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THE NEXUS BETWEEN ECONOMIC POLICY UNCERTAINTY AND STOCK MARKET VOLATILITY IN THE CEE-3 COUNTRIES

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Abstract

A stock market plays a pivotal role in a financial system and is monitored as a yardstick of a healthy economy. It is a stylized fact that there is a positive and significant relationship between financial development and economic growth. However, emerging markets often exhibit more volatile returns than developed markets, and extreme volatility might prevent financial stability. The literature underlines the role of uncertainty in predicting volatility and suggests a strong positive association between economic policy uncertainty and stock market volatility. Against this backdrop, this study examines the dynamic nature of relationships between economic policy uncertainty (in Germany and the US) and long-run stock market volatility of CEE-3 (Central and Eastern European: the Czech Republic, Hungary, and Poland) countries. This study follows two steps in empirical analysis. First, it obtains long-run stock market volatility and then estimates dynamic regression models. The evidence shows a positive and significant one-period lagged impact of economic policy uncertainty on long-run stock market volatility.

Keywords: *Emerging stock markets, long-run volatility, uncertainty*

JEL Classification: *C22, C58, G10, G15*

1. Introduction

The stock market is an essential component of the financial system and plays a crucial role in directing funds from savers to investors (Harrison and Moore 2012). It is also one of the prominent barometers of the macroeconomy (Bai et al. 2021). Its volatility is often used to gauge financial and economic vulnerability and be a guide for policymakers (Botoc 2017). For this reason, modeling stock market volatility is a widely attractive issue in the literature. It has been of interest to scholars, financial analysts, global investors, and policymakers during the last decades because of its implications for financial risk management, hedging strategy, portfolio diversification, and market regulation.

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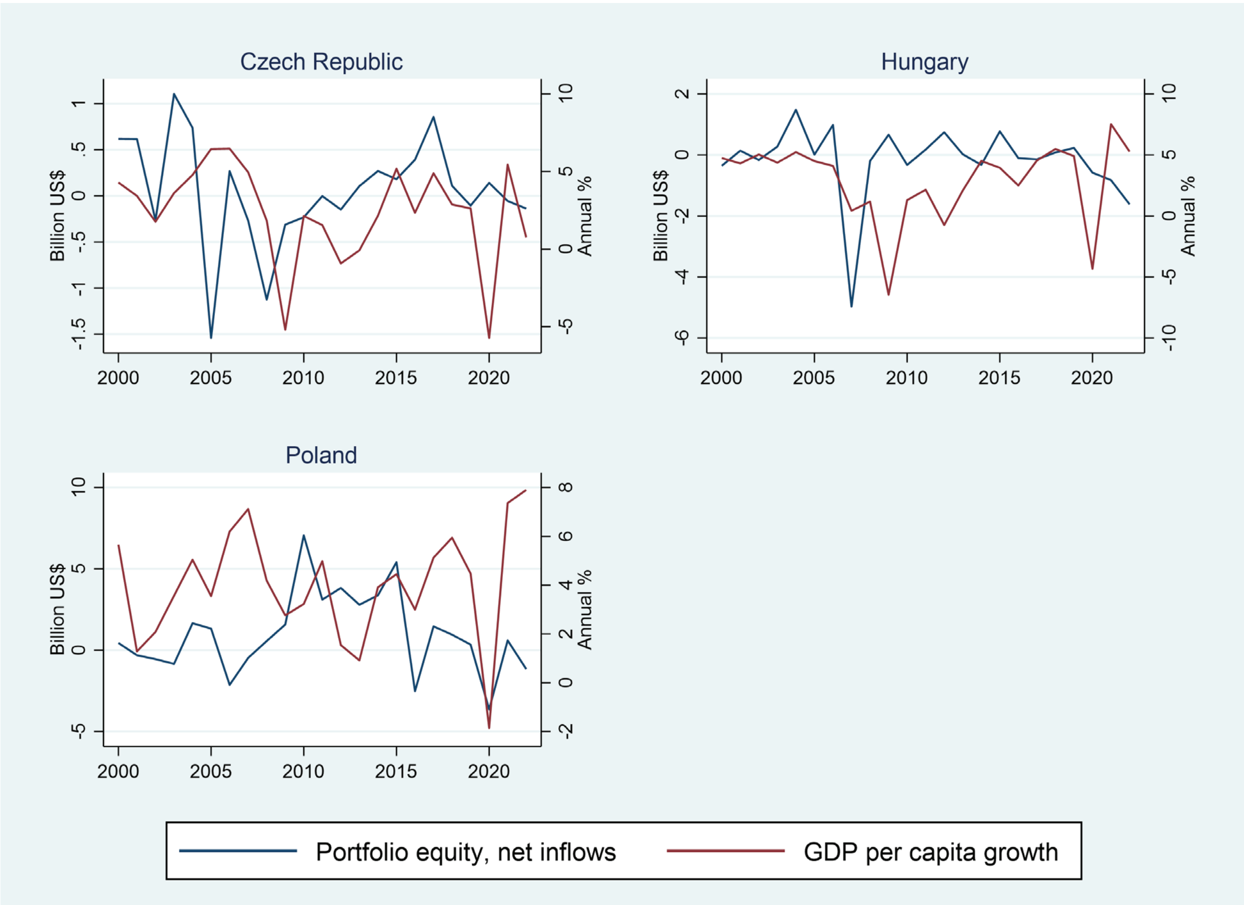
The literature emphasizes a positive and significant relationship between stock market development and economic growth (Lazarov, Miteva-Kacarski, and Nikoloski 2016, Setiawan et al. 2021) in the long run (Nyasha and Odhiambo 2017). Lee (2023) also suggests that financial development positively impacts firm-level growth in CEE-3 countries. Figure 1 provides time series graphs of portfolio equity net inflows and GDP per capita growth in CEE-3 countries from 2000 to 2022. A sharp decline in portfolio equity net inflows worsens economic growth in CEE-3 countries. It is a stylized fact because emerging economies are highly contingent on foreign capital inflows (Angelovska 2020).

