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Global and domestic economic policy uncertainties and tourism stock market: Evidence from China

Abstract

This study investigates the impacts of global economic policy uncertainty (GEPU) and domestic (Chinese) economic policy uncertainty (CEPU) on the long-run volatility of the tourism stock market in China based on an improved GARCH–MIDAS–X model. Empirical results reveal that both CEPU and GEPU have significant negative effects on the long-run volatility of China's tourism stock market. It is further identified that the impact of GEPU on tourism companies' performance is short-lived. The findings suggest that tourism-related practitioners should monitor both CEPU and GEPU when conducting risk assessments related to tourism investment and policymaking.

Keywords: economic policy uncertainty, GARCH–MIDAS model, long-run volatility, tourism stock returns, tourism thematic index

1. Introduction

Tourism is closely related to economic development and plays an increasingly important role in the economy. According to the World Travel & Tourism Council (2021), tourism accounted for approximately 10.3% of global GDP from 2015–2019; it even directly contributed 5.5% of economic growth in 2020 despite the COVID-19 pandemic. Stable tourism development is thus crucial to economic development. It is hence necessary to delineate the influencing factors of tourism development, especially amid COVID-19 and the corresponding economic recovery. The pandemic has intensified uncertainty during the recovery process (Carnahan et al., 2022; Liu and Chen, 2022). Due to the nature of policy decisions and their implementation, economic policies create uncertainty that guides tourism firms' and investors' decisions. Economic policy uncertainty (EPU) has been particularly affected by COVID-19. Increased EPU forces tourism firms to hold more cash, thus reducing capital investment while the cost of capital rises. In addition, as economic uncertainty climbs, individuals reduce or postpone consumer spending. This uncertainty index can be measured by newspaper reporting frequency (Baker et al., 2016); it is likely to inform tourists' travel plans based on perceived issues with security and social stability (Demir and Gozgor, 2018), shaping tourism development in turn. As a result, many scholars have focused on the link between EPU and stock market returns in several respects: emerging Asian stock markets (Dong and Yoon, 2019), Gulf Cooperation Council countries' stock markets (Abdullah, 2020), and developed countries (Mei et al., 2018). Research has also covered various economic sectors, especially in terms of oil prices (Roubaud and Arouri, 2018), gold prices (Gao et al., 2020), bitcoin (Mokni et al., 2020), and commodity markets (Andreasson et al., 2016). Still other areas have been explored as well. Dao et al. (2020) confirmed that EPU can significantly affect the relationship between corporate social responsibility disclosure and corporate financial performance; Ren et al. (2020) found that China's EPU could influence the country's fiscal policy, monetary policy, and a range of macroeconomic indicators. Special attention should be given to EPU's impact on the tourism stock market—EPU is a key aspect of financial markets (Arouri et al., 2016; Demir and Ersan, 2018), and the tourism stock market is pivotal given its provision of financial support to tourism-related companies (Schwert, 1989; Demir et al., 2017; Yu et al., 2018a). Whereas most studies have considered how EPU influences the stock market as a whole (Zhang et al., 2019), listed companies' financial performance is subject to the nature of the industry to which the company belongs. The above studies may not fully reflect consequences for the tourism stock market.

Conclusions also rarely offer reliable guidance for tourism stakeholders and investors, as practical implications are difficult to draw from full-market findings.

EPU can significantly affect tourism stock returns (Demir and Ersan, 2018). Nonetheless, most literature has solely explored the impact of a single global EPU or domestic EPU on the tourism stock market. The tourism industry is borderless; its stock market is bound to receive shocks from changes in the international economic environment. Ersan et al. (2019) aimed to consider different ranges of EPU indices. However, due to data availability, the effects of European and global EPU indices on Turkish tourism companies' returns were explored using EEPU and GEPU. From the perspectives of tourism companies and investors, economic policies enacted by central banks will directly stimulate stock market fluctuations. It is therefore necessary to study the roles of global EPU and domestic EPU on the tourism stock market.

Stock market volatility affects market participants' decision making: it is a core determinant of investment management, risk assessment, and financial supervision. The literature on the tourism stock market has tended to address returns as a proxy variable for stock market changes rather than volatility. Different from prior work, this paper considers daily data to better describe shifts in the tourism stock market. Higher-frequency data series also contain more information than other types. Ways to apply datasets of different frequencies are thus discussed here. Meanwhile, several questions about the relationship between EPU and the tourism stock market merit consideration: 1) How do global EPU and domestic EPU affect the volatility of the tourism stock market?; and 2) Which EPU changes evoke greater sensitivity in tourism stock market volatility—those involving global EPU or domestic EPU? EPU can have short- and long-term impacts on stock market volatility. Distinguishing the duration of these effects has posed a major challenge in research on economic policy impacts when seeking to provide practical guidance for travel industry participants and investors. Lastly, 3) how can both high-frequency daily trading data and low-frequency monthly EPU data be used to detect the impact of EPU on long- and short-term fluctuations in the tourism stock market?

Our research addresses several issues. First, studies on GARCH family models have failed to reveal volatility characteristics over the short and long run across multiple dimensions. It is therefore necessary to assess the separate impacts of exogenous variables on long-term stock market volatility after component decomposition of volatility. Second, same-frequency data modeling is traditionally used to examine associations between exogenous variables and volatility. Noise is inevitably artificially added as the interpolation method converts low-frequency data into high-frequency data. Transforming high-frequency data to low-frequency data through summation, taking the mean, and other approaches is both simple and popular. However, essential information can easily go overlooked. The MIDAS model rectifies this deficiency. Finally, introducing EPU into the volatility model can better explain the causes of China's tourism stock market volatility. Scholars have tended to investigate the role of the EPU index on a country's overall stock market volatility, failing to confirm its impact on stock volatility in specific industries.

We divide short- and long-run components of volatility to more precisely tie the EPU index to tourism stock market volatility. Short-run volatility is estimated using a GARCH model based on daily (squared) returns. Long-run volatility is partially estimated with the MIDAS framework to link the monthly EPU index and daily tourism stock returns; this approach enables us to closely examine the EPU index's direct impact on tourism stock volatility while capturing sources that influence this volatility. We employ a modified GARCH–MIDAS model, which is suitable for our study, to scrutinize the effects of GEPU and CEPU on China's tourism stock market based on the daily CSI Tourism Thematic Index (CTTI) and monthly EPU data. Findings reveal a significant negative influence of GEPU and CEPU on the Chinese tourism stock market's long-run volatility. Results further indicate that GEPU has a briefer effect on tourism stock market volatility than CEPU. These outcomes offer policymakers valuable guidance for policy formulation and operational planning.

This study contributes to relevant work in several ways. First, we introduce EPU into research on the influencing factors of the tourism stock market to explore EPU's impact on the market's volatility. This step marks a departure from the extant literature: exploring the volatility of the tourism stock market provides a better picture of this market's stability. Second, our work enriches the literature by classifying EPU on national and global levels and by comparing the role of each in tourism stock market performance. Third, methodologically and temporally, this study's granularity is more refined than earlier efforts: we leverage daily CTTI data and monthly EPU data and adopt the GARCH–MIDAS model to mitigate the mixed-frequency problem.

The remainder of this paper is organized as follows. The next section presents an overview of literature related to the association between EPU and tourism industry development. Section 3 outlines the GARCH–MIDAS–X model and its estimation method. Section 4 describes and summarizes our dataset. Section 5 provides the empirical results; the robustness analysis is detailed in Section 6. Section 7 concludes our work.

2. Literature review

EPU refers to government policymakers' contributions to the uncertainty surrounding economic, regulatory, or monetary policy, as measured by newspaper coverage frequency (Baker et al., 2016). The relationship between EPU and tourism stock market has become a popular research topic as of late. To clarify the status of such work, we review the literature in three respects: EPU and tourism activities, EPU and stocks, and EPU and tourism companies' performance.

2.1 Economic policy uncertainty and tourism activities

Recent years have witnessed an expanding body of literature on the role of EPU in tourism (Wu and Wu, 2019a; Wu and Wu, 2019b; Wu et al., 2021a; Wu and Wu, 2021), such as in terms of tourism demand, tourist arrivals, tourist expenditure, and operations management. Certain studies have revolved around the relationship between EPU and tourism demand (Canh Phuc et al., 2020; Kuok et al., 2022). Gozgor and Ongan (2017) investigated the effects of EPU on tourism demand in the United States. Balli et al. (2018) detected the relationship between EPUs and tourism demand in OECD countries. Others have explored the EPU–tourism demand link elsewhere (Santamaria and Filis, 2019; Isik et al., 2020; Sharma and Khanna, 2021; Ghosh, 2022). However, related work involving China is scarce.

