI 300. In the short term, EPU and CPU prominently influence the S&P 500–Bitcoin correlation, while in the long term, GPR and TPU exhibit a significant influence, consistent with Al Mamun et al. (2020). Additionally, the impact of uncertainty manifests distinctively within the realms of US and Chinese stock indices. Specifically, it is observed that EMV exerts a long-term significant impact on the correlations involving the S&P 500 and green

bonds, whereas the correlations associated with the CSI 300 and green bonds are primarily influenced by TPUs. Moreover, excluding the oil-stock correlation, CSI 300 displays a comparatively lower volatility in its correlations with diverse assets compared to the S&P 500, implying a higher degree of stability in Chinese stock correlations. More details can be found in Table A3. It is noteworthy that extreme shocks or black swan events trigger drastic changes in correlations. For instance, the correlations exhibited a profound and pivotal transformation in the nascent months of 2020 (see shaded region). It can be attributed to the unprecedented onset of the COVID-19 pandemic, which engendered a discernible alteration in the safe-haven properties of these assets against equities.

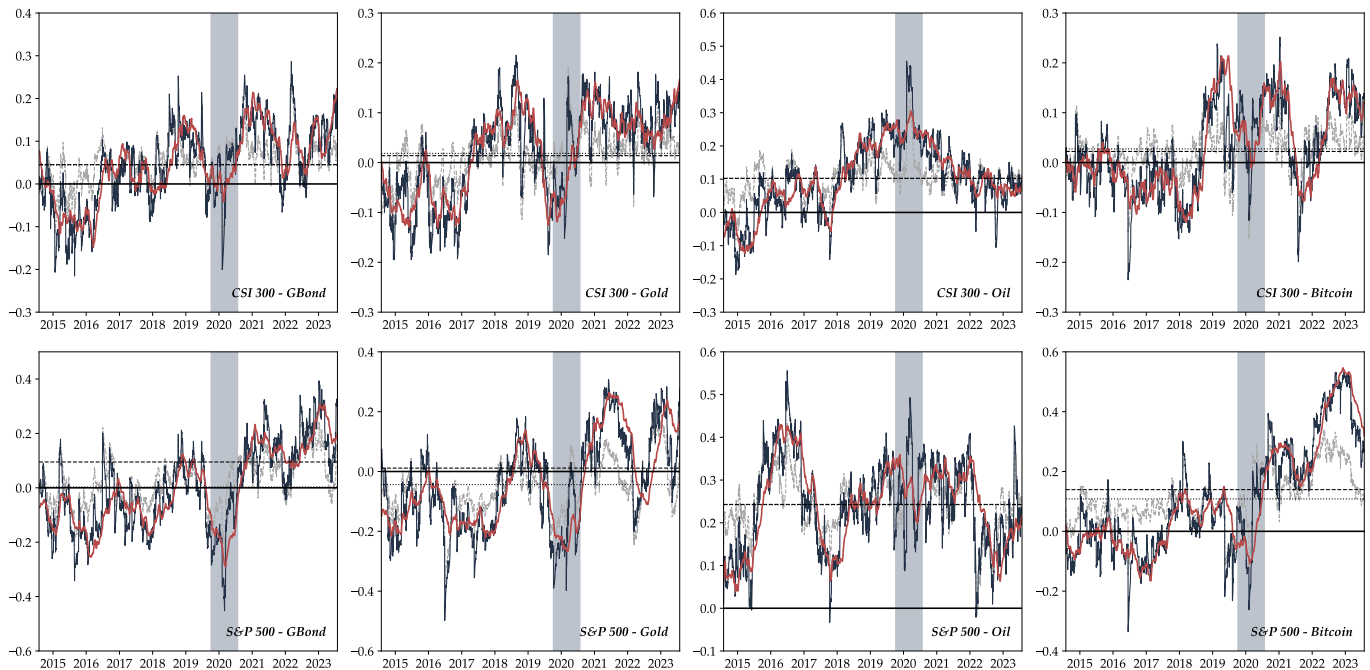


Figure 5. Dynamic short-run and long-run correlations under GPR. Notes: See notes in Figure 1.

4.3. Risk Management Analysis

Risk management strategies like hedging and diversification are of paramount importance for investors to navigate the complexities of market uncertainties (Godil et al. 2020). Building upon the empirical findings presented in the preceding sections, this section contributes further evidence and insights pertaining to portfolio management.

4.3.1. Optimal Weight and Hedge Ratio

Dependent upon the DCC-DAGM model results, this paper calculates optimal weights and hedge ratios and establishes investment strategies to manage hedging assets more efficiently.

Following Kroner and Ng (1998), this study designs diversified portfolios with the optimal weight of hedging assets given by

$$w_{i,j,t} = \frac{h_{j,t} - h_{i,j,t}}{h_{i,t} - 2h_{i,j,t} + h_{j,t}} \quad (9)$$

$$w_{i,j,t} = \begin{cases} 0, & \text{if } w_{i,j,t} < 0 \\ w_{i,j,t}, & \text{if } 0 \leq w_{i,j,t} \leq 1 \\ 1, & \text{if } w_{i,j,t} > 1 \end{cases}$$

where $h_{i,j,t}$ stands for the conditional covariance between returns on assets i and j , and $h_{i,t}(h_{j,t})$ is the conditional variance of returns on assets $i(j)$.

Moreover, this study follows Kroner and Sultan's (1993) approach to compute the optimal hedge ratios (OHRs) to construct hedging portfolios that involve holding a long position in one unit of stock index i hedged by a short position of β_t hedging assets j given by

$$\beta_t = \frac{h_{i,j,t}}{h_{j,t}} \quad (10)$$

Statistics of optimal weights and hedge ratios are displayed in Table A4. The dynamic optimal weights and hedge ratios under different uncertainties are plotted in Figures 6 and 7. These provide some interesting insights. Optimal weights and hedge ratios both show significant time-varying characteristics, suggesting investors should adapt their portfolios to varying market conditions.

Concerning optimal weights, green bonds are the most heavily weighted in order to minimize volatility, followed by gold, oil, and Bitcoin, but the weight of gold has the highest volatility, followed by oil. Additionally, the results show that varying risk conditions have distinct effects on optimal portfolio weights. For instance, US investors should allocate more weight to oil than gold to minimize portfolio risk without compromising portfolio returns under GPR. Regardless of risk considerations, Chinese equity portfolios are prone to allocate a higher proportion to hedging assets compared to their US counterparts. For example, the average values of optimal gold weight range between 46.93% for the S&P 500 and 62.62% for the CSI 300 under EPU. This result suggests that, for a USD 1 CSI 300–gold portfolio, the weight of gold investing should be around USD 0.6262, and the remaining USD 0.3738 should be invested in CSI 300. For a USD 1 S&P 500–gold portfolio, the weight of gold investing should be around USD 0.4693, with the remaining USD 0.5307 invested in the S&P 500.