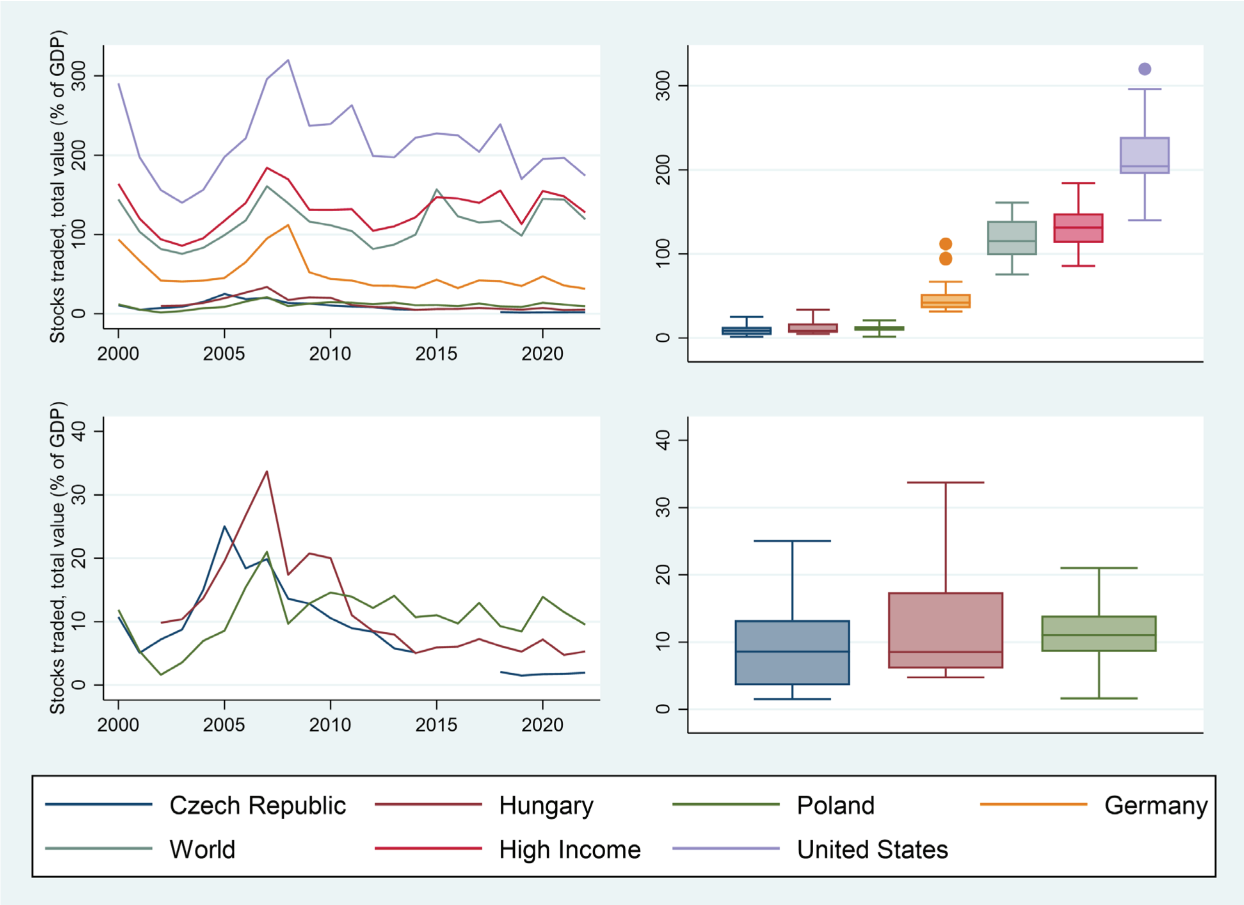
The market capitalization is also positively related to economic growth (Setiawan et al. 2021). The stock indices for CEE-3 countries are the foremost indicators of the real economy (Lyocsa, Baumöhl, and Vyrost 2011). Lyocsa (2014) provides empirical evidence on the unidirectional Granger causality from stock returns to the real economy in CEE-3 countries. Furthermore, stock market returns are positively linked to international portfolio inflows (Angelovska 2020). Figure 2 gives both time series graphs and box plots of total values of stock traded (% of GDP), and the lower panel is for CEE-3 countries. Although the degree of integration of CEE stock markets with European financial markets has continuously increased (Harkmann 2014, Chirila and Chirila 2022), Figure 2 shows that the market capitalization as a percentage of GDP in CEE-3 countries has regularly decreased since the global financial crisis. Besides, those ratios are highly lower than those of other markets, as shown in Figure 2. These findings mean that CEE-3 stock markets are undervalued compared to historical averages and other stock markets. Middleton, Fifield, and Power (2008) also emphasize the substantial benefits of investing in CEE stock markets.

Figure 1. Portfolio equity and GDP per capita growth



Data source: World Bank

Figure 2. Total values of stocks traded



Data source: World Bank

The real economy encounters significant fluctuations, and it affects the returns of assets. The typical theoretical explanations of the fluctuations are based on real shocks; however, the recent literature emphasizes the role of uncertainty in predicting stock market volatility (Liu and Zhang 2015, Bekiros, Gupta, and Kyei 2016, Balcilar et al. 2019, Yu and Huang 2021, Fameliti and Skintzi 2024). Numerous direct and indirect economic and financial factors also effectively drive stock market volatilities (Bai et al. 2021). Stock returns are highly associated with economic fundamentals (Chen and Chiang 2016), and worsening economic conditions lead to higher stock market volatility (Chen et al. 2016). Chiu et al. (2018) suggest a strong link between the long-run component of volatility and macroeconomic fundamentals, while the short-run component is more closely related to investors' sentiment than the real economy.

The literature underlines various forms of uncertainty as a source of stock market fluctuations (Fameliti and Skintzi 2024). The widely used uncertainty measures apart from economic policy uncertainty are financial uncertainty (Su, Fang, and Yin 2019, Jiang, Liu, and Lu 2024), news-based uncertainty (Su, Fang, and Yin 2019, Xu et al. 2021), uncertainty in government policy (Pastor and Veronesi 2012), implied volatility (Shu and Chang 2019, Fameliti and Skintzi 2024), news implied volatility (Fang et al. 2018), infectious disease equity market volatility (Bai et al. 2021, Coronado, Martinez, and Romero-Meza 2022, Fameliti and Skintzi 2024), Twitter-based uncertainty (Kropinski 2024). Many empirical studies show that economic policy uncertainty, proposed by Baker, Bloom, and Davis (2016), is a crucial factor for financial market volatilities (Bai et al. 2021). Baker, Bloom, and Davis (2016) developed new indices of economic policy uncertainty for twelve major economies, including the United States, and showed a strong positive association between the economic policy uncertainty index and implied stock market volatility. They also argued that the policy uncertainty is related to reduced investment and employment. A rise in economic policy uncertainty leads to deteriorated investment opportunities (Lee, Jeon, and Nam 2021) and decreased stock market returns (Sum 2013, Arouri et al. 2016, Christou et al. 2017, Peng, Huiming, and Wanhai 2018, Xu et al. 2021).