More specifically, studies have covered the impacts of EPU, geopolitical risks (GPR), and the World Uncertainty Index on tourist arrivals. The effects of EPU on tourist arrivals have been examined in the United States, the United Kingdom, Croatia, and other countries, with EPU shown to influence tourist arrival numbers (Ongan and Gozgor, 2018; Uzuner et al., 2020; Payne et al., 2022). The respective roles of GPR and EPU have also been studied with regard to tourist arrivals in India, South Korea, and China (Tiwari et al., 2019; Kazakova and Kim, 2021; Zhang et al., 2022). Tiwari et al. (2019)discovered that the impact of GPR on tourism arrivals exceeded that of EPU in India. Kazakova and Kim (2021) noted that GPR and EPU affected Korean tourist arrivals, but the country's tourism industry could resist these influences. Zhang et al. (2022) discussed the role of uncertainty on tourist arrivals in China and identified significant time-varying characteristics. The impact direction was also found to change: as the lag period increased, the influence gradually declined (Zhang et al., 2022). Respective analyses of tourist arrivals in Australia and 19 emerging economies indicated that the World Uncertainty Index affected arrival numbers in these cases (Gozgor et al., 2021; Ding et al., 2022).

The impact of EPU on tourist expenditure and operations management has also been studied extensively. Evidence suggests that EPU affects tourist expenditure and demand (Gozgor and Demir, 2018; Kim and In-sin, 2020; Hailemariam and Ivanovski, 2021). EPU has additionally been found to influence tourism investment in OECD countries (Demir et al., 2020). Akron et al. (2020) and Altaf (2022) examined the role of EPU in hotel business investment in the United States and India, respectively, and noted that EPU adversely affected investment. Garcia-Gomez et al. (2022) further analyzed the effect of EPU on U.S. tourism companies' performance and observed an asymmetric impact. Madanoglu and Ozdemir (2019) determined that EPU led to a decline in future hotel occupancy, room rates, and income per available room. Several authors have also concentrated on the impacts of EPU on tourism flows (Tekin, 2015; Singh et al., 2019; Gholipour et al., 2022), business tourism (Tsui et al., 2018), and inbound tourism (Khan et al., 2021).

EPU evidently has a significant impact on tourism activities. Many studies have addressed the relationship between EPU and tourism. Several scholars have examined the impact of EPU on tourism demand (Gozgor and Ongan, 2017; Ongan and Gozgor, 2018; Isik et al., 2020; Sharma and Khanna, 2021; Kuok et al., 2022). Others have considered the association between EPU and tourist arrivals (Tendai and Chikobvu, 2017; Ongan and Gozgor, 2018; Tiwari et al., 2019; Ding et al., 2022; Payne et al., 2022). Despite interest surrounding the connection between EPU and the stock market in general (Liu and Zhang, 2015; Liu et al., 2017; Mei et al., 2018; Wei et al., 2017), much less is known about EPU and tourism stock market in particular. Yet most related studies have focused on tourism demand, tourist arrivals, and tourist expenditure; less is understood about tourism stock market. For instance, it adversely affects hotel investment policies (Akron et al., 2020), which subsequently shape the tourism stock market's development—and, by extension, tourism development. The relationship between EPU and tourism stock market thus warrants exploration. Moreover, EPU negatively influences the stock market's volatility. A handful of researchers have assessed the impact and predictive performance of EPU on returns in the tourism stock market (Demir and Ersan, 2018; Ersan et al., 2019); focal countries have included Turkey, Europe, and the United States based on yearly or monthly data (Demir and Ersan, 2018; Ersan et al., 2019; Kumar, 2021; Hadi et al., 2022; Jiang et al., 2022). With deepening globalization, continued cross-border exchange and development are shaping the economic environment. China's stock market is known as the "policy market"; economic regulatory policies issued by the central bank will directly affect travel industry practitioners' and investors' judgment, leading to investment losses in the short term. Investors' confidence will diminish as a result. Among the factors responsible for great fluctuations in China's stock market, policy uncertainty is a prime culprit. It is accordingly important to consider CEPU. Examining the effects of global EPU and domestic EPU on the volatility of the tourism stock market makes a valuable contribution to the literature.

2.2 Economic policy uncertainty and the stock market

Economic policies guide economic development; investors are accordingly concerned about EPU's impact on the stock market (Wang et al., 2021). Past studies have extensively examined that the relationship between EPU and the overall stock market. This line of research provides useful references for the research design of the present study. From a methodological point of view, scholars have adopted numerous approaches to investigate this relationship. Methods include quantile regression (Kannadhasan and Das, 2020; Huang and Liu, 2022; Jiang et al., 2022), ordinary least square (OLS) (Mbanyele, 2021; Zhang et al., 2021), and modified value-at-risk (Liu et al., 2021; Youssef et al., 2021; Ding et al., 2022; Zhang et al., 2022). EPU entails monthly data, while stock data are primarily daily. The MIDAS model has been introduced to address the mixed-frequency problem and prevent information loss from high-frequency data (Nguyen and Valadkhani, 2020). Some studies have combined the MIDAS model with others to better study the relationship between EPU and stocks' volatility. Yu et al. (2021) and Yu et al. (2021) both applied a GARCH–MIDAS model to analyze the respective impacts of CEPU and GEPU on stocks. Yu et al. (2018a) and Yu et al. (2018b) employed this type of model to examine EPU's role in the stock market in the United States and Korea, respectively. A GARCH–MIDAS model has been leveraged to determine how EPU affects Chinese banking and non-banking stocks along with the transmission structure of financial shocks between 10 sectors (Su and Liu, 2021; Wang et al., 2021). Others have used modified MIDAS models for analysis, such as CARR–MIDAS (Wu et al., 2021c), copula–MIDAS (Wu et al., 2022), and DCC–MIDAS (Fang et al., 2018; Fang et al., 2017; Yu et al., 2018a).

Although most studies have addressed either domestic or global EPU in isolation, a few have considered both simultaneously. Tsai (2017) investigated EPU's effects in China, Japan, Europe, and the United States on global stock markets. Qian et al. (2020) examined the impacts of EPU and GEPU in the United States, Europe, Russia, and China on global stock markets and noticed that GEPU had the strongest influence on the stock market. Qian et al. (2020) explored the effects of GEPU and CEPU on the Chinese stock market, in which GEPU fluctuations were found to lead to sharp changes in this market. Additionally, both domestic and international EPU affect the stock market's volatility (Mei et al., 2018; Wu et al., 2022). However, how global EPU and domestic EPU affect the tourism stock market's performance is still unknown. Our study aims to bridge this gap. It is hence necessary to consider global EPU and domestic EPU when scrutinizing how EPU influences the tourism stock market.

2.3 Economic policy uncertainty and the tourism stock market volatility

Tourism listed companies' operating performance is closely tied to their stock prices (Bae et al., 2002). Scholars have assessed the impact of EPU on tourism stock market to determine how it influences tourism companies' performance. Demir and Ersan (2018) adopted OLS to analyze the effects of European and domestic EPU on tourism stock prices in Turkey based on monthly data. Demiralay and Kilincarslan (2019) also referred to monthly data when employing the classical linear regression model and quantile regression to study the impact of GPR on travel and leisure (T&L) stocks globally and in the Asia-Pacific region, North America, and Europe. Bashir and Kumar (2022) subsequently investigated investor attention and EPU in relation to T&L stocks in these four regions based on OLS and quantile regression. Ersan et al. (2019)explored the influence of EPU on the STOXX Europe 600 Travel & Leisure Price Index using an OLS model with monthly data. Kumar (2021) expanded upon this effort by applying the copula-based conditional value-at-risk method to analyze the impact of uncertainty on European T&L stocks from the perspectives of EPU, GPR, the financial market, and crude oil price uncertainty. Aharon (2022) identified the effects of the Consumer Sentiment Index, EPU, and the Volatility Index on T&L stocks in the United States via OLS, GARCH, and quantile regression, respectively. Hadi et al. (2022) analyzed the effects of financial and economic uncertainty on U.S. tourism subsector stocks based on the time-varying vector autoregression model.

Most relevant studies have concentrated on Europe and the United States. Among those concerning China, Jiang et al. (2022) used the quantile-on-quantile and causality-in-quantiles approaches to evaluate the impacts of GPR and categorical EPU on Chinese tourism stock returns based on monthly data. China is both an economic and tourist power; the volatility of its tourism stock market is thus likely to be impactful. GEPU must also be considered when studying China's tourism stock market volatility. Research is therefore needed to probe the effects of GEPU and CEPU on Chinese tourism stock market.