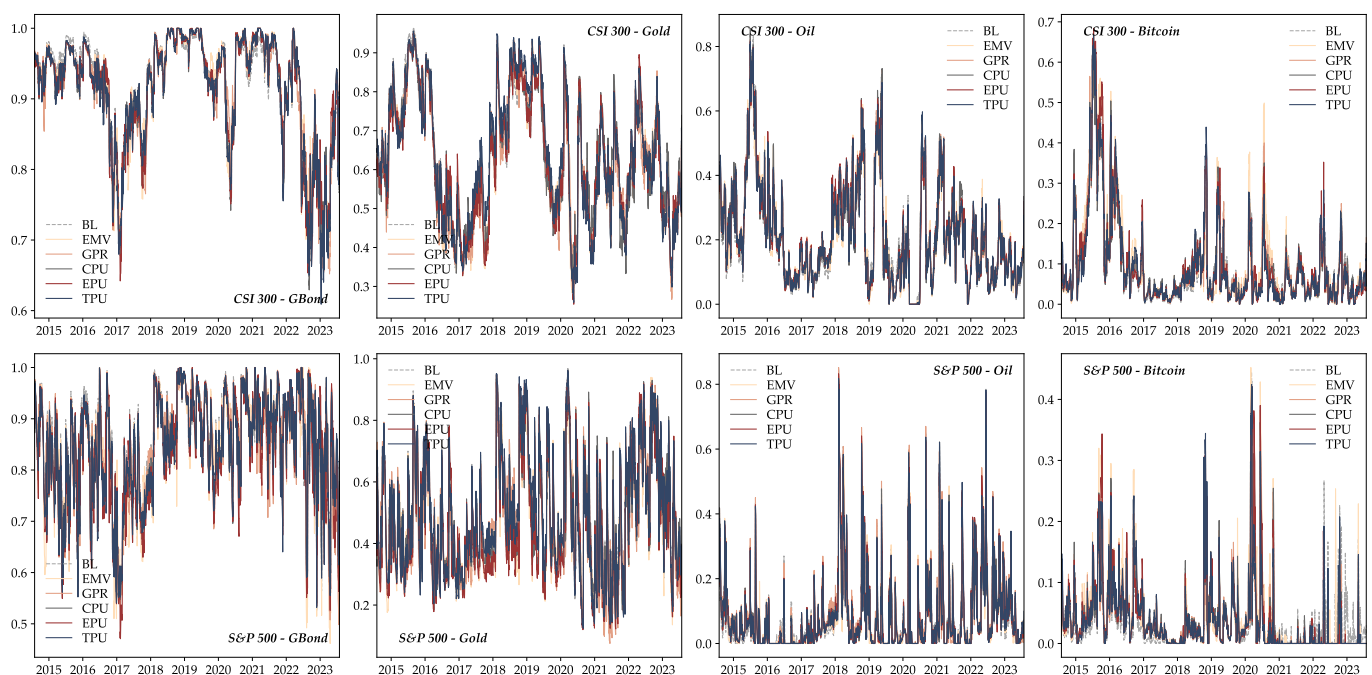


Figure 6. Time-varying optimal weights. Notes: The solid lines in the legend represent the results calculated under five risks, and BL (grey dashed line) denotes results obtained by the baseline models.

The hedge ratio can be thought of as the cost of hedging. OHRs notably spiked during the COVID-19 pandemic, indicating escalated hedging costs due to heightened contract demand, aligning with Dai et al. (2022), Zhang et al. (2021a), and Akhtaruzzaman et al. (2021). As with optimal weights, distinct risks have various impacts on OHRs of different assets. By way of illustration, TPU exerts the most substantial impact on elevating hedging

costs within S&P 500–gold portfolios, while EMV prominently increases hedging costs within S&P 500–green bond portfolios (see Table A4 for details). The numbers of hedging assets required to hedge the S&P 500 in descending order are oil, gold, Bitcoin, and green bonds. Conversely, for CSI 300, the order is green bonds, oil, gold, and Bitcoin. Regarding hedge ratio volatility, green bonds exhibit the highest volatility, followed by gold, oil, and Bitcoin. Moreover, the volatility of OHRs for CSI 300 is generally lower than for S&P 500, except for oil, indicating that managing the cost of hedging US stocks necessitates more frequent portfolio adjustments, while hedging Chinese stocks shows greater stability. Furthermore, it is noteworthy that some values of OHRs are negative, suggesting that the hedge can be formed by either being long or short on both assets.

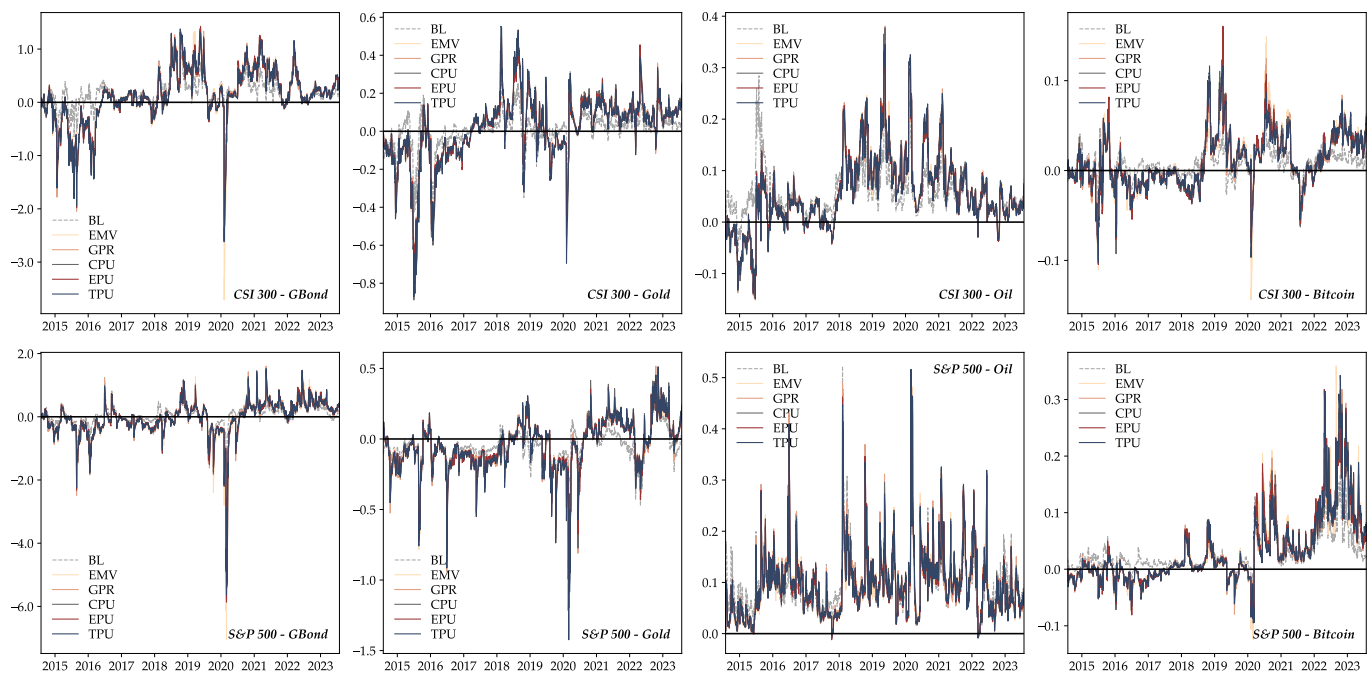


Figure 7. Time-varying optimal hedge ratios. Notes: See notes in Figure 6.

4.3.2. Hedging Effectiveness

Optimal weights and hedge ratios demonstrate how to formulate an appropriate diversification or hedge to minimize risk. They do not, however, assist in determining if it is executed effectively. Following Ku et al. (2007) and Jin et al. (2020), this paper obtains the hedging effectiveness (HE) to compare the performance of these portfolios. Hedging effectiveness estimates the percentage of the variance eliminated from an unhedged portfolio by hedging (Hamma et al. 2021). More specifically, this paper quantifies the variance reduction for each hedged portfolio versus an unhedged portfolio, as shown below:

$$HE = 1 - \frac{Var_{P,t}}{Var_{S,t}} \quad (11)$$

where $Var_{P,t}$ and $Var_{S,t}$ are the variance of two types of portfolios and single stock indexes, respectively. The HE of a perfect hedge is 1, whereas HE is 0 if hedging is ineffective in reducing portfolio volatility. Higher HE values imply greater hedging success.