Economic policy uncertainty can potentially affect decisions taken by economic agents such as consumption, saving, and investment decisions, and then it might escalate risk in financial markets (Arouri et al. 2016, Liu et al. 2017, Ziwei, Youwei, and Feng 2020). It is more likely to decrease stock prices in response to a rise in economic policy uncertainty (Ko and Lee 2015, Luo and Zhang 2020). Stock prices probably respond to policy-generated uncertainty because the uncertainty affects macroeconomic fundamentals like consumption, investment, and production. Thus, it is expected that the higher the uncertainty, the more stock market volatility (Chang et al. 2015). There are various channels for propagating the effects of policy uncertainty throughout the economic and financial system. Chiang (2019) characterizes two distinct channels in disseminating the impact of economic policy uncertainty: the first one is through business operations, and the second one is related to market expectations. Pastor and Veronesi (2012) also emphasize the role of a rise in firms' expected profitability (pushes stock price up) and an increase in discount rates (pushes stock price down). They use a general equilibrium model to highlight the link between risk premia and volatility of stock returns when examining the impact of uncertainty in government policy on stock returns.

Emerging markets often display more volatile stock returns than developed markets (Boubaker and Raza 2016). Some studies suggest a negative relationship exists between a stock's return and its volatility (Albu, Lupu, and Calin 2015, Arouri et al. 2016, Yang and Jiang 2016). A certain amount of stock market volatility is reasonable due to the competition among investors, which causes a natural repeating characteristic of stock market prices. Extreme price volatility generally emerges in emerging stock markets due to their small size and illiquidity (Angelovska 2020). However, excessive stock market volatility is undesirable for investors and policymakers. It is likely to disrupt the functioning of stock markets, preclude establishing financial stability, and prevent firms from increasing risk capital. As investors switch their preferences away from riskier assets in response to very high volatility, this risk aversion will probably force them to dissuade their investment decisions and inevitably affect macroeconomic indicators (Harrison and Moore 2012).

Many empirical studies focus on the effects of economic policy uncertainty on stock market volatility in developed stock markets (Mei et al. 2018, Chiang 2019, Su, Fang, and Yin 2019, Chang 2022, Shin, Naka, and Wang 2024) and in emerging stock markets (Yu, Fang, and Sun 2018, Su, Fang, and Yin 2019, Li et al. 2020, Yu, Huang, and Xiao 2021, Ghani and Ghani 2024, Wang, Yin, and Li 2024, Zeng et al. 2024), and highlight the prediction power of the uncertainty indices (Liu and Zhang 2015, Yu and Huang 2021, Fameliti and Skintzi 2024). Most empirical findings suggest positive relationships between economic policy uncertainty and stock market volatility. The empirical evidence indicates that economic policy uncertainty contributes helpful information for forecasting stock market volatility. Balcilar et al. (2019) also point out the role of policy uncertainties in predicting emerging stock market volatility, providing mixed empirical evidence.

The literature pays relatively little attention to the stock markets of CEE-3 countries, although a considerable amount of literature has been published on the role of economic policy uncertainty on stock market volatility for developed and emerging countries. Recently, Kropinski (2024) examined the impact of Twitter-based uncertainty measures on the stock returns of CEE countries. The empirical studies put forward that there are long-run relationships between macroeconomic fundamentals and stock markets of CEE countries (Barbic and Condic-Jurkic 2011, Ligocka 2023). The CEE stock markets exhibit long memory in returns and conditional variances (Kasman, Kasman, and Torun 2009, Necula and Radu 2012). Botoc (2017) points out that bad news results in more volatility than good news in CEE stock markets. There is a considerable degree of integration of CEE stock markets with the stock markets of Germany and the US (Botoc and Anton 2020).

Macroeconomic variables are crucial determinants of long-run stock market volatility (Conrad and Loch 2015), and those variables are expected to impact long-run volatility rather than short-run volatility (Girardin and Joyeux 2013). Likewise, Wang, Yin, and Li (2024) find a positive and significant relationship between economic policy uncertainty and long-run stock market volatility. Harrison and Moore (2012) suggest that, on average, GARCH-type models are better than other popular models for forecasting the stock market volatility of CEE countries. Engle, Ghysels, and Sohn (2013) propose a model to distinguish long-run and short-run volatility, and it is called a GARCH-MIDAS approach. Furthermore, the GARCH-MIDAS approach provides a superior variance forecast than traditional GARCH models (Asgharian, Hou, and Javed 2013). Accordingly, it has recently become one of the most popular methodologies to investigate the role of uncertainty indices on long-run stock market volatility (Fang et al. 2018, Belcaid and El Ghini 2019, Su, Fang, and Yin 2019, Li et al. 2020, Yu and Huang 2021, Yu, Huang, and Xiao 2021, Ghani and Ghani 2024). Some studies also benefit the MIDAS framework (Wang, Yin, and Li 2024, Zeng et al. 2024).

Against this backdrop, this study examines the dynamic nature of the relationships between economic policy uncertainty and long-run stock market volatility of CEE-3 countries, namely the Czech Republic, Hungary, and Poland. Dajcman (2013) finds high correlations between CEE stock markets and stock markets of the US and Eurozone. Grabowski (2019) also shows that CEE-3 stock markets are the recipients of volatility and have received much volatility from Germany and the US. For this reason, this study uses economic policy uncertainty indices for Germany and the US, developed by Baker, Bloom, and Davis (2016). This study follows two steps in empirical analysis. First, it estimates the GARCH-MIDAS model for each CEE-3 stock market. This model lets us decompose daily stock market volatility into short- and long-run components. Second, this study conducts dynamic regression analysis to investigate the link between economic policy uncertainty (in Germany and the US) and long-run stock market volatility in CEE-3 countries. This study also includes two uncertainty indices as control variables in dynamic regression models. The first is the implied volatility of Eurozone stock markets, and the second is infectious disease equity market volatility, proposed by Baker et al. (2020). To our knowledge, the literature has not studied dynamic associations between economic policy uncertainty in developed economies and long-run stock market volatility in CEE-3 countries. This study fills this gap in the literature. It provides new empirical evidence on uncertainty and stock market volatility.

The second section introduces the data set and methodology, the third provides empirical results, and the last concludes.

2. Data and methodology

This study conducts the empirical analysis in two stages. First, it decomposes the conditional volatilities of stock market returns into short- and long-run components using the GARCH-MIDAS approach. Then, this study benefits from the ARDL method to investigate dynamic relationships between economic policy uncertainty and long-run stock market volatility. This section introduces the data set used in the first stage of the empirical analysis. It also presents the building blocks of the GARCH-MIDAS and ARDL methods.

2.1. Data Set

This study focuses on the stock markets of (Central and Eastern European) CEE-3 countries: the Czech Republic, Hungary, and Poland. It uses the following daily stock market indices: the PX index for the Czech Republic, the BET index for Hungary, and the WIG index for Poland. The empirical analysis is carried out from April 3rd, 2006 to October 16th, 2020. The daily stock market indices are obtained from the Datastream database.