The preceding literature review points to several knowledge gaps. First, although abundant work has explicated the relationship between EPU and tourism activities, the most popular topics appear to be tourism demand, tourist expenditure, and tourist arrivals. Comparatively, few studies have examined the impact of EPU on the volatility of the tourism stock market—yet EPU plays a key part in the tourism sector. Second, several scholars have adopted the GARCH–MIDAS model to study EPU's influence on the whole stock market; however, no study has applied this model to investigate the impact of EPU on the volatility of the tourism stock market. Third, Ersan et al. (2019) and Qin et al. (2021) explored the effects of different ranges of the EPU index on tourism stock market returns using European EPU, global EPU, and Chinese EPU, respectively. More remains to be uncovered about how domestic and international EPU affect the volatility of the tourism stock market; in particular, both global EPU and EPU are considered here. Fourth, insight into EPU's effects on tourism stock market is largely limited to European and American countries. It is vital to study the impact of EPU on the volatility of China's tourism stock market to benefit tourism development in both China and the world. Fifth, findings related to EPU's impact on tourism stock market have primarily been based on monthly data, but most stock data are daily. We therefore leverage a GARCH–MIDAS model to detect the effects of global EPU and domestic EPU on the volatility of the tourism market based on daily stock market data and EPU monthly data. We also consider the impact of consumer confidence on this market's volatility.

3. Methodology

A mixed-frequency GARCH–MIDAS model, proposed by Engle et al. (2013), is employed in this study to solve the mixed-frequency problem mentioned above. High-frequency data are conventionally transformed into low-frequency data for modeling and analysis under the low-(same) frequency framework. However, data frequency conversion causes some information to either be lost or to fail to align with study objectives. The GARCH–MIDAS model allows for the extraction of two volatility components: short-term fluctuations and the long-run component. This model has been widely adopted to elucidate relationships between stock volatility and economic variables (Asgharian et al., 2015; Conrad and Loch, 2015; Girardin and Joyeux, 2013). However, the model has yet to be applied to tourism stock market.

To investigate the effect of EPU on the long-run volatility of CTTI, we use the GARCH–MIDAS model (Engle et al., 2013) to rectify the data frequency mismatch between daily stock returns and the monthly EPU index. The MIDAS model can include data from mixed frequencies in the same model. The GARCH–MIDAS model is specified as follows ($g_{i,t}$ and τ_t denote the short-run variance and long-run variance components, respectively):

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}}\,\varepsilon_{i,t}, \quad \forall i = 1,\ldots,N_t, \tag{1}$$

where $r_{i,t}$ is the return of CTTI on day *i* of month *t*. Its conditional variance is decomposed into a short-term component $g_{i,t}$ and a long-term component τ_t. μ denotes daily expected returns. $\varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1)$ with $\Phi_{i-1,t}$ is the information set up on day (*i*-1) of period *t*. In accordance with (Engle and Rangel, 2008), we assume that the volatility dynamics of the component $g_{i,t}$ constitute a daily GARCH(1,1) process with $\alpha > 0, \beta > 0$, and $\alpha + \beta < 1$:

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

where α and β respectively denote the parameters of the ARCH and GARCH terms in the GARCH (1, 1) process of the short-term component $g_{i,t}$ of the conditional variance of CTTI's return. The realized volatility is used to represent long-run volatility. It is common to measure the realized volatility RV_t to model long-run volatility τ_t. Instead, we specify the τ_t component by smoothing the realized volatility using the MIDAS regression and MIDAS filtering:

$$\tau_t = m + \theta\sum_{k=1}^{K}\varphi_k(w_1, w_2)RV_{t-1}, \tag{3}$$

where θ measures the impact of exogenous explanatory variables on the long-run volatility of MIDAS regression. The achievable variance can be expressed as the sum of squares of log-returns of N trading days:

$$RV_t = \sum_{i=1}^{N} r_{i,t}^2, \tag{4}$$

where *RV* is the monthly realized volatility of CTTI's return, which is the sum of squares of the daily return rate of all trading days in *N* days. Here, *N* refers to a given month, quarter, or year. The fixed time window and the rolling time window can be used in empirical research to calculate *RV*; the length of the time window can then be divided into a fixed-length (e.g., there are 22 fixed trading days each month) and an indefinite length (i.e., according to the natural month to determine actual trading days; that is, the trading days in each month change, such that a month does not necessarily contain 22 trading days). We use the indefinite length calendar to calculate the monthly RV.

Furthermore, the weight function $\varphi_k(w_1, w_2)$ in Equation (3) is usually set to obey a beta polynomial structure, defined as follows:

$$\varphi_k(w_1, w_2) = \frac{(l/(K+1))^{w_1-1}(1-l/(K+1))^{w_2-1}}{\sum_{j=1}^{K}(j/(K+1))^{w_1-1}(1-j/(K+1))^{w_2-1}}, \tag{5}$$

where K is equal to the number of periods, we further modify this equation by adding economic variables along with the RV to examine these variables' effects on the long-run volatility of CTTI's return. In addition to the two uncertainty variables, we include the monthly consumer confidence index (CCI) as a control variable in line with Demir and Ersan (2018). Then, we specify the long-run component τ_t by smoothing RV in the spirit of MIDAS regression filtering:

$$\log \tau_t = m + \theta^{RV} \sum_{k=1}^{K} \varphi_k\left(w_1, w_2\right) RV_{t-k} + \theta^{CCI} \sum_{k=1}^{K} \varphi_k\left(w_1, w_2\right) CCI_{t-k} \tag{6}$$

Equations (1) – (6) produce a GARCH–MIDAS model for time-varying conditional variance with RV and the CCI within the parameter space $\Theta = \left\{\mu, \alpha, \beta, m, \theta^{RV}, \theta^{CCI}, w_1, w_2\right\}$.

As described, the EPU has an important influence on the volatility of stock returns. We thus introduce related variables, represented by X, in the Equation (6) of the GARCH–MIDAS model. Yao et al. (2019) proposed the GARCH–MIDAS–X model combining macroeconomic variables. Equation (6) can hence be transformed into the following:

$$\log \tau_t = m + \theta^{RV} \sum_{k=1}^{K} \varphi_k\left(w_1, w_2\right) RV_{t-k} + \theta^{CCI} \sum_{k=1}^{K} \varphi_k\left(w_1, w_2\right) CCI_{t-k} + \theta^{EPU} \sum_{k=1}^{K_l} \varphi_k\left(w_1, w_2\right) X_{t-k}^{EPU}, \tag{7}$$

where $X_{t\text{-}k}^{EPU}$ represents the change rate of EPU.

Finally, the total conditional variance can be written as

$$\sigma_{i,t}^2 = \tau_t \cdot g_{i,t} \tag{8}$$

According to the GARCH–MIDAS model built using Equations (1)–(6), its log-likelihood function (LLF) is

$$LLF = -\frac{1}{2} \sum_{t=1}^{T} \times \left[\log(2\pi) + \log g_{i,t}(\Phi)\tau_t(\Phi) + \frac{(r_{i,t} - \mu)^2}{g_{i,t}(\Phi)\tau_t(\Phi)} \right] \tag{9}$$

It is worth considering the extent of CTTI volatilities that can be explained by the four types of

GARCH–MIDAS–X models. To address this subject, we follow Conrad and Kleen (2020) in computing the variance ratio (VR) to measure the relative importance of the long-run volatility, defined as

$$VR = \frac{Var(\ln \tau_t)}{Var(\ln g_{i,t}\tau_t)} \times 100\% \tag{10}$$

VR reflects the proportion of the total log volatility that can be attributed to the long-term component. Moreover, we apply four models, similarly to Asgharian et al. (2013). The models vary in their definitions of the long-term conditional component τ_t; the equation for the short-term variance $g_{i,t}$, remains the same in all cases. First, we use the monthly realized volatility and change rate of CCI (CCIg) in the long-term component of the variance in this specification. The GARCH–MIDAS–(RV + CCIg) model is the basic model in which the long-term conditional component is defined using Equation (6). The second model is the GARCH–MIDAS–(RV + CCIg + GEPUg) model, in which we add an additional exogenous GEPUg as X in the long-term conditional component defined by Equation (7). Here, we modify the GARCH–MIDAS–(RV + CCIg) model by adding the change rate of GEPU to the MIDAS model. Third, in the GARCH–MIDAS–(RV + CCIg + CEPUg) model, we add an additional exogenous CEPUg as X in the long-term conditional component and add the change rate of GEPU to the MIDAS model. Fourth, in the GARCH–MIDAS–(RV + CCIg + GEPUg + CEPUg) model, we add the GEPU and CEPU change rates to the MIDAS model. This modification is supposed to capture information explained by both the macroeconomic factor and the monthly RV.