Given investors are more concerned about downside risk than upside risk, this paper assesses downside risk using the value-at-risk (VaR), expected shortfall (ES), and lower partial moment (LPM). The VaR signifies the maximal anticipated loss a portfolio may face within a defined period under a given confidence level. A Conditional VaR (CVaR), or ES, gauges expected losses exceeding the VaR threshold, quantifying a portfolio's tail risk (Artzner 1997). LPMs by Bawa (1975) are frequently used to quantify the moment of returns

that fall short of a certain threshold and are required to generate risk-adjusted performance indicators. The decrease in the LPM and (C)VaR (Cotter and Hanly 2012) is specified as

$$LPM \text{ Reduction} = 1 - \frac{LPM_{1,P}}{LPM_{1,S}} \quad (12)$$

$$(C)VaR \text{ Reduction} = 1 - \frac{(C)VaR_{5\%,P}}{(C)VaR_{5\%,S}} \quad (13)$$

where $LPM_{1,P}$ and $LPM_{1,S}$ represent 1-th LPM (the LPM order is 1, meaning that the investor is risk neutral) of two portfolios and a single stock index, respectively. $(C)VaR_{5\%,P}$ and $(C)VaR_{5\%,S}$ represent the VaR or ES of two portfolios and a single stock index at the 5% confidence level, respectively.

The statistics of HE are reported in Table A5. Figures 8 and 9 depict time-varying HE under different uncertainties. Regarding diversified portfolios, the HE of S&P 500–green bond and S&P 500–gold portfolios demonstrate higher volatility compared to their Chinese counterparts. Conversely, crude oil and Bitcoin show the opposite trend. The diversified portfolio incorporating green bonds exhibits the highest HE, while Bitcoin demonstrates the lowest. For example, allocating 84.75% weight to green bonds diversifies 84.23% of S&P 500 return variance while 10.21% of it mitigates 10.05% of CSI 300 return variance under EMV. Clearly, portfolio volatility is determined by both asset weights and their individual volatilities. Concerning hedging portfolios, for both S&P 500 and CSI 300, the hedging portfolio incorporating oil exhibits the highest HE, with varying rankings for other assets. For the S&P 500, the HE follows the descending order of oil, Bitcoin, gold, and green bonds, while for the CSI 300, the sequence is oil, green bonds, gold, and Bitcoin. For instance, 7.06% of the return variance of a USD 1 long position in the S&P 500 can be hedged by shorting USD 0.939 of oil, while 2.25% of the return variance of a USD 1 short position in the CSI 300 can be hedged by longing USD 0.559 of oil under CPU (see Table A4 for hedge ratios). Notably, US hedging portfolios demonstrate higher volatility compared to their Chinese counterparts, indicating a greater stability of HE in Chinese hedging portfolios.

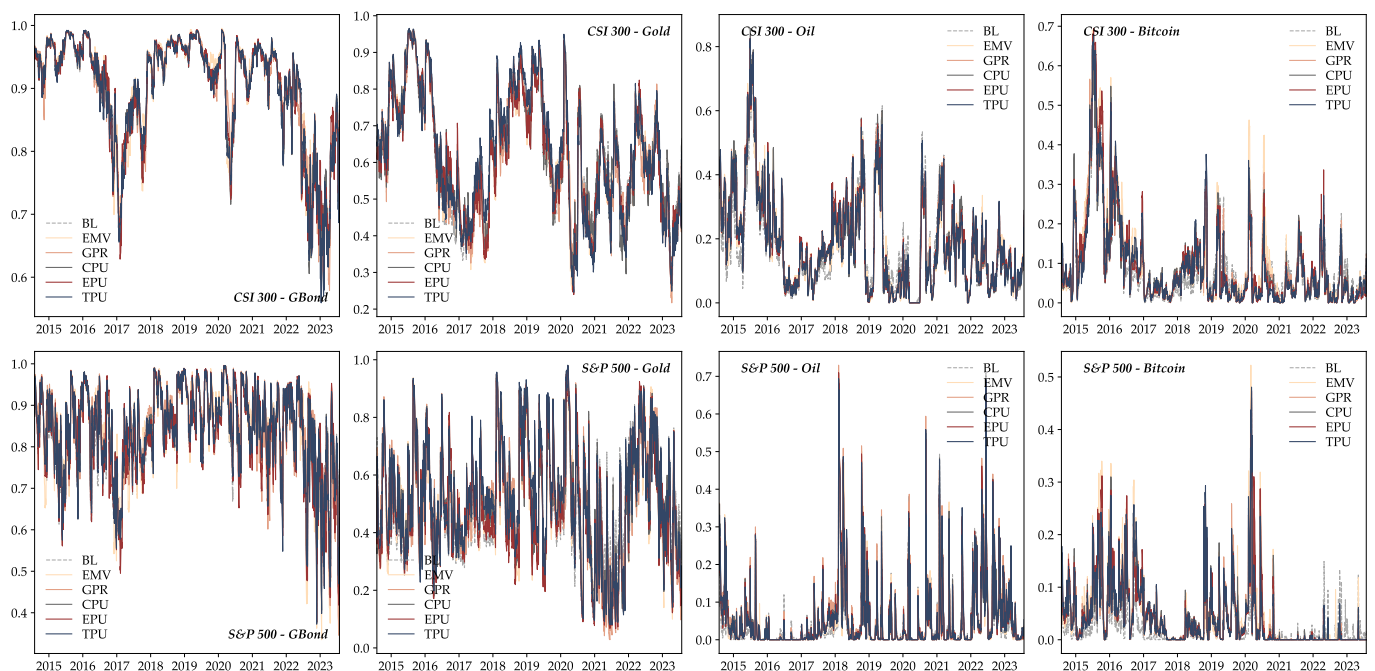


Figure 8. Time-varying hedging effectiveness of diversified portfolios. Notes: See notes in Figure 6.

Chinese portfolios tend to exhibit higher HE compared to US portfolios in diversified portfolios, while in hedging portfolios, US portfolios display a greater HE than Chinese portfolios. This suggests that hedging is more effective in reducing volatility and risk for US stocks, while diversification is more effective for Chinese stocks in this context. For an average HE, it is noteworthy that uncertainty measures do not manifest evidently and uniformly advantageous outcomes in risk mitigation for diversified portfolios compared to the baseline model. However, they prove to be notably effective in hedging portfolios. Visually, the HE for diversified portfolios in Figure 8 exhibits a degree of overlap, while in Figure 9, depicting the HE for hedging portfolios, conspicuous distinctions emerge during specific temporal intervals. Additionally, the hedge effectiveness attained by the baseline model exhibits significantly lower volatility than others in both diversified and hedging portfolios. This can be attributed to the increased frequency of investors adjusting their investment portfolios through exogenous variables, causing more pronounced fluctuations in HE. Moreover, Figures 8 and 9 illustrate a wide range of variations in the HE of diversified portfolios over time, in contrast to the relatively small profile observed in hedging portfolios. Additionally, diverse risks exert varying impacts on risk reduction in diversified or hedging portfolios across various countries. The downside risk reduction results presented in Table A6 support the HE results.