Equation (1) provides a logarithmic difference formula to compute stock market returns:

$$r_{i,t} = 100 \times \left[ln(p_{i,t}) - ln(p_{i,t-1})\right] \quad (1)$$

where r_{it} is a log-return, and p_{it} is a value of the daily index of stock market i at time t.

Figure 3 provides time series plots of stock market returns in CEE-3 countries. As consistent with the stylized fact about time series of financial assets, it reveals the volatility clustering in those returns across the global financial crisis and the COVID-19 pandemic. The return of the WIX index fluctuates in a narrower band than those of the BET and PX indices during the global financial crisis, while it fluctuates in a broader band than other returns during the pandemic.

Table 1 gives the stock market returns' descriptive statistics and diagnostic tests. There are 2571 observations for each stock market to estimate long-run volatilities. The log-returns have negatively skewed and leptokurtic distributions. The CEE-3 stock markets are attractive for risk-seeking investors due to the leptokurtic distributions of the returns. This study conducts various diagnostic tests for the returns. First, the Jarque-Bera tests reject the null hypothesis of normally distributed returns. Then, the ARCH-LM tests reject the null hypothesis of no existing ARCH effect in all cases. Besides, the Ljung-Box Q squared tests reject the null hypothesis of no serial correlation for the squared log-returns at a 5% significance level, while the Ljung-Box Q tests cannot reject the null hypothesis of no serial correlation for the log-returns.

Before estimating the volatility model, this study examines time series specifications of the returns. To do this, it conducts the augmented Dickey-Fuller (ADF) unit root tests with an intercept and with a trend and an intercept, respectively (Dickey and Fuller 1981). Besides, the Phillips-Perron (PP) unit root tests have been conducted with an intercept and with a trend and an intercept, respectively (Phillips and Perron 1988). The latter unit root test considers problems regarding serial correlations. Eight lags are used for the Newey-West standard errors (Newey and West 1987) while carrying out the PP unit root tests. The number of lags is computed in line with the Newey-West recommendation: $m = 4(T/100)^{\frac{2}{9}}$ where T is the sample size (Wooldridge 2013). Table A.1 presents the results of unit root tests for the returns. Those tests reject the null hypothesis of a unit root in all cases. Overall, these findings indicate that the stock market returns of CEE-3 countries are stationary for the period analyzed.

Figure 3. Stock market returns

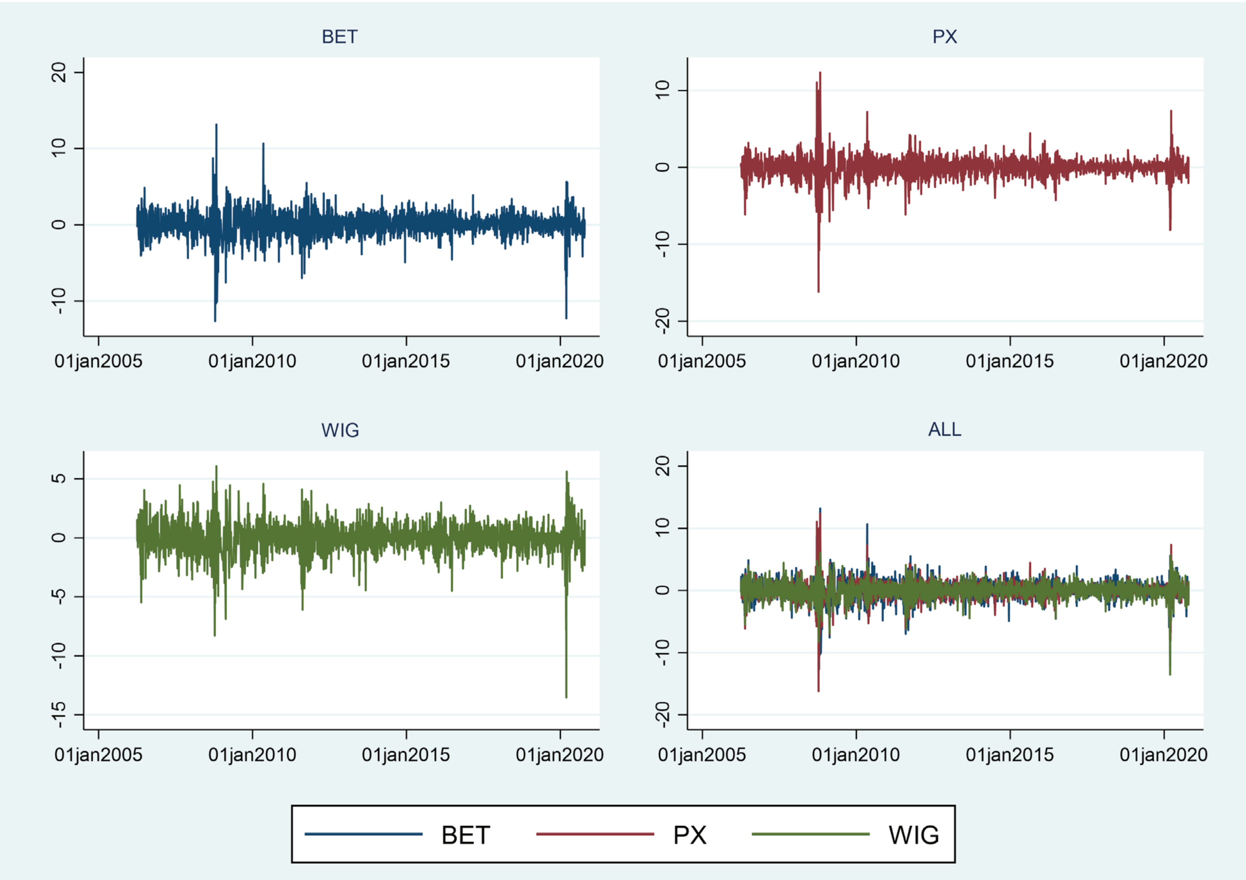


Table 1. Descriptive statistics and diagnostic tests

	BET	PX	WIG
Mean	0.0283	-0.0103	0.0044
Median	0.0643	0.0257	0.0274
Maximum	13.177	12.364	6.0837
Minimum	-12.648	-16.185	-13.526
Std. Dev.	1.5006	1.3392	1.2204
Skewness	-0.5192	-0.5838	-0.9906
Kurtosis	13.738	24.072	12.753
Jarque-Bera	12468.71 [0.000]	47715.88 [0.000]	10612.35 [0.000]
ARCH 1-2	169.50 [0.000]	362.83 [0.000]	74.341 [0.000]
ARCH 1-5	163.82 [0.000]	202.14 [0.000]	103.43 [0.000]
ARCH 1-10	88.497 [0.000]	173.81 [0.000]	54.751 [0.000]
Q(20)	16.976 [0.524]	17.113 [0.515]	11.231 [0.884]
$Q^2(20)$	30.601 [0.031]	43.633 [0.000]	58.426 [0.000]
Observations	2571	2571	2571

Note: The significance levels of tests are given in square brackets. ARCH 1-2, ARCH 1-5, and ARCH 1-10 test the null hypothesis of no existing ARCH effect up to order two, five, and ten in the residuals, respectively. Q(20) and $Q^2(20)$ are the Ljung-Box serial correlation test statistics for returns with 20 lags and squared returns with 20 lags, respectively.