4. Data

We combine daily CTTI returns with monthly EPU indices; our sample period covers January 5, 2009–April 30, 2022. CTTI (stock code: 930633) reflects China's tourism stock market; associated datasets are taken from the Wind database. CTTI consists of representative stocks from scenic spots, travel agencies, hotels, and other companies that benefit from tourism. The index was established to convey the tourism industry's performance and to provide insight for investors in terms of scenic spots, travel agencies, hotels, and other industries. As of February 2020, CTTI reflected the behaviour of 10 listed T&L companies, such as Shanghai Jin Jiang International Hotels Co., Ltd., Shenzhen Overseas Chinese Town Co., Ltd., and Songcheng Performance Development Co., Ltd. The daily return is calculated as follows:

$$r_{i,t} = \ln p_{i,t} - \ln p_{i-1,t}, \ \ t = 1, 2, ..., T \tag{11}$$

where $p_{i,t}$ represents the closing price at day *i* of month *t*, and *T* refers to the sample size. We then use a monthly dataset from January 2009 to April 2022 to study the impact of EPU on the volatility of CTTI. CCI data are obtained from the CEInet Statistics Database. These data reflect the strength of consumer confidence, a leading indicator that can quantify consumers' evaluations of current economic conditions and their subjective feelings about economic prospects and consumer psychology. CCI can also predict economic trends and consumption trends. It consists of a consumer satisfaction index and a consumer expectation index. The index dynamics reflect changes in the CCI. The higher the index value, the stronger consumers' confidence. CEPU and GEPU data are obtained from the Economic Policy Uncertainty website (http://www.policyuncertainty.com/) for this study. All EPU indices were monthly, spanning January 2009–April 2022. Davis, et al. (2019) referred to two mainland Chinese newspapers, *Renmin Daily* and *Guangming Daily*. To build China's EPU index, they obtained the number of articles each month containing at least one term among three term sets on economy, policy, and uncertainty. We performed a keyword search for "uncertainty", "unpredictable", "commercial", "economic", "finance", "currency", "securities", "the CBRC", "finance", "the people's bank", "National Development and Reform Commission (NDRC)", "open and reform", "tax", "national debt", "central bank", "government deficit", and "tariff" in selected articles related to EPU, the statistical index, and standardized treatment. The GEPU index is a GDP-weighted average of national EPU indices for 21 countries.

Here, we calculate the change rate of EPU (EPUg) and CCI by taking the difference in the logarithm between two consecutive values (Yu et al., 2018b). The monthly change rate of EPU is calculated by the first order logarithm difference of the EPU index:

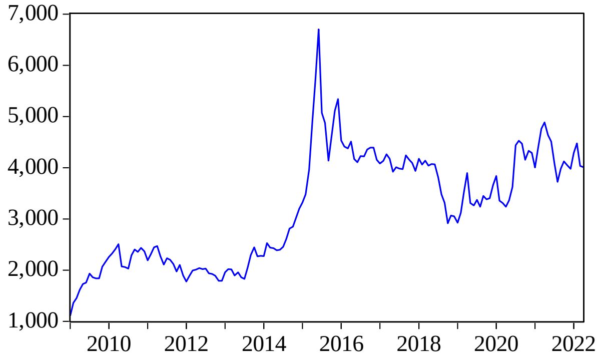
$$\begin{aligned} GEPUg &= (\ln(GEPU_t) - \ln(GEPU_{t-1})) \times 100\% \\ CEPUg &= (\ln(CEPU_t) - \ln(CEPU_{t-1})) \times 100\% \\ CCIg &= (\ln(CCI_t) - \ln(CCI_{t-1})) \times 100\% \end{aligned} \tag{12}$$

Table 1. Descriptive statistics for various CTTI series and EPU indices.

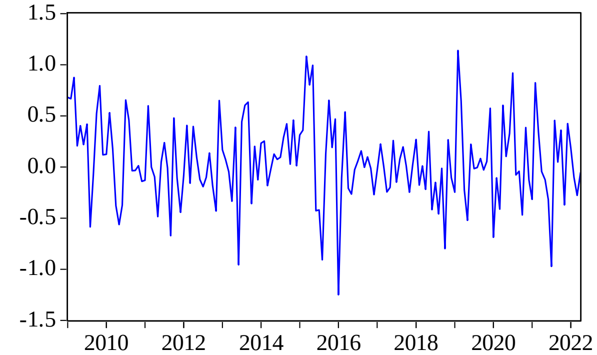
Variables	Mean	Std. Dev.	Skewness	Kurtosis	J-B Statistics	ADF
r_{CTTI}	0.0577	1.7873	-0.4667	5.5418	989.2145***	-52.5053***
CCI	110.0893	9.0891	0.3532	1.8777	11.7230***	-1.6825
CCIg	-0.0010	0.0311	-3.9039	34.6575	7087.7170***	-9.0591***
GEPU	173.0641	69.5494	1.1343	3.8517	39.1461***	-3.8213**
GEPUg	0.0042	0.1817	0.4928	4.2526	16.9354***	-10.2609***
CEPU	224.5050	250.1626	2.0614	8.0337	282.2421***	-4.7040***
CEPUg	0.0091	0.9853	-0.4914	5.1496	37.2449***	-10.5223***

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

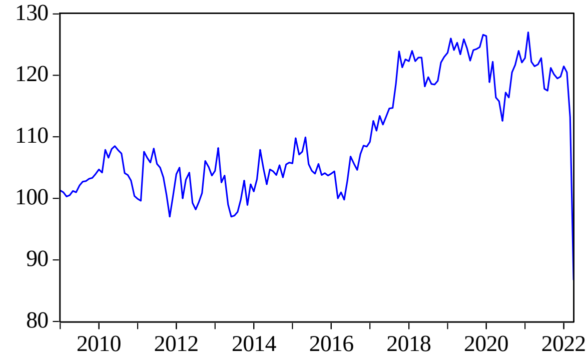
Descriptive statistics of the closing price of CTTI and return series are listed in Table 1. The return possesses significant right-skew and peak features, indicating that the student-t distribution (with a thicker tail than the normal distribution) should be considered when describing the return series' distribution function. The J-B statistic, which tests whether the sequence distribution is normal, significantly rejects the assumption that the closing price and the return sequence of CTTI obey the normal distribution. In addition, the augmented Dickey-Fuller test results on CTTI's returns significantly reject the null hypothesis of the existence of unit root. The series is therefore stationary and suitable for subsequent modeling analysis.



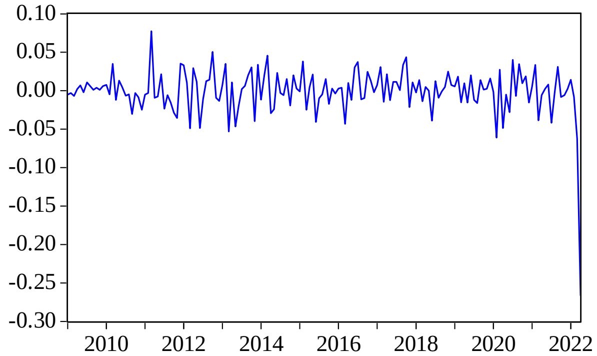
(a) CTTI closing price



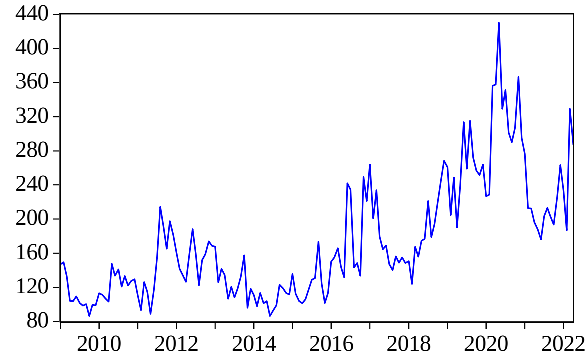
(b) CTTI return



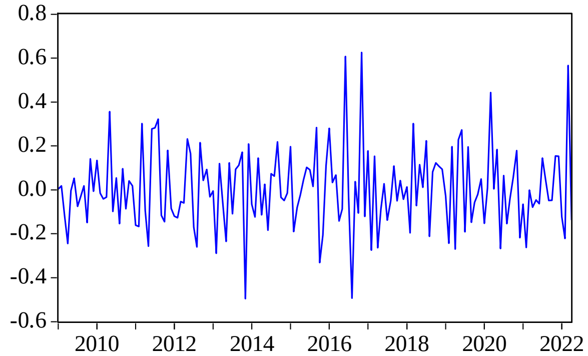
(c) CCI



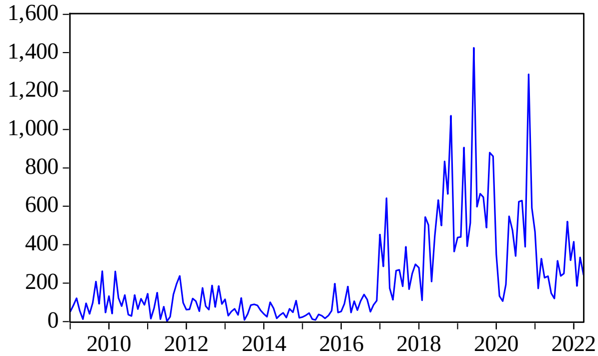
(d) CCIg



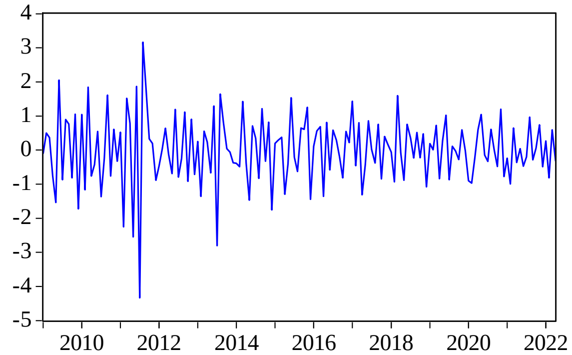
(e) GEPU



(f) GEPUg



(g) CEPU



(h) CEPUg

Figure 1. Daily closing price, CTTI return, and change rates in CCI, GEPU and CEPU.