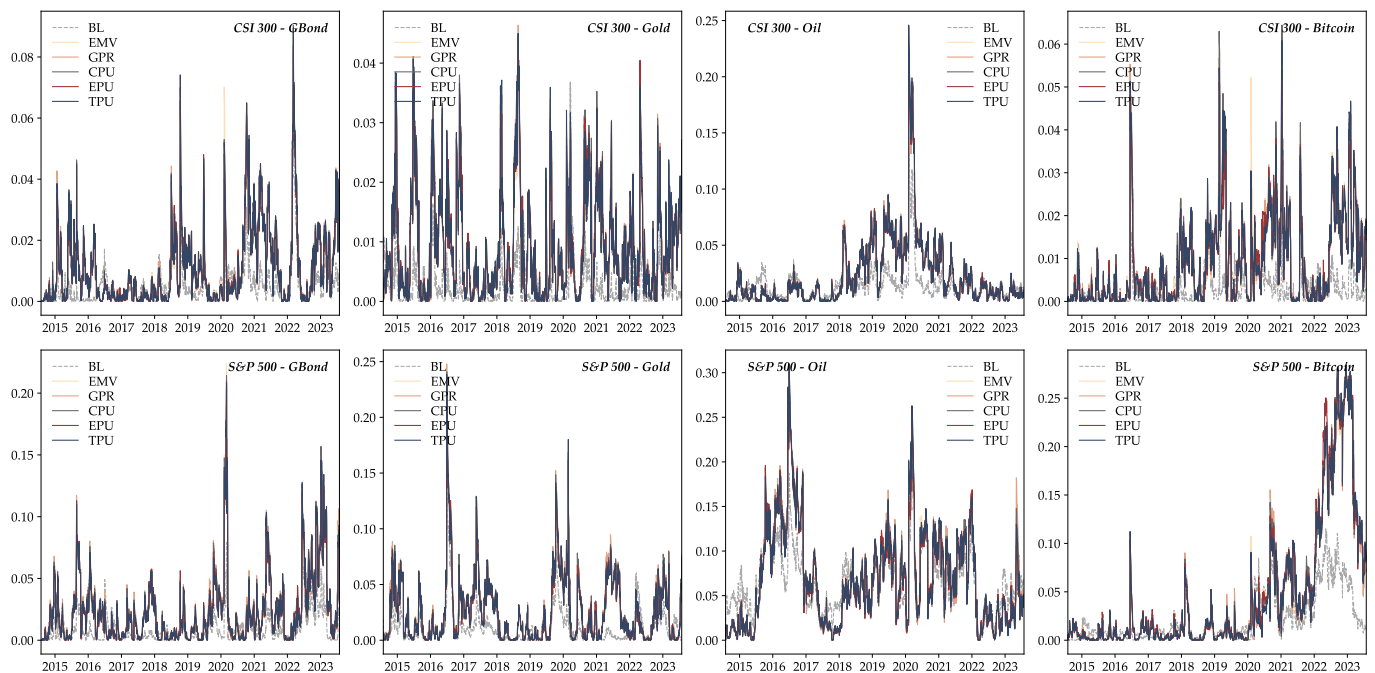


Figure 9. Time-varying hedging effectiveness of hedging portfolios. Notes: See notes in Figure 6.

5. Conclusions

This paper examines the asymmetric impact of five risks (CPU, EMV, EPU, TPU, and GPR) on six asset returns (S&P 500, CSI 300, green bonds, gold, oil, and Bitcoin) using the DAGM model. It further employs the DCC-MIDAS model to determine dynamic conditional correlations between stock indices and hedging assets. The study then constructs diversified and hedging portfolios for in-depth analysis under various risk conditions. The empirical results can be summarized as follows. First, positive and negative risk variations have asymmetric impacts on the volatility of assets of interest. In the short term, indicated by the first asymmetry from return itself, only oil and S&P 500 show significant leverage effects while others do not. The US stock market is more sensitive to negative shocks in returns compared to the Chinese stock market. In the long term, namely the second asymmetry, positive and negative risk fluctuations have symmetric or asymmetric impacts on asset returns, and the net effect is distinct. Second, risks affect correlations between

stock indices and other assets differently in both the short and long term. For the S&P 500, long-term correlations are generally weaker than short-term ones, and correlations of the Chinese stock market are more stable than those of the US stock market. Both short- and long-term correlations are strengthened during extreme events such as COVID-19. Third, hedging is more effective in reducing volatility and risk for US stocks, while diversification is more effective for Chinese stocks in this context, indicating differences in risk management in emerging and developed countries. In diversified portfolios, Chinese portfolios benefit from heavier allocations to green bonds and gold, while US portfolios favor greater weighting in oil and Bitcoin. In hedging portfolios, Chinese stocks are significantly cheaper to hedge than US stocks, except for using green bonds.

Nevertheless, this paper has limitations. Firstly, it restricts its research scope to six assets, potentially overlooking other investment opportunities. It also neglects variations in outcomes across stock market sectors and may not provide generalizable results due to limited country selection. Secondly, constrained by data availability, the empirical analysis has a limited sample range. Furthermore, the study relies on GARCH family models, warranting the exploration of alternative models to verify the robustness of the findings.

The field of portfolio management in the face of multiple risks offers ample opportunities for further exploration. Future research could delve into alternative investments as risk management tools in the dynamic global financial landscape. Additionally, studying country-specific and diverse risk factors, encompassing both financial and non-financial markets, would enrich our comprehension of the complex relationship between risks and asset returns.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Empirical results for GJR-GARCH-MIDAS models.

	α	γ	β	m	θ	ω
CSI 300						
EPU	0.0685 *** (0.0135)	0.0113 (0.0201)	0.9194 *** (0.0170)	−8.3393 *** (0.4171)	−8.2092 *** (0.5412)	2.1651 *** (0.6939)
CPU	0.0730 *** (0.0142)	0.0146 (0.0248)	0.9100 *** (0.0207)	−8.3781 *** (0.3637)	−7.9229 *** (0.4792)	1.0085 *** (0.2635)
TPU	0.0728 *** (0.0135)	0.0100 (0.0222)	0.9167 *** (0.0185)	−8.2424 *** (0.3989)	1.3263 ** (0.6754)	1.0011 *** (0.2711)
EMV	0.0720 *** (0.0134)	0.0112 (0.0214)	0.9166 *** (0.0175)	−8.2778 *** (0.3896)	−1.7397 *** (0.6639)	3.0936 *** (1.1246)
GPR	0.0725 *** (0.0134)	0.0064 (0.0204)	0.9183 *** (0.0173)	−8.3142 *** (0.4098)	2.8985 ** (1.4580)	3.3888 *** (1.2977)
S&P 500						
EPU	0.0588 * (0.0312)	0.2455 *** (0.0557)	0.7952 *** (0.0352)	−8.7642 *** (0.4118)	−1.8095 *** (0.5265)	22.8813 *** (0.4225)
CPU	0.0586 * (0.0333)	0.2599 *** (0.0565)	0.7844 *** (0.0368)	−8.8232 *** (0.4109)	3.5732 *** (0.8432)	1.0010 *** (0.3493)
TPU	0.0553 * (0.0334)	0.2652 *** (0.0562)	0.7782 *** (0.0366)	−8.8951 *** (0.3753)	−2.1221 *** (0.6562)	1.9052 *** (0.7139)
EMV	0.0593 * (0.0324)	0.2573 *** (0.0533)	0.7859 *** (0.0345)	−8.8109 *** (0.3600)	−1.0351 *** (0.2698)	21.0665 *** (2.6770)
GPR	0.0566 * (0.0338)	0.2622 *** (0.0554)	0.7821 *** (0.0371)	−8.8511 *** (0.3723)	−3.1628 *** (0.8383)	2.7832 *** (0.9730)

Table A1. Cont.