2.2. The GARCH-MIDAS Approach

In the first part of the empirical analysis, this study uses a generalized autoregressive conditional heteroscedasticity (GARCH)-mixed data sampling (MIDAS) model proposed by Engle, Ghysels, and Sohn (2013) to estimate the long-run volatility of CEE-3 stock markets. This approach provides a better variance forecast than standard GARCH models (Asgharian, Hou, and Javed 2013). As mentioned earlier, the literature has extensively used the MIDAS framework due to its superiority in predicting stock market volatility. The GARCH-MIDAS model enables us to decompose stock market volatility into two components: the first is related to short-run (daily) fluctuations, and the second is long-run (monthly) fluctuations, called a secular component.

Equation (2) shows the process of a univariate GARCH-MIDAS model:

$$r_{i,t} - E_{i-1,t}(r_{i,t}) = \sqrt{\tau_t \cdot g_{i,t}}\xi_{i,t} \quad \forall i = 1, \dots, N_t \tag{2}$$

where $\xi_{i,t} | \Phi_{i-1,t} \sim N(0,1)$, and $\Phi_{i-1,t}$ is information set up to the day $(i-1)$ of period t. $r_{i,t}$ is a log-return for ith day of any arbitrary period t (month, quarter, biannual). This study uses t as a month. In this case, $r_{i,t}$ denotes a log return for ith day of month t, and N_t represents the number of trading days in a given month. Thus, the model estimates at least two components of stock market volatility. First, $g_{i,t}$ is a short-term component and accounts for daily fluctuations in stock market returns. Second, τ_t indicates a slowly moving secular component and explains monthly fluctuations in returns. $E_{i-1,t}(\bullet)$ is a conditional expectation given information set up to $(i-1)$th day of period t. It is supposed $E_{i-1,t}(r_{i,t}) = \mu$. Then, one can rewrite Equation (2) as in Equation (3):

$$r_{i,t} = \mu + \sqrt{\tau_t \cdot g_{i,t}}\xi_{i,t} \tag{3}$$

Equation (4) provides a short-run component of stock market volatility ($g_{i,t}$), and the short-run component is assumed to follow a GARCH (1,1) process:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{4}$$

with the restrictions that $\alpha > 0, \beta \geq 0$, and $\alpha + \beta < 1$.

A long-run component of stock market volatility (τ_t) is also modeled by using a MIDAS regression. It rules out a restriction that the secular component (τ_t) is fixed over period t, and then allows τ_t to vary by daily frequency throughout the period t.

Equation (5) gives the secular component of the volatility:

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) RV_{i-k}^{(rw)} \quad (5)$$

where $m^{(rw)}$ and $\theta^{(rw)}$ denotes an intercept and a slope for the rolling window MIDAS filter, respectively. Those parameters have to satisfy the following stationarity conditions: $0 < m^{(rw)}$, and $0 < \theta^{(rw)} < 1$ (Yang, Cai, and Hamori 2018). $RV_i^{(rw)}$ is the rolling-window realized volatility, and it equals to $\sum_{c=1}^{N'} r_{i-c}^2$. $\phi_k(\omega_1, \omega_2)$ represents the MIDAS weighing scheme.

Equation (6) and Equation (7) provide the beta lag polynomial and exponential weighting, respectively. Those equations describe the MIDAS weighting scheme:

$$\phi_k(\omega) = \frac{(k/K)^{\omega_1 - 1}(1-k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(j/K)^{\omega_1 - 1}(1-j/K)^{\omega_2 - 1}} \quad (6)$$

$$\phi_k(\omega) = \frac{\omega^k}{\sum_{j=1}^{K} \omega^j} \quad (7)$$

The beta lag polynomial is quite flexible in including various lag structures. It can represent either a monotonically increasing/decreasing or a hump-shaped (unimodal) weighting scheme. Ghysels, Sinko, and Valkanov (2007) provide further details regarding various patterns obtained with the beta lags. Equations from (2) to (7) construct a GARCH-MIDAS model for time-varying conditional variance with the rolling-window realized volatility. The parameter space of the model is as follows: $\Theta = \{\mu, \alpha, \beta, m^{(rw)}, \theta^{(rw)}, \omega_1, \omega_2\}$. It is fixed both for different time spans t (month, quarter, or semester) and for different numbers of lags (K) in the MIDAS weighing scheme (Engle, Ghysels, and Sohn 2013). The GARCH-MIDAS approach uses the quasi-maximum likelihood method to estimate those parameters, and this estimation method provides consistent and asymptotically normal estimations (Wang and Ghysels 2015).

2.3. The ARDL Model

Most of the time, the effects of economic policies do not take place instantaneously; however, those effects are generally distributed over time. Thus, it is crucial to model the dynamic nature of economic relationships with an appropriate approach. One can model dynamic relationships in three different ways: (i) distributed lag model, (ii) autoregressive distributed lag model, and (iii) modeling serially correlated errors (Hill, Griffiths, and Lim 2011). Financial time series will likely correlate with their past values over time. It is also very likely that periods of high (low) volatility of stock market returns will tend to follow periods of high (low) volatility. Accordingly, Yang and Jiang (2016) show that the fluctuations of stock returns are much affected by their previous values. In addition, there is strong evidence of the presence of long memory in conditional variance in CEE stock markets (Kasman, Kasman, and Torun 2009). Thus, this study utilizes an autoregressive distributed lag (ARDL) approach to explore dynamic relations among uncertainty measures and long-run stock market volatility. The distinctive feature of the ARDL method is that it employs lagged values of the regressand as explanatory variables in a regression model. Like distributed lag models, an ARDL model also contains lagged values of regressors. It captures the dynamic effects of lagged variables and can eliminate autocorrelation problems in errors (Hill, Griffiths, and Lim 2011).