Table 1 lists summary statistics for the monthly CCI, GEPU and CEPU index data; their movement is illustrated in Figure 1. The CCI is on an upward trend but declines significantly during events such as the stock market crisis, the U.S.–China trade policy tensions, and COVID-19 pandemic, and it rapidly reaches its lowest value in 2022. EPU is a measure of economic resource allocation and operational state intervention and regulation of fiscal policy, monetary policy, and other related policies. Uncertainty affects various individual financial decisions as well as the stock market index. Before 2010, the most obvious volatility was related to global economic and political events (i.e., the area between relatively consistent overall movements). Numerical volatility intensified thereafter with several noteworthy peak periods. That CEPU is highly volatile and peaks around recession periods; persistently high volatility spikes in our sample coincided with the global financial crisis in 2010 and the European debt crisis in 2012. Brexit, the inauguration of former U.S. President Donald Trump, trade wars, and intensifying U.S.–China trade policy tensions led the CEPU to reach its peak. GEPU also exhibited significant fluctuations: the Eurozone crisis in 2013, the European immigration crisis in 2015, the Brexit referendum, and Trump's election produced GEPU peaks in their respective periods. At the end of 2015, the China stock market crisis clearly affected CTTI's closing price, which descended quickly from 7000 to 3000 points. In terms of the time volatility of the return series, CTTI returns in 2015–2016 and 2018–2019 showed relatively significant volatility clustering. The volatility clustering demonstrates significant continuity characteristics. The COVID-19 pandemic has also recently generated sharp fluctuations in the global economy. The GEPU hence peaked whereas the CEPU fell to its recently lowest value. Due to the COVID-19 pandemic outbreak, the GEPU reaches its new peak; CEPU seems relatively smooth because of China government's quick and effective protective measures. During COVID-19, the volatility of CTTI and GEPUg increases significantly, and CTTI and CEPUg fluctuation is more consistent in magnitude, indicating that COVID-19 has a worldwide impact on global economic conditions. Overall, the EPU index reflects basic trends in economic policy uncertainty.

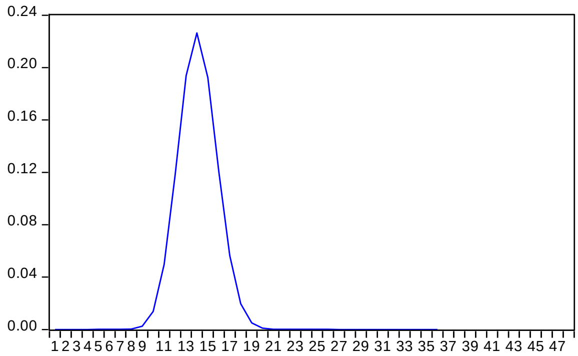
5. Empirical results

5.1 Estimation of GARCH–MIDAS–X models

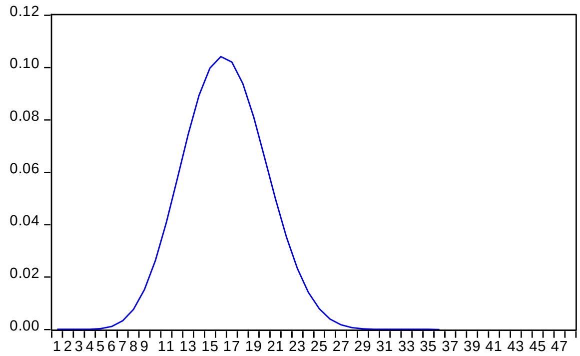
In this section, we present how to select lag weights for GARCH–MIDAS and the estimation results of the GARCH–MIDAS specification that involves RV, CCI, and EPU (RV + EPU model) at the same time. In addition, we show the different weighting schemes of the GARCH–MIDAS–X models.

Before estimating the parameters of the GARCH–MIDAS–X models, we need to determine the lag lengths of RV and EPU. We select optimal MIDAS lags based on the values of polynomial MIDAS weights or the shape of the beta function (Xu et al., 2019) rather than using the Akaike information criterion or the Bayesian information criterion.

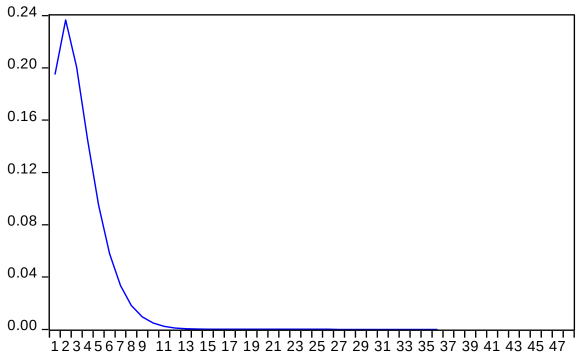
We consider the standard GARCH–MIDAS model with only one exogenous variable. We estimate this model with different lags and choose an appropriate lag for each variable according to the estimated weights approaching zero. Second, we use the selected optimal MIDAS lags for each corresponding variable in the GARCH–MIDAS–X model. The estimated lag weights for GARCH–MIDAS variations are pictured in Figure 2 (Xu et al., 2019). Corresponding results are summarized in Table 2; the "Zero lag" column denotes the lag at which weights approach zero. For example, we estimate the weight function of GEPUg with a lag of 36 months. Figure 2 shows that the estimated weights of CCIg, and CEPUg always decay to zero around 27 months of lags. GEPUg decays to zero around 12 months of lags. We then extend the zero lags to obtain the "Chosen lag" column, where we use lags to ensure sufficient information without excessive calculation.



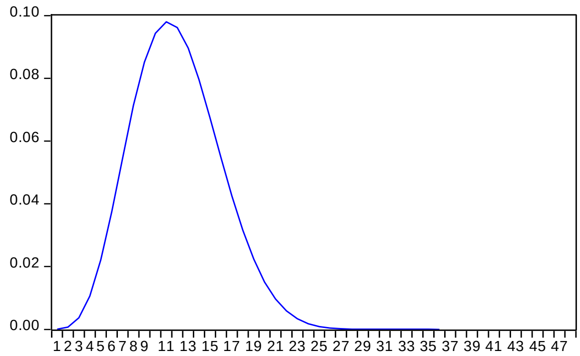
(a) Weighting Scheme of RV with 3 MIDAS lag years



(b) Weighting Scheme of CCIg with 3 MIDAS lag years



(c) Weighting Scheme of GEPUg with 3 MIDAS lag years



(d) Weighting Scheme of CEPUg with 3 MIDAS lag years

Figure 2. Different weighting schemes of exogenous variables for GARCH–MIDAS–X models.

Note: Lags refer to the beta polynomial lag K; the weight is the unrestricted weight w.

The variables of interest differ significantly in their estimated lags. GEPU has the most prominent weight on long-term fluctuations among the three variables, peaking at 0.24 across three months. The CEPU has an effective lag interval of about 27 months and reaches a maximum impact weight of 0.1 at about 12 months. The maximum values of the influence weights for CCI and CEPU are similar, peaking after roughly 1.5 years.

In essence, GEPU greatly affects the long-term volatility of China's tourism stock market, although the period of this impact is fairly brief (i.e., approximately one year). The CCI and CEPU influence this stock market's long-run volatility for about 2.5 years each. This section also addresses the time and maximum weight values of individual exogenous variables on the long-term volatility of CTTI.

Table 2. Optimal lag selection for exogenous variables.

Variable	Zero lag	Chosen lag
RV	21 months	27 months
CCIg	27 months	27 months
GEPUg	12 months	36 months
CEPUg	27 months	36 months

Note: Zero lag denotes the lag at which weights approach zero.