	α	γ	β	m	θ	ω
Green bond						
EPU	0.0497 *** (0.0190)	0.0042 (0.0142)	0.9409 *** (0.0166)	−11.1385 *** (0.3561)	−1.6032 *** (0.2722)	2.5119 *** (0.4376)
CPU	0.0499 *** (0.0193)	0.0039 (0.0140)	0.9402 *** (0.0173)	−11.1669 *** (0.3119)	−0.5607 *** (0.1810)	3.9462 *** (1.2879)
TPU	0.0533 *** (0.0203)	0.0028 (0.0141)	0.9391 *** (0.0178)	−11.1909 *** (0.3487)	−1.3696 ** (0.5318)	1.0021 * (0.5201)
EMV	0.0487 ** (0.0195)	0.0041 (0.0138)	0.9417 *** (0.0171)	−11.1606 *** (0.3652)	1.1281 *** (0.3792)	1.9090 *** (0.4717)
GPR	0.0455 ** (0.0192)	0.0060 (0.0134)	0.9444 *** (0.0168)	−11.1678 *** (0.3692)	−0.3353 *** (0.0099)	53.4786 *** (4.9185)
Gold						
EPU	0.0291 ** (0.0130)	−0.0091 (0.0128)	0.9682 *** (0.0135)	−9.2942 *** (0.2086)	−8.1935 *** (0.8913)	1.0010 *** (0.2942)
CPU	0.0231 * (0.0124)	−0.0042 (0.0108)	0.9733 *** (0.0174)	−9.2879 *** (0.2601)	−2.7295 *** (0.7121)	1.1581 *** (0.2350)
TPU	0.0380 * (0.0225)	−0.0158 (0.0222)	0.9471 *** (0.0369)	−9.3703 *** (0.1097)	−1.9933 * (1.0656)	1.0010 *** (0.3732)
EMV	0.0400 * (0.0233)	−0.0178 (0.0215)	0.9563 *** (0.0260)	−9.3444 *** (0.1617)	−5.8925 *** (1.4482)	1.0010 ** (0.3919)
GPR	0.0261 * (0.0155)	−0.0056 (0.0123)	0.9696 *** (0.0216)	−9.3300 *** (0.2622)	4.7512 *** (0.6982)	1.0010 ** (0.4045)
Crude oil						
EPU	0.0482 *** (0.0162)	0.1014 *** (0.0283)	0.8871 *** (0.0203)	−7.2363 *** (0.3289)	−1.4578 *** (0.3032)	16.6725 *** (2.7048)
CPU	0.0491 *** (0.0173)	0.1015 *** (0.0304)	0.8845 *** (0.0233)	−7.2648 *** (0.3255)	1.8140 *** (0.6268)	1.1171 ** (0.5207)
TPU	0.0510 *** (0.0178)	0.1019 *** (0.0307)	0.8819 *** (0.0239)	−7.2458 *** (0.3092)	−0.7394 *** (0.6502)	2.1591 *** (0.3836)
EMV	0.0428 ** (0.0173)	0.0970 *** (0.0306)	0.8902 *** (0.0252)	−7.3414 *** (0.2814)	10.8881 *** (0.6102)	1.6725 *** (0.2242)
GPR	0.0451 *** (0.0172)	0.1060 *** (0.0319)	0.8845 *** (0.0255)	−7.3156 *** (0.3173)	13.0378 *** (0.6495)	1.2213 *** (0.3963)
Bitcoin						
EPU	0.1365 *** (0.0447)	0.0574 (0.0590)	0.8008 *** (0.0495)	−5.3989 *** (0.5829)	−11.7293 *** (2.3877)	2.5547 *** (0.8650)
CPU	0.1248 ** (0.0496)	0.0546 (0.0525)	0.8275 *** (0.0597)	−5.2172 *** (0.6587)	−4.9410 ** (1.9879)	1.1463 ** (0.4782)
TPU	0.1153 ** (0.0513)	0.0551 (0.0521)	0.8350 *** (0.0707)	−5.3482 *** (0.6318)	−1.8477 ** (0.9120)	2.8357 *** (0.7055)
EMV	0.1252 ** (0.0543)	0.0464 (0.0485)	0.8330 *** (0.0653)	−5.2446 *** (0.6366)	0.7103 ** (0.2978)	58.9370 *** (0.1654)
GPR	0.1113 ** (0.0448)	0.0559 (0.0488)	0.8431 *** (0.0563)	−5.2200 *** (0.6260)	−11.0058 *** (1.7109)	1.0011 *** (0.2811)

Notes: See notes in Table 7.

Table A2. Statistics of standardized residuals.

	Skewness	Kurtosis	J-B	L-B(10)	ARCH(10)
CSI 300					
EPU	−0.319	2.110	490.102 ***	6.677 [0.671]	3.884 [0.952]
CPU	−0.327	2.177	520.933 ***	6.231 [0.717]	4.311 [0.932]
TPU	−0.292	2.010	441.718 ***	6.313 [0.708]	3.959 [0.949]
EMV	−0.331	2.156	512.796 ***	5.818 [0.758]	4.516 [0.921]
GPR	−0.304	2.005	442.449 ***	5.905 [0.749]	4.245 [0.936]
Baseline	−0.295	1.942	415.250 ***	6.087 [0.731]	3.787 [0.956]

Table A2. Cont.

	Skewness	Kurtosis	J-B	L-B(10)	ARCH(10)
S&P 500					
EPU	−0.688	2.741	947.981 ***	8.866 [0.545]	7.733 [0.655]
CPU	−0.791	2.995	1156.002 ***	8.628 [0.568]	6.808 [0.743]
TPU	−0.761	2.796	1021.092 ***	8.745 [0.557]	6.135 [0.804]
EMV	−0.741	2.644	925.753 ***	8.741 [0.557]	4.202 [0.938]
GPR	−0.744	2.648	929.553 ***	7.461 [0.681]	6.348 [0.785]
Baseline	−0.746	2.682	949.136 ***	8.640 [0.567]	6.310 [0.789]
GB					
EPU	−0.204	1.819	350.377 ***	6.982 [0.727]	6.814 [0.743]
CPU	−0.200	1.797	341.970 ***	7.386 [0.689]	7.118 [0.714]
TPU	−0.177	1.799	339.143 ***	6.738 [0.750]	6.512 [0.771]
EMV	−0.199	1.806	345.048 ***	6.162 [0.724]	9.756 [0.462]
GPR	−0.188	1.691	303.000 ***	6.922 [0.733]	6.931 [0.732]
Baseline	−0.197	1.752	325.459 ***	6.087 [0.731]	7.602 [0.668]
Gold					
EPU	−0.209	2.846	834.331 ***	7.274 [0.699]	3.459 [0.968]
CPU	−0.229	3.049	958.176 ***	6.720 [0.752]	4.766 [0.906]
TPU	−0.164	3.144	1006.818 ***	6.885 [0.736]	4.505 [0.922]
EMV	−0.167	2.994	914.855 ***	6.256 [0.793]	5.358 [0.866]
GPR	−0.138	2.806	801.156 ***	6.783 [0.746]	3.768 [0.957]
Baseline	−0.194	2.910	868.496 ***	6.580 [0.764]	3.433 [0.969]
Oil					
EPU	−0.427	2.962	957.572 ***	8.376 [0.592]	5.066 [0.887]
CPU	−0.460	3.048	1021.224 ***	8.430 [0.587]	5.366 [0.865]
TPU	−0.452	3.049	1019.080 ***	8.378 [0.592]	5.451 [0.859]
EMV	−0.485	2.791	879.832 ***	8.396 [0.590]	6.383 [0.782]
GPR	−0.446	2.922	940.659 ***	8.697 [0.561]	5.602 [0.847]
Baseline	−0.457	3.026	1006.829 ***	8.160 [0.613]	5.616 [0.846]
Bitcoin					
EPU	−0.073	9.394	8887.109 ***	9.725 [0.465]	9.239 [0.510]
CPU	−0.092	8.874	7931.548 ***	8.349 [0.595]	8.078 [0.621]
TPU	−0.239	9.494	9097.868 ***	9.695 [0.468]	9.209 [0.512]
EMV	−0.013	7.872	6239.620 ***	9.670 [0.470]	9.416 [0.493]
GPR	−0.118	8.042	6517.904 ***	8.890 [0.543]	8.583 [0.572]
Baseline	−0.058	7.307	5377.056 ***	9.603 [0.476]	8.652 [0.565]

Notes: The Jarque–Bera test is used to investigate the normality. The Ljung–Box and ARCH–LM tests at 10 lags are utilized to examine the existence of serial correlation and ARCH effect in the standardized residuals. The *p*-values of test statistics are reported in square brackets. *** denotes statistical significance at 1% level.

Table A3. Statistics of correlations.

	S&P 500 Mean	Max.	Min.	Std. Dev.	CSI 300 Mean	Max.	Min.	Std. Dev.
Panel: Short term								
GB								
EPU	0.0052	0.3705	−0.4578	0.1506	0.0444	0.2894	−0.2200	0.0924
CPU	0.0037	0.3961	−0.4631	0.1528	0.0441	0.3008	−0.2301	0.0932
TPU	0.0048	0.3819	−0.4566	0.1510	0.0446	0.2993	−0.2279	0.0931
EMV	0.0027	0.3738	−0.4730	0.1500	0.0440	0.2986	−0.2648	0.0931
GPR	0.0031	0.3936	−0.4526	0.1537	0.0444	0.2867	−0.2153	0.0933
Gold								
EPU	−0.0421	0.2909	−0.4732	0.1530	0.0187	0.2105	−0.1956	0.0930
CPU	−0.0423	0.2929	−0.4908	0.1553	0.0185	0.2117	−0.2028	0.0938
TPU	−0.0440	0.2871	−0.4882	0.1531	0.0178	0.2121	−0.2015	0.0937
EMV	−0.0436	0.2815	−0.4660	0.1504	0.0184	0.2020	−0.1995	0.0923
GPR	−0.0438	0.3078	−0.4980	0.1566	0.0184	0.2154	−0.1949	0.0933

Table A3. Cont.