Equation (8) provides a general specification of an $ARDL\ (p, q)$model used in the empirical analysis:

$$log\eta_t = \alpha + \Sigma_{i=1}^{p} \varphi_i log\eta_{t-i} + \Sigma_{k=1}^{m} \Sigma_{j=0}^{q} \delta_{kj} X_{kt-j} + \gamma t + \epsilon_t \quad (8)$$

where $log\eta_t$ is the natural logarithm of long-run volatilities, α is a constant term, p is the maximum number of lags of the regressand, m is the number of regressors included in the model, q is the maximum number of lags of regressors, and ϵ_t is the error term. φ_i, δ_{kj}, and γ are the coefficients associated with autoregressive terms, lags of the m regressors, and a linear trend, respectively. This study includes a trend term into a regression model to consider time-specific effects on long-run stock market volatility.

3. Empirical results

Many economic and financial factors effectively drive stock market volatilities through direct and indirect channels (Bai et al. 2021). The literature emphasizes the role of macroeconomic variables on stock market volatility, especially on long-run components (Barbic and Condic-Jurkic 2011, Asgharian, Hou, and Javed 2013, Engle, Ghysels, and Sohn 2013, Girardin and Joyeux 2013, Conrad and Loch 2015, Chiu et al. 2018, Tastan and Gungor 2019). Likewise, Ligocka (2023) finds that macroeconomic variables influence CEE stock markets in the long run rather than the short run. The short-run stock market volatility is more closely related to investors' sentiment than the real economy (Chiu et al. 2018). The literature also highlights uncertainty measures in driving stock market volatilities. (Liu et al. 2017, Li et al. 2020, Zeng et al. 2024, Kropinski 2024).

The uncertainty measures, financial, economic, or policy-generated, can inevitably affect the behaviors of investors, macro-financial fundamentals, and stock markets. Ghani and Ghani (2024) suggest that economic policy uncertainty in the US is a powerful predictor of emerging stock market volatility. Accordingly, it is essential to examine the effectiveness of the uncertainty mechanism (Skrinjaric and Orlovic 2020). The empirical evidence points out a significant link between uncertainty and stock market volatility; thus, this relation should not be overlooked. However, the literature pays relatively little attention to the role of uncertainty on volatility in CEE-3 stock markets, although a considerable amount of literature has been published for developed and emerging countries.

This study carries out empirical analysis in two stages. First, it estimates the GARCH-MIDAS model for each stock market to decompose the conditional volatilities of CEE-3 stock market returns into short- and long-run components. Then, it benefits from an ARDL approach to examine the dynamic relationships between economic policy uncertainty and long-run stock market volatility.

This section provides the estimation results of the long-run volatility of CEE-3 stock market returns and introduces the data set used in the second stage of the empirical analysis. Finally, it gives the parameter estimates of ARDL models for each stock market.

3.1. The long-run stock market volatility

This study estimates the GARCH-MIDAS models for log-returns of CEE-3 stock markets from April 3rd, 2006 to October 16th, 2020 to obtain the long-run stock market volatility. It prefers to estimate those models with rolling-window realized volatility, as in Girardin and Joyeux (2013) and Tastan and Gungor (2019), rather than with fixed-window realized volatility, as in Engle, Ghysels, and Sohn (2013), because the rolling window approach efficiently overcomes the problem of structural changes (Feng, Zhang, and Wang 2024).

The number of lags of the MIDAS weights is determined by the model based on the Bayesian information criterion. Thirty-two MIDAS lags are used to estimate the GARCH-MIDAS models. Those models consider twenty-two daily observations ($N=22$) for the number of trading days for each month. As a result, the models utilize 704 initial observations, (22 x 32 = 704), and thus exploit roughly three years of daily observations to estimate the MIDAS weighting scheme. That is why the monthly data set begins from 2009 instead of 2006.

Table 2 provides the parameter estimates of the GARCH-MIDAS models for each stock market. Almost all parameters are statistically significant at a 1% level, while the others are also statistically significant at

Table 2. GARCH-MIDAS parameter estimates

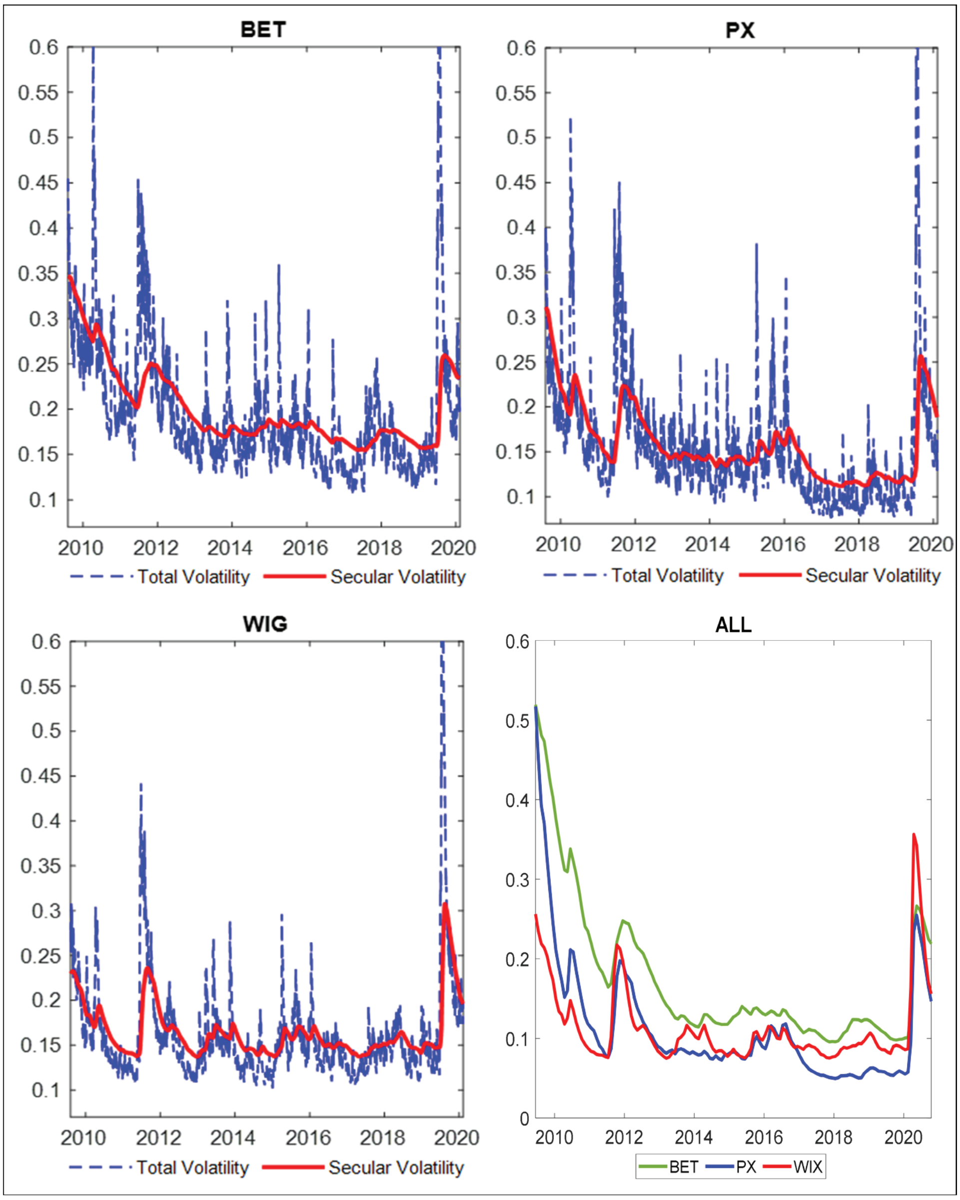
	BET	PX	WIG
μ	0.000547*** (0.0002)	0.000254* (0.0001)	0.000301* (0.0001)
α	0.10452*** (0.0093)	0.13646*** (0.0110)	0.07788*** (0.0074)
β	0.83737*** (0.0166)	0.78881*** (0.0195)	0.85982*** (0.0217)
m	0.00767*** (0.0007)	0.00592*** (0.0005)	0.00744*** (0.0005)
θ	0.15870*** (0.0109)	0.15976*** (0.0112)	0.14347*** (0.0121)
ω	4.2082*** (1.1175)	8.6790*** (2.2712)	12.280** (5.2118)
LLF	8749.08	9383.16	9318.15
BIC	-17449.2	-18717.1	-18587.1