The weighting schemes for the four GARCH–MIDAS–X models appear in Figure 3. GEPU has the largest weight, and its decaying cycle is more rapid than that of CEPU. The impact of GEPU on the tourism stock market's volatility is accordingly short-lived. CEPU rapidly approaches zero in 36 months. Domestic policymakers' economic policies can readily influence the domestic financial market when subjected to external impacts from global economic changes, and domestic economic information (i.e., the change rate of the CEPU index) is further reflected in CTTI's long-run volatility. CEPU and GEPU are thus efficient indicators for CTTI.

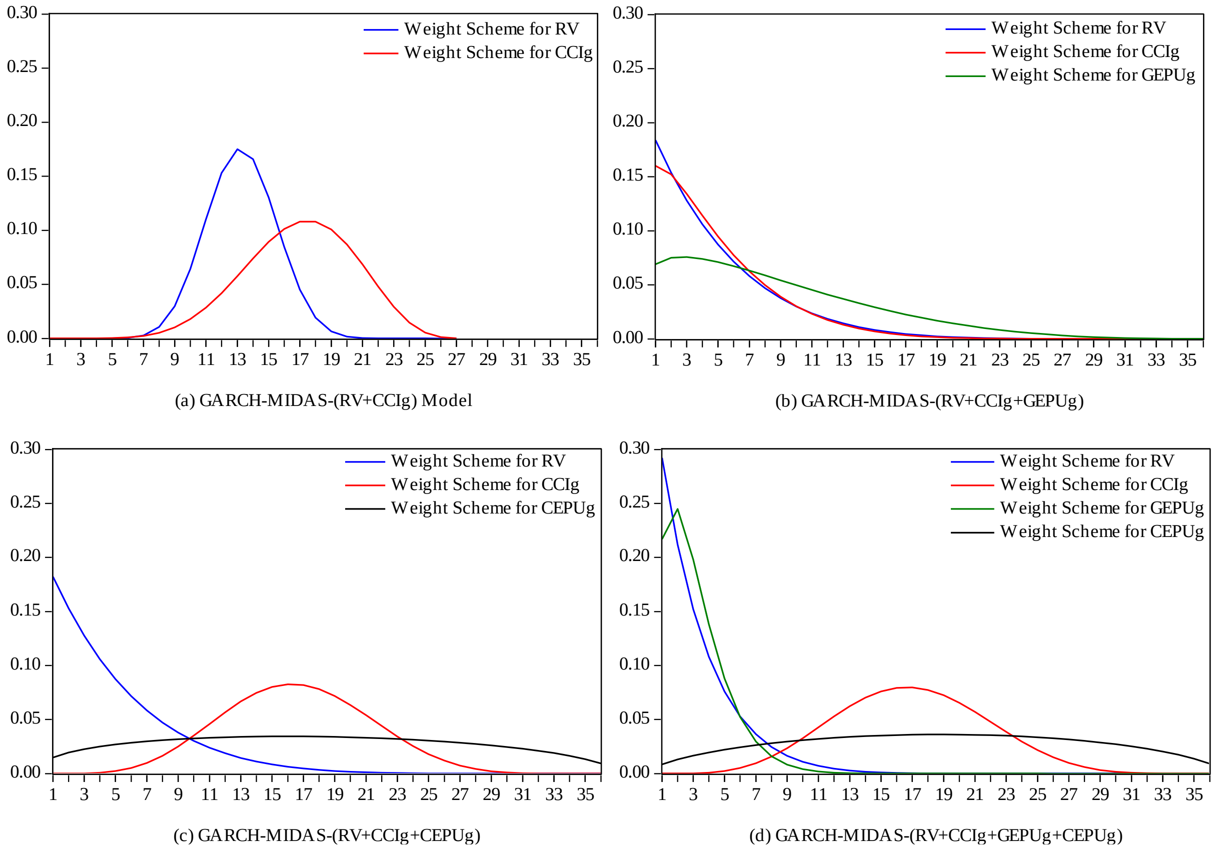


Figure 3. Different weighting schemes of exogenous variables for GARCH–MIDAS–X models.

Note: Horizontal axis denotes the lag period in months.

Results from estimating the GARCH–MIDAS–X model for CTTI returns throughout the sample period appear in Table 3, along with the VRs of the four MIDAS models. This table lists the parameters for all GARCH–MIDAS models. α and β are consistently significant. The α parameters are all slightly greater than zero, indicating that positive shocks minimally influence short-term fluctuations in natural resource returns. All β parameters are close to 1; that is, previous fluctuations greatly affect short-term CTTI fluctuations, with short-term fluctuations demonstrating strong memory and sustainability. Additionally, the sums of α and β are noticeably close to 1, reflecting a high degree of persistence in natural resources' volatility. Finally, the parameter θ measures the effects of monthly uncertainty shocks on the long-run volatility of CTTI. θ^{RV} , θ^{CCIg} , θ^{GEPUg} , and θ^{CEPUg} capture the respective impacts of realized volatility, CCI, CEPU, and GEPU on the long-run volatility of CTTI. The sign of the parameter θ is significantly positive, revealing that a rise in an exogenous variable prompts greater volatility in the tourism stock market. The opposite is also true.

Table 3. Parameter estimates of GARCH–MIDAS–X models (2009/1/5–2022/4/30).

Parameters	GARCH–MIDAS–X Models			
	GARCH–MIDAS–(RV+CCIg)	GARCH–MIDAS–(RV+CCIg+GEPUg)	GARCH–MIDAS–(RV+CCIg+CEPUg)	GARCH–MIDAS–(RV+CCIg +GEPUg+CEPUg)
μ	0.0003 (0.0003)	0.0004 (0.0003)	0.0005* (0.0003)	0.0005* (0.0003)
α	0.0565*** (0.0145)	0.0612*** (0.0144)	0.0606*** (0.0169)	0.0601*** (0.0175)
β	0.9296*** (0.0202)	0.9284*** (0.0231)	0.8943*** (0.0372)	0.8982*** (0.0422)
m	-8.0352*** (0.2255)	-7.8618*** (0.6083)	-8.0841*** (0.1371)	-8.3502*** (0.1653)
θ^{RV}	-38.4722* (22.8738)	-18.3975* (11.0823)	-32.3487* (18.0626)	-9.6970 (19.3301)
θ^{CCIg}	0.5131* (0.2857)	0.9396* (0.4899)	1.3487*** (0.4038)	1.7244*** (0.4353)
θ^{GEPU_g}		-0.2187** (0.1061)		-0.0332*** (0.0174)
θ^{CEPU_g}			-0.1321*** (0.0356)	-0.1379*** (0.0340)
$w_{1,RV}$	18.1788 (23.5300)	53.3815 (176.1415)	15.9580** (7.9127)	1.0020 (4.5818)
$w_{2,RV}$	20.2303 (26.7195)	1.0015 (8.1891)	29.6373** (14.7514)	12.4599 (21.2253)
$w_{1,CCIg}$	8.6520*** (3.2297)	10.4511*** (4.5703)	7.1177*** (2.1171)	6.4387*** (1.5734)
$w_{2,CCIg}$	5.5899** (2.8321)	12.1937*** (9.7767)	8.0515*** (2.7343)	7.6493*** (2.0633)
$w_{1.GEPUg}$		1.0001*** (0.2927)		2.0913*** (1.0322)
$w_{2.GEPU_g}$		1.0007*** (0.2700)		23.5725*** (10.6175)
$w_{1.CEPU_g}$			1.4702*** (0.2757)	1.6395*** (0.3300)
$w_{2.CEPU_g}$			1.5165*** (0.1629)	1.6135*** (0.1958)
VR[%]	26.9557	38.5348	54.9653	68.6475