	S&P 500 Mean	Max.	Min.	Std. Dev.	CSI 300 Mean	Max.	Min.	Std. Dev.
<i>Panel: Short term</i>								
<i>Oil</i>								
EPU	0.2411	0.5524	−0.0513	0.1061	0.1025	0.4688	−0.1795	0.1082
CPU	0.2428	0.5550	−0.0359	0.1081	0.1031	0.4947	−0.1857	0.1091
TPU	0.2424	0.5567	−0.0297	0.1070	0.1028	0.4960	−0.1814	0.1087
EMV	0.2430	0.5474	−0.0131	0.1059	0.1030	0.4869	−0.1791	0.1087
GPR	0.2421	0.5560	−0.0331	0.1089	0.1027	0.4553	−0.1870	0.1089
<i>Bitcoin</i>								
EPU	0.1087	0.5298	−0.3230	0.1873	0.0294	0.2310	−0.2121	0.0882
CPU	0.1084	0.5342	−0.3207	0.1848	0.0291	0.2539	−0.2195	0.0900
TPU	0.1080	0.5311	−0.3349	0.1844	0.0292	0.2466	−0.2265	0.0888
EMV	0.1067	0.5284	−0.3281	0.1827	0.0273	0.2522	−0.2308	0.0893
GPR	0.1083	0.5343	−0.3352	0.1854	0.0274	0.2516	−0.2352	0.0894
<i>Panel: Long term</i>								
<i>GB</i>								
EPU	−0.0044	0.3083	−0.2794	0.1396	0.0445	0.2215	−0.1476	0.0800
CPU	−0.0045	0.3087	−0.2821	0.1404	0.0445	0.2193	−0.1486	0.0801
TPU	−0.0044	0.3090	−0.2788	0.1397	0.0449	0.2206	−0.1486	0.0799
EMV	− 0.0052	0.3051	−0.2785	0.1393	0.0447	0.2226	−0.1478	0.0799
GPR	−0.0049	0.3085	−0.2899	0.1409	0.0445	0.2232	−0.1479	0.0801
<i>Gold</i>								
EPU	−0.0378	0.2667	−0.2626	0.1435	0.0196	0.1669	−0.1318	0.0842
CPU	−0.0378	0.2649	−0.2666	0.1442	0.0202	0.1665	−0.1328	0.0841
TPU	− 0.0385	0.2642	−0.2648	0.1432	0.0198	0.1672	−0.1324	0.0837
EMV	−0.0382	0.2632	−0.2647	0.1432	0.0202	0.1672	−0.1332	0.0839
GPR	−0.0383	0.2638	−0.2672	0.1447	0.0201	0.1668	−0.1310	0.0836
<i>Oil</i>								
EPU	0.2415	0.4340	0.0298	0.0959	0.1023	0.3043	−0.1214	0.0987
CPU	0.2416	0.4311	0.0348	0.0966	0.1030	0.3048	−0.1206	0.0985
TPU	0.2415	0.4331	0.0300	0.0961	0.1026	0.3049	−0.1220	0.0987
EMV	0.2421	0.4355	0.0287	0.0963	0.1030	0.3059	−0.1230	0.0990
GPR	0.2416	0.4293	0.0387	0.0970	0.1030	0.3049	−0.1235	0.0990
<i>Bitcoin</i>								
EPU	0.1059	0.5557	−0.1835	0.1852	0.0313	0.2162	−0.1186	0.0870
CPU	0.1073	0.5515	−0.1699	0.1842	0.0311	0.2167	−0.1209	0.0870
TPU	0.1076	0.5546	−0.1716	0.1831	0.0312	0.2155	−0.1201	0.0864
EMV	0.1063	0.5534	−0.1707	0.1821	0.0305	0.2126	−0.1206	0.0864
GPR	0.1084	0.5467	−0.1664	0.1836	0.0309	0.2144	−0.1198	0.0869

Notes: Bold numbers represent the highest absolute values among the five risks.

Table A4. Statistics of optimal weights and hedge ratios.

	S&P 500 Mean	Max.	Min.	Std. Dev.	CSI 300 Mean	Max.	Min.	Std. Dev.
<i>Panel: Optimal weight</i>								
<i>GB</i>								
EPU	0.8392	1.0000	0.4709	0.1058	0.9132	1.0000	0.6421	0.0791
CPU	0.8443	1.0000	0.5403	0.0974	0.9134	1.0000	0.6293	0.0783
TPU	0.8439	1.0000	0.5320	0.0985	0.9131	1.0000	0.6090	0.0798
EMV	0.8475	1.0000	0.4616	0.1043	0.9156	1.0000	0.6450	0.0787
GPR	0.8441	1.0000	0.4983	0.1007	0.9144	1.0000	0.6520	0.0774
Baseline	0.8490	1.0000	0.5254	0.0960	0.9150	1.0000	0.6425	0.0788
<i>Gold</i>								
EPU	0.4693	0.9582	0.1200	0.1871	0.6262	0.9499	0.2543	0.1562
CPU	0.4787	0.9609	0.1374	0.1775	0.6323	0.9500	0.3085	0.1535
TPU	0.4876	0.9627	0.1245	0.1849	0.6394	0.9558	0.2591	0.1643
EMV	0.4757	0.9595	0.1356	0.1816	0.6272	0.9557	0.2758	0.1600
GPR	0.4733	0.9617	0.0752	0.1863	0.6264	0.9495	0.2667	0.1601
Baseline	0.4788	0.9716	0.1372	0.1790	0.6295	0.9630	0.2642	0.1579

Table A4. Cont.