Note: The numbers in the parentheses are standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. LLF indicates the optimal log-likelihood function value. BIC is the Bayesian information criterion.

conventional levels. Optimal weights monotonically decrease over the lags (Girardin and Joyeux 2013). Table 2 presents only the estimation of ω_2 because the optimal ω_1 is equal to one. Thus, ω in Table 2 corresponds to ω_2 in Equation (5). The estimated GARCH-MIDAS models satisfy the stationarity conditions, $\alpha+\beta<1$, $0<\theta<1$, and $m>0$. Besides, the weighting function is rapidly declining because the weighting parameter ω is higher than one for each model.

Figure 4 gives time series plots of the conditional volatilities of CEE-3 stock markets and their secular components derived from the GARCH-MIDAS models. The dashed (blue) line denotes the total volatility, and the thick (red) line represents slowly moving secular components. The short-run volatility of CEE-3 stock markets mostly exhibit similar patterns to each other, while the short-run volatility of the WIG index fluctuates within the narrower band during the tranquil period. Those volatilities spiked to their highest levels in response to the COVID-19 pandemic. The lower right panel of Figure 4 provides jointly the long-run volatility of CEE-3 stock markets. Those volatilities plummeted after the European sovereign debt crisis and increased dramatically at the onset of the pandemic. The long-run volatility of the BET index is higher than those of other indices except at the time of the pandemic, while the volatility of the WIG index is above those of others during the pandemic.

Figure 4. Volatility decomposition



3.2. The stock market volatility and economic policy uncertainty

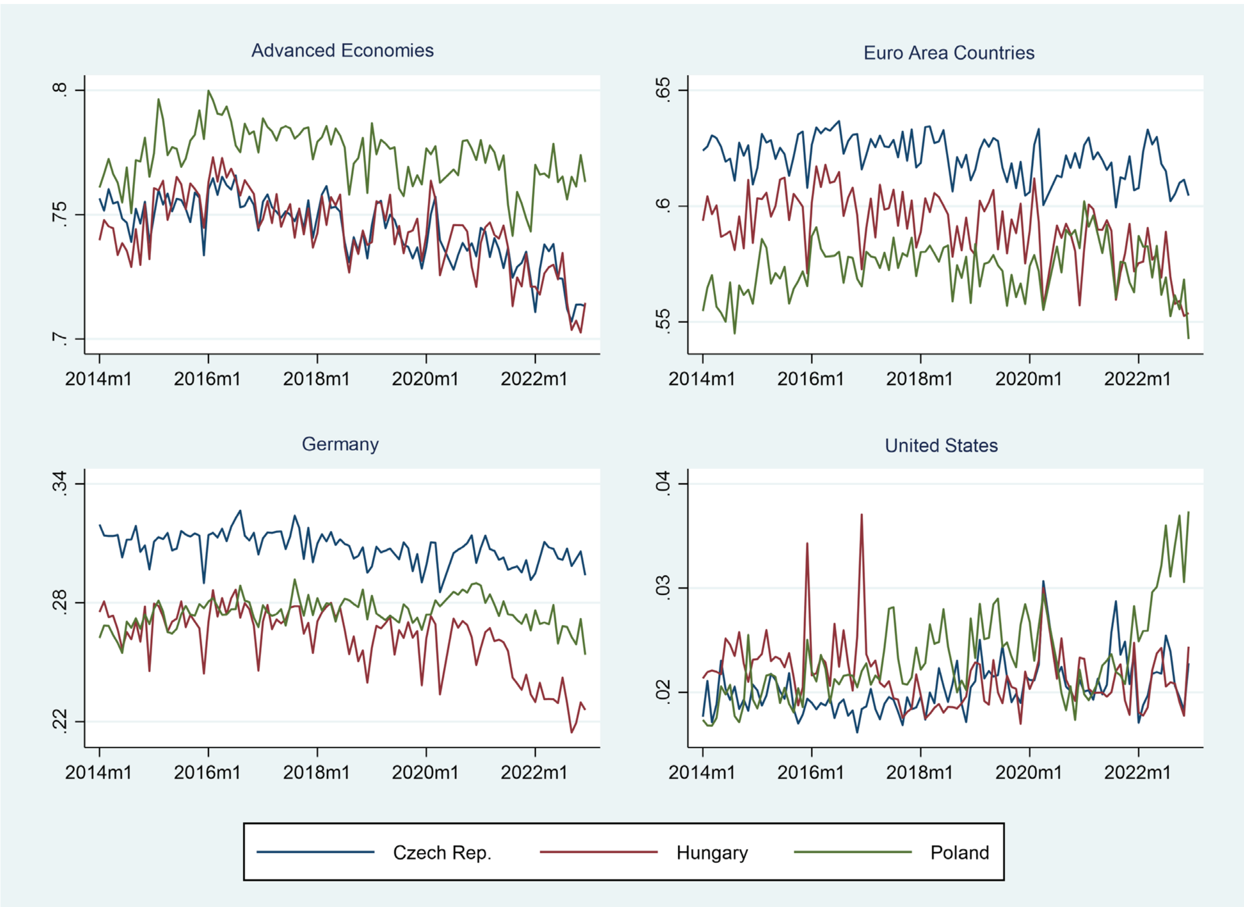
This study focuses on dynamic relationships between economic policy uncertainty and long-run stock market volatility in CEE-3 countries. It is essential to determine which countries' economic policies can potentially affect the stock markets of CEE-3 countries. For this purpose, this study benefits from the trade shares of the countries in the total trade of CEE-3 countries because those shares can be used to specify how important a particular country is for the CEE-3 economies in terms of international linkages.