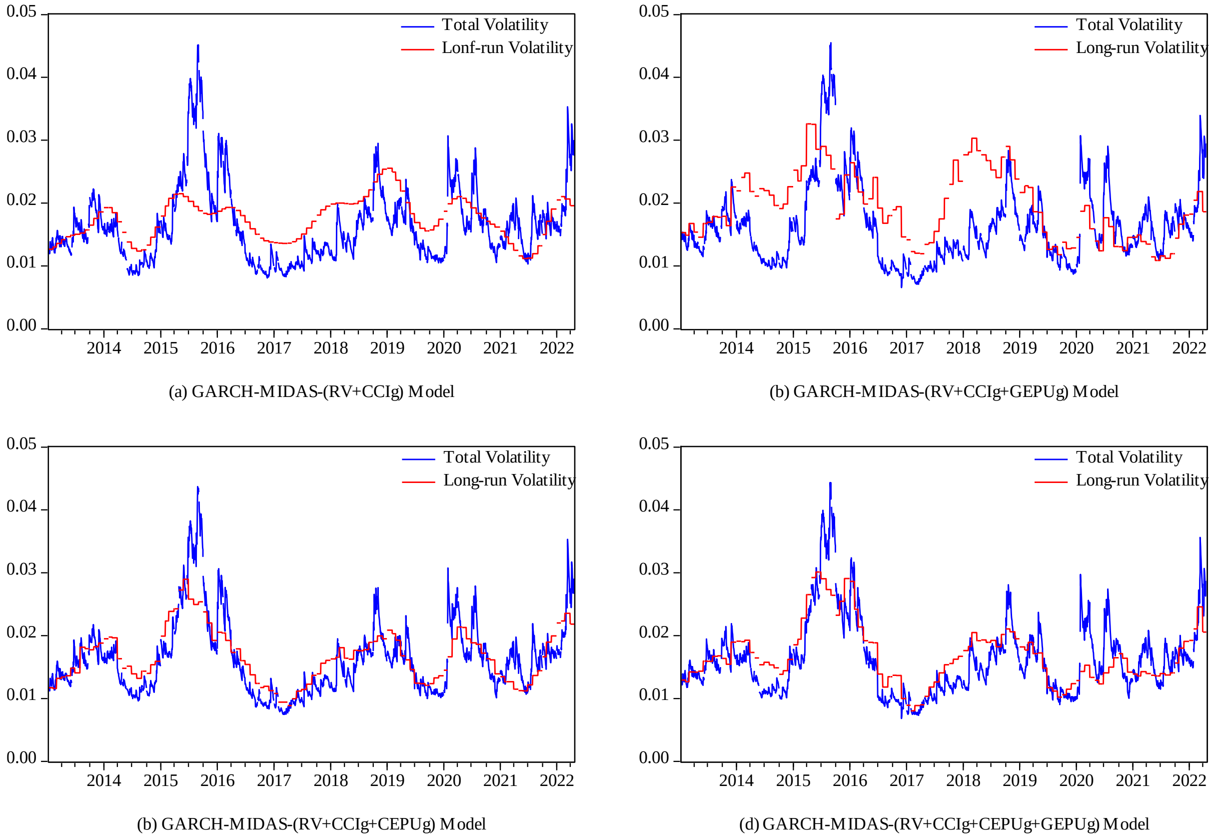
Note: This table reports the estimates of GARCH–MIDAS–X model coefficients. The period covers January 5, 2009–April 30, 2022. The numbers in parentheses represent the standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Notably, θ^{RV}, θ^{CCI}, θ^{GEPUg}, and θ^{CEPUg} are significant in all models. These exogenous variables are thus stable in our estimation. A significantly positive θ^{CCIg} conveys investors' optimism about the tourism sector's current economic conditions; investors generally believe they will benefit from their investments in this case. Their investments therefore increase, leading to higher prices and greater volatility in the tourism stock market. Meanwhile, the signs of θ^{GEPUg} and θ^{CEPUg} are significantly negative. A rise in CEPU or GEPU indicates lower long-term CTTI volatility. In the face of climbing domestic and GEPU, the government can launch economic policies that optimize the economic and financial structure. This course of action minimizes stock market volatility risk and contributes to the CTTI's lower long-run volatility. This outcome is logical from a financial theory perspective: policy-related uncertainty can spark negative changes in expected future cash flows due to higher discount rates and greater investment risks. Such circumstances produce lower equity returns. The resulting negative risk-return relationships trigger economic and political ambiguity while weakening consumer confidence. Consumers may then choose other safe-haven assets for investment, a tendency that can quickly permeate the market and reduce CTTI's volatility. Upon comparing the dynamics of the two EPU indices in Figure 1, it is clear that although China's stock market globalization is accelerating, CEPU and GEPU demonstrate distinct trends. Their effects on the volatility of China's tourism stock market are heterogeneous. The value of θ^{CEPUg} does not change significantly, whereas that of θ^{GEPUg} decreases significantly. Domestic economic policies thus primarily influence China's tourism stock market in the face of local and GEPU shocks. The Chinese stock market is also gradually assimilating into the global economy.

Lastly, the VR of the GARCH–MIDAS–(RV +CCIg + CEPUg) model is 54.97%, which is higher than 38.53% in the GARCH–MIDAS–(RV +CCIg + GEPUg) model. The GARCH–MIDAS–(RV +CCIg + CEPUg + GEPUg) model contributes 68.65% of the total log volatility. Adding CEPUg and GEPUg can therefore better explain CTTI's volatility. Overall, both domestic and global economic policies shape tourism companies' long-run volatility, and CEPU influences CTTI's long-run volatility more effectively.

5.2 Comparison of conditional (total) volatility and long-term components

The variance and long-run volatility of the GARCH–MIDAS–X model are plotted in Figure 4. The solid line indicates total volatility ($\tau_t \cdot g_{i,t}$), and the dashed line denotes long-run volatility (τ_t) determined by different models. As anticipated, the variance and long-run volatility correspond to global economic conditions. EPU indices exert a lagged effect on long-run volatility, which is common in financial markets. The volatility components also vary; this outcome exemplifies one advantage of a mixed model with uncertainty variables. The models' short- and long-run components demonstrate similar trends, although the long-run correlation is smoother.



(a) GARCH-MIDAS-(RV+CCIg) Model

(b) GARCH-MIDAS-(RV+CCIg+GEPUg) Model

(b) GARCH-MIDAS-(RV+CCIg+CEPUg) Model

(d) GARCH-MIDAS-(RV+CCIg+CEPUg+GEPUg) Model

Figure 4. Variance and long-run volatility of GARCH–MIDAS–X models.

Note: This figure shows the total volatility and long-run volatility of CTTI estimated by the GARCH–MIDAS–X model. The MIDAS equation may include RV; RV, and GEPUg; RV, and CEPUg; as well as RV, GEPUg and CEPUg. The sample period is from January 5, 2009, to April 30, 2022. The variance and long-run volatility are both at a daily frequency.

As depicted in Figure 4, long-run volatility rose sharply in 2015. This timing corresponded to a stock crisis in China, and CEPU and GEPU fluctuated greatly. Figures 4(b) and 4(c) indicate that the increased CEPUg and GEPUg adversely influence CTTI's long-run volatility and fluctuate in the same direction as total volatility. Total volatility reached its lowest point in 2016 during the stock market recession. Intensifying U.S.–China trade policy tensions also amplified long-run volatility. Moreover, with the outbreak of the COVID-19 pandemic in 2020, society and the economy underwent tremendous turbulence; their fluctuation reached a new peak in 2022 as COVID-19 spiralled out of control globally. Upon comparing (a) and other pictures in Figure 4, it is clear that after adding EPU, the long-run volatility data corresponding to (b), (c), and (d) are portrayed more accurately. This finding reinforces that CTTI returns are affected by both domestic and global economic policies.

Our empirical results also show that CEPU and GEPU each significantly influence the long-run volatility of China's tourism stock market. Policymakers should take CEPU and particularly GEPU into account when seeking to accurately forecast tourism stock market volatility to evaluate the risks associated with tourism investment and policymaking.

6. Robustness analysis

6.1 Shortening of CTTI sample period before COVID-19

In this section, we extend our analysis by evaluating the robustness of GARCH–MIDAS–X estimates in terms of our study horizon. For comparison and to facilitate an investigation of CTTI's volatility before and after the emergence of COVID-19, we shorten the sample from January 5, 2009, to December 31, 2019. Table 4 lists empirical results for the in-sample period. The November turning point is chosen because COVID-19 cases were initially detected in mainland China in December (Wu et al., 2021b).

The findings in Table 4 are fairly similar to those in Table 3, confirming the robustness of our results. Notably, though, θ^{CEPU} and θ^{GEPU} are observably negative on CTTI. CCI, GEPU, and CEPU thus still play a more critical role in long-run volatility when the sample is shortened. According to the values of VR, CCI, GEPU, and CEPU each account for a greater proportion of the long-run volatility of CTTI, suggesting that they are the main factors influencing this volatility before the COVID-19 pandemic. Infectious disease may influence the volatility of CTTI more during the pandemic. However, this conjecture calls for further testing. In brief, CTTI is more closely linked with CCI, GEPU, and CEPU before the pandemic than during it.

6.2 Asymmetric structure in GARCH–MIDAS–X model

This section presents robustness checks with respect to the GARCH–MIDAS–X model with asymmetric effects. Leverage effects are frequently found in equity returns (Chen, 2013; Dhaoui et al., 2018; Guo et al., 2018; He et al., 2019). The economic intuition is that negative shocks promote volatility more than positive shocks. To account for asymmetric effects, we modify the short-run component of the GARCH–MIDAS–X model with the GJR specification (Glosten et al., 1993) in Equation (13):

$$g_{i,t} = \left(1-\alpha-\beta-\frac{\gamma}{2}\right)+\left[\alpha+\gamma\cdot 1\left(r_{i-1,t}<0\right)\right]\frac{\left(r_{i-1,t}-\mu\right)^2}{\tau_t}+\beta g_{i-1,t} \tag{13}$$

where $1(\cdot)$ is an indicator function. A positive γ signifies the leverage effects, and the following conditions must be satisfied: $\alpha > 0$, $\alpha+\gamma > 0$, $\beta > 0$, and $\alpha+\beta+\gamma/2 > 0$.