	S&P 500 Mean	Max.	Min.	Std. Dev.	CSI 300 Mean	Max.	Min.	Std. Dev.
<i>Panel: Optimal weight</i>								
<i>Oil</i>								
EPU	0.0790	0.8325	0.0000	0.1112	0.2169	0.8161	0.0000	0.1541
CPU	0.0765	0.8081	0.0000	0.1086	0.2133	0.8566	0.0000	0.1557
TPU	0.0777	0.8183	0.0000	0.1093	0.2147	0.8150	0.0000	0.1538
EMV	0.0768	0.8260	0.0000	0.1112	0.2117	0.7985	0.0000	0.1514
GPR	0.0804	0.8518	0.0000	0.1131	0.2162	0.8227	0.0000	0.1558
Baseline	0.0765	0.8479	0.0000	0.1115	0.2162	0.8501	0.0000	0.1560
<i>Bitcoin</i>								
EPU	0.0367	0.4217	0.0000	0.0574	0.0976	0.6841	0.0000	0.1168
CPU	0.0355	0.4062	0.0000	0.0532	0.0951	0.6082	0.0000	0.1057
TPU	0.0352	0.4244	0.0000	0.0529	0.0951	0.6670	0.0000	0.1108
EMV	0.0393	0.4523	0.0000	0.0589	0.1021	0.6637	0.0000	0.1212
GPR	0.0339	0.3826	0.0000	0.0476	0.0943	0.6464	0.0000	0.1065
Baseline	0.0324	0.4451	0.0000	0.0506	0.0981	0.6557	0.0000	0.1116
<i>Panel: Hedge ratio</i>								
<i>GB</i>								
EPU	−0.0258	1.4091	−5.8637	0.5422	0.1373	1.4284	−2.5609	0.5013
CPU	−0.0299	1.4756	−5.7445	0.5523	0.1307	1.3166	−2.6222	0.5016
TPU	−0.0255	1.5261	−5.6416	0.5414	0.1353	1.3785	−2.6103	0.5050
EMV	−0.0404	1.4183	−7.0555	0.5784	0.1328	1.3849	−3.7112	0.5310
GPR	−0.0344	1.6044	−5.8048	0.5525	0.1372	1.3342	−2.1577	0.4937
Baseline	0.0476	1.2438	−3.6794	0.3429	0.1768	1.1907	−1.7684	0.2749
<i>Gold</i>								
EPU	−0.0419	0.4543	−1.1975	0.1702	0.0136	0.4757	−0.8009	0.1680
CPU	−0.0410	0.4753	−1.1995	0.1765	0.0137	0.4879	−0.8879	0.1744
TPU	−0.0461	0.5119	−1.4235	0.1813	0.0118	0.5528	−0.8708	0.1803
EMV	−0.0432	0.4545	−1.3513	0.1728	0.0117	0.4599	−0.8235	0.1697
GPR	−0.0434	0.5167	−1.1002	0.1749	0.0143	0.5347	−0.7853	0.1686
Baseline	−0.0507	0.4106	−0.8170	0.1194	0.0076	0.3178	−0.4260	0.0936
<i>Oil</i>								
EPU	0.0938	0.4859	−0.0120	0.0605	0.0563	0.3340	−0.1494	0.0699
CPU	0.0939	0.5161	−0.0089	0.0607	0.0559	0.3775	−0.1465	0.0711
TPU	0.0941	0.5160	−0.0089	0.0607	0.0559	0.3453	−0.1484	0.0706
EMV	0.0940	0.5073	−0.0040	0.0603	0.0552	0.3518	−0.1506	0.0697
GPR	0.0942	0.4902	−0.0089	0.0620	0.0563	0.3805	−0.1513	0.0713
Baseline	0.0960	0.5226	−0.0031	0.0548	0.0581	0.2843	−0.0596	0.0452
<i>Bitcoin</i>								
EPU	0.0307	0.3176	−0.0876	0.0588	0.0106	0.1605	−0.1045	0.0299
CPU	0.0301	0.3079	−0.0881	0.0576	0.0105	0.1500	−0.0991	0.0307
TPU	0.0296	0.3426	−0.0949	0.0584	0.0101	0.1166	−0.1027	0.0295
EMV	0.0301	0.3591	−0.1247	0.0592	0.0096	0.1488	−0.1440	0.0319
GPR	0.0294	0.3179	−0.0795	0.0574	0.0101	0.1375	−0.0964	0.0296
Baseline	0.0288	0.2230	−0.0458	0.0338	0.0079	0.0808	−0.0841	0.0164

Notes: Bold numbers represent the highest absolute values among the five risks.

Table A5. Statistics of hedging effectiveness.

	S&P 500 Mean	Max.	Min.	Std. Dev.	t-Statistic	CSI 300 Mean	Max.	Min.	Std. Dev.	t-Statistic
<i>Panel: Diversified portfolio</i>										
<i>GB</i>										
EPU	0.8332	0.9960	0.3765	0.1105	−70.652 ***	0.8990	0.9934	0.5902	0.0865	−54.679 ***
CPU	0.8389	0.9960	0.3776	0.1016	−74.265 ***	0.8992	0.9931	0.5910	0.0858	−55.022 ***
TPU	0.8381	0.9960	0.3725	0.1030	−73.556 ***	0.8987	0.9932	0.5592	0.0879	−53.910 ***
EMV	0.8423	0.9967	0.3349	0.1094	−67.477 ***	0.9015	0.9955	0.5933	0.0871	−52.934 ***
GPR	0.8387	0.9958	0.3459	0.1062	−71.116 ***	0.9001	0.9924	0.5790	0.0858	−54.507 ***
Baseline	0.8382	0.9960	0.4122	0.1002	−75.607 ***	0.9007	0.9932	0.6089	0.0845	−55.002 ***
<i>Gold</i>										
EPU	0.4916	0.9784	0.0672	0.1928	−123.440 ***	0.6159	0.9620	0.2396	0.1612	−111.557 ***
CPU	0.5008	0.9799	0.0784	0.1824	−128.142 ***	0.6220	0.9645	0.2633	0.1572	−112.524 ***
TPU	0.5104	0.9812	0.0800	0.1904	−120.364 ***	0.6295	0.9658	0.2459	0.1696	−102.250 ***
EMV	0.4983	0.9796	0.0893	0.1869	−125.656 ***	0.6169	0.9646	0.2263	0.1653	−108.508 ***
GPR	0.4972	0.9803	0.0283	0.1919	−122.626 ***	0.6162	0.9616	0.2170	0.1648	−109.005 ***
Baseline	0.5027	0.9804	0.1077	0.1777	−131.028 ***	0.6231	0.9648	0.2449	0.1615	−109.213 ***

Table A5. Cont.

	S&P 500 Mean	Max.	Min.	Std. Dev.	t-Statistic	CSI 300 Mean	Max.	Min.	Std. Dev.	t-Statistic
<i>Panel: Diversified portfolio</i>										
<i>Oil</i>										
EPU	0.0501	0.7097	0.0000	0.0846	−525.330 ***	0.1879	0.8255	0.0000	0.1489	−255.278 ***
CPU	0.0484	0.6855	0.0000	0.0822	−542.040 ***	0.1847	0.8573	0.0000	0.1511	−252.579 ***
TPU	0.0490	0.6939	0.0000	0.0831	−535.887 ***	0.1860	0.8249	0.0000	0.1493	−255.220 ***
EMV	0.0488	0.7067	0.0000	0.0852	−522.650 ***	0.1831	0.8179	0.0000	0.1471	−259.990 ***
GPR	0.0517	0.7297	0.0000	0.0865	−513.176 ***	0.1874	0.8261	0.0000	0.1508	−252.191 ***
Baseline	0.0448	0.7088	0.0000	0.0833	−536.951 ***	0.1828	0.8114	0.0000	0.1454	−263.056 ***
<i>Bitcoin</i>										
EPU	0.0399	0.4740	0.0000	0.0603	−745.328 ***	0.0953	0.6948	0.0000	0.1177	−359.681 ***
CPU	0.0387	0.4608	0.0000	0.0572	−786.952 ***	0.0930	0.6426	0.0000	0.1070	−396.644 ***
TPU	0.0387	0.4808	0.0000	0.0587	−766.538 ***	0.0932	0.6768	0.0000	0.1123	−377.923 ***
EMV	0.0418	0.5225	0.0000	0.0635	−706.105 ***	0.1005	0.6904	0.0000	0.1232	−341.629 ***
GPR	0.0374	0.3960	0.0000	0.0538	−837.241 ***	0.0925	0.6574	0.0000	0.1076	−394.870 ***
Baseline	0.0241	0.4471	0.0000	0.0441	−1034.793 ***	0.0935	0.6534	0.0000	0.1101	−385.391 ***
<i>Panel: Hedging portfolio</i>										
<i>GB</i>										
EPU	0.0227	0.2095	0.0000	0.0271	−1689.109 ***	0.0105	0.0838	0.0000	0.0120	−3851.773 ***
CPU	0.0233	0.2144	0.0000	0.0280	−1630.750 ***	0.0106	0.0905	0.0000	0.0123	−3760.641 ***
TPU	0.0228	0.2085	0.0000	0.0276	−1659.759 ***	0.0107	0.0896	0.0000	0.0124	−3747.663 ***
EMV	0.0225	0.2237	0.0000	0.0272	−1684.056 ***	0.0106	0.0892	0.0000	0.0123	−3755.614 ***
GPR	0.0236	0.2048	0.0000	0.0281	−1626.581 ***	0.0107	0.0822	0.0000	0.0121	−3841.412 ***
Baseline	0.0085	0.0791	0.0000	0.0118	−3931.693 ***	0.0051	0.0652	0.0000	0.0067	−6941.402 ***
<i>Gold</i>										
EPU	0.0252	0.2240	0.0000	0.0284	−1603.897 ***	0.0090	0.0443	0.0000	0.0085	−5489.032 ***
CPU	0.0259	0.2408	0.0000	0.0296	−1539.483 ***	0.0091	0.0448	0.0000	0.0087	−5334.586 ***
TPU	0.0254	0.2383	0.0000	0.0293	−1556.556 ***	0.0091	0.0450	0.0000	0.0086	−5376.640 ***
EMV	0.0245	0.2172	0.0000	0.0281	−1626.047 ***	0.0089	0.0408	0.0000	0.0083	−5615.465 ***
GPR	0.0264	0.2480	0.0000	0.0301	−1514.439 ***	0.0090	0.0464	0.0000	0.0086	−5365.987 ***
Baseline	0.0113	0.1517	0.0000	0.0166	−2785.107 ***	0.0024	0.0370	0.0000	0.0036	−13085.813 ***
<i>Oil</i>										
EPU	0.0694	0.3052	0.0000	0.0534	−815.887 ***	0.0222	0.2198	0.0000	0.0296	−1544.519 ***
CPU	0.0706	0.3081	0.0000	0.0546	−796.502 ***	0.0225	0.2447	0.0000	0.0308	−1484.160 ***
TPU	0.0702	0.3099	0.0000	0.0542	−803.216 ***	0.0224	0.2460	0.0000	0.0305	−1500.522 ***
EMV	0.0702	0.2996	0.0000	0.0537	−810.347 ***	0.0224	0.2371	0.0000	0.0303	−1509.488 ***
GPR	0.0705	0.3091	0.0000	0.0545	−798.197 ***	0.0224	0.2073	0.0000	0.0295	−1552.297 ***
Baseline	0.0651	0.2188	0.0000	0.0339	−1290.985 ***	0.0136	0.1480	0.0000	0.0153	−3014.941 ***
<i>Bitcoin</i>										
EPU	0.0469	0.2807	0.0000	0.0695	−642.251 ***	0.0086	0.0534	0.0000	0.0095	−4867.274 ***
CPU	0.0459	0.2854	0.0000	0.0688	−649.241 ***	0.0089	0.0644	0.0000	0.0103	−4509.391 ***
TPU	0.0457	0.2820	0.0000	0.0684	−652.881 ***	0.0087	0.0608	0.0000	0.0101	−4605.092 ***
EMV	0.0447	0.2792	0.0000	0.0666	−671.739 ***	0.0087	0.0636	0.0000	0.0101	−4591.221 ***
GPR	0.0461	0.2854	0.0000	0.0690	−647.428 ***	0.0087	0.0633	0.0000	0.0103	−4524.398 ***
Baseline	0.0218	0.1151	0.0000	0.0247	−1856.221 ***	0.0027	0.0233	0.0000	0.0033	−14223.883 ***