Table 4. Parameter estimates of GARCH–MIDAS–X models before COVID-19 (2009/1/5–2019/12/31).

Parameters	GARCH–MIDAS–X Models			
	GARCH–MIDAS–(RV+CCIg)	GARCH–MIDAS–(RV+CCIg +GEPUg)	GARCH–MIDAS–(RV+CCIg +GEPUg)	GARCH–MIDAS–(RV+CCIg +CEPUg+GEPUg)
μ	0.0004 (0.0003)	0.0005* (0.0003)	0.0005* (0.0003)	0.0005 (0.0003)
α	0.0396*** (0.0135)	0.0337** (0.0160)	0.0255* (0.0131)	0.0233* (0.0121)
β	0.9502*** (0.0222)	0.9436*** (0.0033)	0.9300*** (0.0416)	0.9250*** (0.0326)
m	-8.4641*** (0.2896)	-8.0756*** (0.2177)	-8.1614*** (0.1399)	-8.2660*** (0.1334)
θ^{RV}	-30.7808 (36.6430)	-60.9513** (27.8126)	-77.7490*** (21.9515)	-58.4349*** (20.5298)
θ^{CCIg}	1.2926* (0.7654)	0.9553** (0.3981)	1.9390*** (0.3503)	2.7864*** (0.9573)
θ^{GEPU_g}		-0.4412*** (0.0538)		-0.2516*** (0.0898)
θ^{CEPU_g}			-0.1564*** (0.0328)	-0.1694** (0.0472)
$w_{1,RV}$	18.0072 (24.2539)	29.8937* (17.5098)	28.0442 (24.1738)	36.5262 (28.9823)
$w_{2,RV}$	5.1681 (3.3514)	77.5329* (41.6082)	59.9988 (52.2337)	56.3595 (56.3703)
$w_{1,CCIg}$	9.4547** (3.7978)	11.3135*** (3.5481)	7.5346*** (1.8447)	4.9926*** (1.7940)
$w_{2,CCIg}$	14.4491** (6.7710)	19.5329** (8.0637)	8.9855*** (2.1066)	4.9980** (2.2621)
$w_{1.GEPUg}$		3.4362*** (0.9038)		1.6020*** (0.4510)
$w_{2.GEPU_g}$		2.2165*** (0.3414)		3.6840 (2.3668)
$w_{1.CEPU_g}$			4.9750*** (1.9773)	6.4822*** (1.7578)
$w_{2.CEPU_g}$			2.7162*** (0.5981)	2.9453*** (0.5445)
VR[%]	41.1587	69.2060	82.8944	86.8754

Note: This table reports the estimates of GARCH–MIDAS–X model coefficients before the COVID-19 pandemic. The period covers January 5, 2009–April 30, 2022. The numbers in parentheses represent the standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Asymmetric GARCH–MIDAS–X model estimates (2009/1/5–2022/4/30).

Parameters	GARCH–MIDAS–X Models			
	GARCH–MIDAS–(RV+CCIg)	GARCH–MIDAS–(RV+CCIg+GEPUg)	GARCH–MIDAS–(RV+CCIg+CEPUg)	GARCH–MIDAS–(RV+CCIg+GEPUg+CEPUg)
μ	0.0004 (0.0003)	0.0005* (0.0003)	0.0003 (0.0003)	0.0003 (0.0003)
α	0.0580*** (0.0103)	0.0512*** (0.0100)	0.0346* (0.0186)	0.0429*** (0.0041)
β	0.9322*** (0.0174)	0.9437*** (0.0159)	0.8718*** (0.0724)	0.8024*** (0.0060)
γ	0.0024 (0.0173)	0.0010 (0.0154)	0.0625 (0.0647)	0.1279*** (0.0369)
m	-8.0298*** (0.2646)	-7.5887** (0.4542)	-8.1187*** (0.1445)	-8.0029*** (0.1449)
θ^{RV}	-48.2995** (27.3746)	-33.4962 (20.8939)	-40.9195* (22.6902)	-54.5533*** (19.8914)
θ^{CCIg}	1.0052* (0.5355)	1.3813* (0.7755)	1.5972*** (0.4135)	1.4720*** (0.0174)
θ^{GEPU_g}		-0.6606* (0.3597)		-0.2085** (0.0854)
θ^{CEPU_g}			-0.1274*** (0.00360)	-0.2140*** (0.0365)
$w_{1,RV}$	6.3076 (6.5234)	8.8727 (8.3379)	33.9515** (14.7207)	12.9198 (8.9094)
$w_{2,RV}$	85.2931 (81.2187)	12.3714 (11.7024)	17.7207** (8.7294)	36.4889 (28.2938)
$w_{1,CCIg}$	11.7697*** (4.3147)	11.6373** (4.9520)	9.7323*** (2.5988)	9.9214*** (2.8087)
$w_{2,CCIg}$	18.5379** (8.5184)	22.5849** (10.6455)	19.4779*** (5.3231)	18.9646*** (6.3412)
$w_{1.GEPUg}$		1.2094*** (0.2156)		3.1353** (1.2868)
$w_{2.GEPU_g}$		1.2345*** (0.2007)		7.5310 (5.5453)
$w_{1.CEPU_g}$			1.5864*** (0.2042)	1.8429*** (0.2208)
$w_{2.CEPU_g}$			2.8654*** (0.6027)	3.0650*** (0.3347)
VR[%]	43.5462	68.6826	74.6932	88.5937

Note: This table reports the estimates of asymmetric GARCH–MIDAS–X model coefficients. The period covers January 5, 2009–April 30, 2022. The numbers in parentheses represent the standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5 presents the results with the same sample as in Table 3. Findings are quite robust when considering the asymmetric structure in short-term volatility. The coefficients of RV, CCI, GEPU and CEPU are consistent with the result in Table 3. Leverage effects are present in CTTI, as the values of γ are positive when CEPU and GEPU are added separately. Bad news therefore generates higher volatility than good news.

7. Conclusion

This study addresses a growing but nevertheless limited topic in the economic literature on tourism concerning the impact of EPU on Chinese tourism stock market' volatility. To the best of our knowledge, this study is the first to investigate the impacts of CEPU and GEPU on the long-run volatility of CTTI in China using a multivariate GARCH–MIDAS–X model. Our findings respond to three questions: how does EPU affect Chinese tourism companies' performance? How does the impact vary between domestic EPU and global EPU on Chinese tourism companies' performance? How can the mixing problem be addressed (i.e., to make full use of data on high-frequency tourism stock market and low-frequency EPU)?

Our empirical results show that the model incorporating EPU with GARCH–MIDAS–(RV) outperforms the benchmark models. CEPU and GEPU each have significant negative effects on the long-run volatility of China's tourism stock market. The impact of GEPU on tourism companies' volatility is short-lived compared with CEPU. Furthermore, the long-run volatility of CTTI can be well captured upon adding the EPU index.

The above results reinforce the critical role of EPU in the volatility of China's tourism stock market. Our conclusions offer implications for market participants, policymakers, and the tourism industry. First, investors—especially institutional investors—can incorporate EPU indices into their volatility models to improve models' estimation and forecasting accuracy. The negative impacts of global and domestic (i.e., Chinese) economic policy uncertainty on the tourism stock market's long-run volatility imply that investors will frequently exit the economy and invest in "safe-haven" financial assets; increased economic policy uncertainty conventionally comes with higher investment risk and negative equity returns. When economic policies change, investors must manage risk more carefully and should adjust their portfolios to hedge against property losses.

Second, the CCI positively affects the long-run volatility of CTTI, indicating that consumers are optimistic about current economic conditions. Increased investments cause the price of the tourism stock market to rise and amplify the CTTI's long-run volatility. Investors can effectively seize opportunities by monitoring consumer confidence indicators and by using options and other financial derivative hedging tools to adjust the tourism stock market's position.

In addition, policymakers need to recognize the heterogeneous effects of EPU indices on the tourism stock market's long-run volatility. EPU can influence tourism firms' investment activities. Policymakers should provide investment incentives to promote local investors' stock market participation and maintain overall economic performance.

Finally, this study's findings can guide the tourism industry's sustainable development. The sustainability of a country's tourism industry depends heavily on a region's capacity to respond to economic policy conditions and to effectively address risks. EPU's potential to significantly influence and predict long-run tourism stock market volatility appears particularly pertinent for sustainable tourism.

Although this study has implications for practitioners and academics, several limitations remain to be addressed. First, we focused on the impacts of different EPUs on China's tourism stock market; other macroeconomic influencing factors and different countries' stock markets should be included in future research. Second, the pandemic's impacts on tourism companies' volatility deserve further exploration.

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