Notes: Bold numbers represent the maximum values among the five risks. The *t*-test is used to examine whether there is a significant difference between hedging effectiveness and one whose null hypothesis is $H_0 : HE = 1$. *** denotes statistical significance at 1% level.

Table A6. Downside risk reduction measures.

	S&P 500 EPU	CPU	TPU	EMV	GPR	Baseline	CSI 300 EPU	CPU	TPU	EMV	GPR	Baseline
<i>Panel: Diversified portfolio</i>												
<i>VaR reduction</i>												
GB	0.6969	0.6964	0.6963	0.6956	0.6970	0.6967	0.7583	0.7586	0.7586	0.7583	0.7584	0.7584
Gold	0.4524	0.4530	0.4534	0.4526	0.4543	0.4523	0.5121	0.5117	0.5110	0.5132	0.5126	0.5112
Oil	−0.0533	−0.0516	−0.0494	−0.0519	−0.0666	−0.0563	0.1670	0.1692	0.1690	0.1701	0.1703	0.1654
Bitcoin	−0.0539	−0.0465	−0.0556	−0.0393	−0.0327	−0.0562	0.1494	0.1482	0.1473	0.1561	0.1519	0.1505
<i>ES reduction</i>												
GB	0.7042	0.7050	0.7055	0.7050	0.7022	0.7033	0.7801	0.7817	0.7817	0.7807	0.7808	0.7797
Gold	0.4801	0.4800	0.4878	0.4831	0.4819	0.4860	0.5609	0.5585	0.5617	0.5634	0.5664	0.5618
Oil	−0.1510	−0.1506	−0.1292	−0.1313	−0.1764	−0.1544	0.1882	0.1944	0.1959	0.1930	0.1924	0.1831
Bitcoin	−0.1136	−0.0979	−0.1161	−0.0700	−0.0760	−0.1155	0.1919	0.1823	0.1814	0.1980	0.1879	0.1784

Table A6. Cont.

	S&P 500 EPU	CPU	TPU	EMV	GPR	Baseline	CSI 300 EPU	CPU	TPU	EMV	GPR	Baseline
Panel: Diversified portfolio												
LPM reduction												
GB	0.6450	0.6446	0.6446	0.6437	0.6453	0.6440	0.7266	0.7271	0.7272	0.7269	0.7271	0.7268
Gold	0.3910	0.3924	0.3918	0.3914	0.3937	0.3912	0.4596	0.4595	0.4590	0.4597	0.4602	0.4591
Oil	−0.0342	−0.0318	−0.0306	−0.0343	−0.0370	−0.0320	0.0898	0.0900	0.0897	0.0898	0.0910	0.0894
Bitcoin	−0.0434	−0.0416	−0.0425	−0.0331	−0.0384	−0.0407	0.0869	0.0837	0.0827	0.0910	0.0842	0.0866
Panel: Hedging portfolio												
VaR reduction												
GB	−0.0359	−0.0331	−0.0328	−0.0463	−0.0356	−0.0003	0.0372	0.0376	0.0378	0.0372	0.0379	0.0358
Gold	−0.0093	−0.0081	−0.0139	−0.0135	−0.0042	0.0157	0.0367	0.0374	0.0365	0.0371	0.0373	0.0369
Oil	0.0540	0.0556	0.0541	0.0579	0.0584	0.0600	0.0430	0.0431	0.0429	0.0434	0.0432	0.0491
Bitcoin	0.0691	0.0652	0.0655	0.0580	0.0601	0.0701	0.0298	0.0303	0.0308	0.0296	0.0308	0.0332
ES reduction												
GB	−0.0832	−0.0764	−0.0772	−0.0962	−0.0782	−0.0013	0.0072	0.0076	0.0078	0.0030	0.0161	0.0093
Gold	−0.0171	−0.0157	−0.0342	−0.0335	−0.0077	0.0149	0.0196	0.0198	0.0193	0.0196	0.0206	0.0192
Oil	0.0694	0.0725	0.0717	0.0792	0.0781	0.0690	−0.0076	−0.0121	−0.0123	−0.0126	−0.0075	0.0078
Bitcoin	0.0697	0.0603	0.0560	0.0507	0.0533	0.0795	0.0027	0.0028	−0.0047	−0.0070	−0.0053	−0.0079
LPM reduction												
GB	−0.0299	−0.0273	−0.0278	−0.0327	−0.0284	−0.0274	−0.0099	−0.0092	−0.0091	−0.0098	−0.0097	−0.0073
Gold	−0.0351	−0.0329	−0.0360	−0.0368	−0.0304	−0.0286	−0.0057	−0.0050	−0.0061	−0.0054	−0.0053	−0.0051
Oil	0.0139	0.0156	0.0147	0.0171	0.0180	0.0174	−0.0004	−0.0009	−0.0007	0.0000	−0.0010	0.0042
Bitcoin	0.0020	−0.0012	0.0010	−0.0057	0.0011	−0.0057	−0.0161	−0.0151	−0.0141	−0.0169	−0.0149	−0.0101

Notes: To simplify calculations, this paper assumes the threshold return is zero. Bold numbers represent the maximum values among the five risks.

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