Figure 5 provides time series plots of the trade shares of selected regions and countries in the total trade of CEE-3 countries. The trade share denotes the percentage of the total trade (exports plus imports) of one country or region with another country or region in the total trade of the latter country or region with the world. Those shares are calculated using a monthly data set for exports and imports obtained from the International Monetary Fund Direction of Trade Statistics (DOTS) from January 2014 to December 2022 (the data for May and June 2020 is missing).

The upper right panel of Figure 5 puts forward that the trade shares of the Euro area countries are, on average, about 60 percent of the total trade of CEE-3 countries. Among those countries, Germany has the lion's share of the total trade of CEE-3 countries, and its share is, on average, nearly 30 percent of the total trade of CEE-3 countries. It is shown that the CEE-3 countries are economically embedded in European countries, especially in Germany. Besides, Arendas, Chovancova, and Pavelka (2020) suggest that the German stock market is Granger-causing the development of CEE-3 stock markets. The volatility spillover from the developed European stock markets like Germany to CEE stock markets is significant. (Chirila and Chirila 2022).

On the other hand, the US is the major contributor and the critical transmitter of risk spillover (Bai et

Figure 5. Trade shares



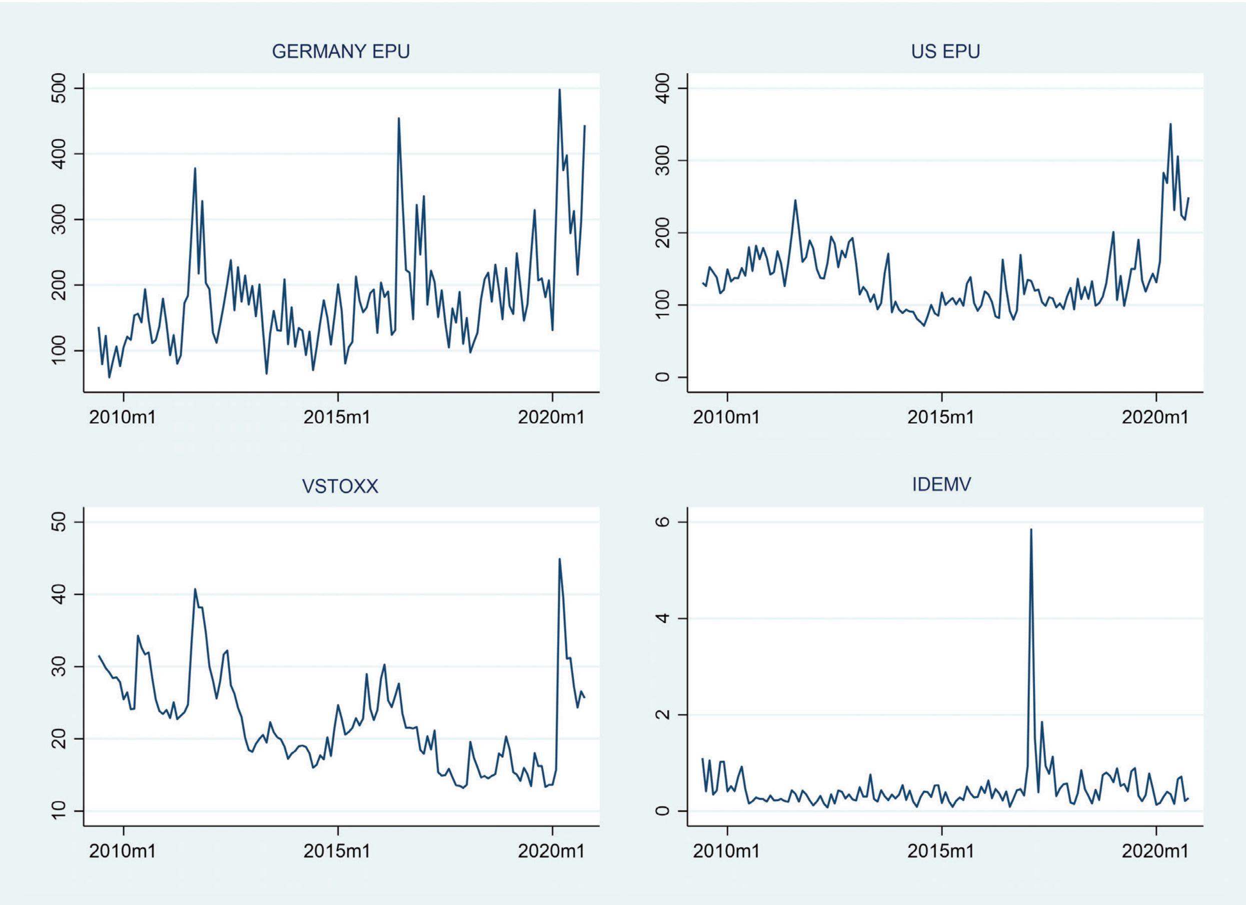
Data source: The International Monetary Fund Direction of Trade Statistics al. 2019) due to its dominant position in the global financial system (Shi and Wang 2023). Furthermore, there exists substantial evidence of co-movement between the US and CEE stock markets (Boubaker and Raza 2016), although the trade share of the United States (US) is, on average, below three percent of the total trade of CEE-3 countries, as shown in the lower right panel of Figure 5. The influence of Germany on the CEE stock market is more potent than that of the US due to its strong trade linkages (Botoc and Anton 2020) and its leading role in European countries. As a result, this study opts to use economic policy uncertainty in Germany and the US to examine dynamic relations between economic policy uncertainty and long-run stock market volatility in CEE-3 countries.

The literature highlights various forms of uncertainty as a source of stock market fluctuations (Fameliti and Skintzi 2024). Many empirical studies show that economic policy uncertainty, proposed by Baker, Bloom, and Davis (2016), is a crucial factor for financial market volatilities (Bai et al. 2021). For this reason, this study uses economic policy uncertainty indices developed by Baker, Bloom, and Davis (2016) to measure economic policy uncertainty in Germany and the US.

Bai et al. (2021) examine the impact of infectious disease equity market volatility on long-run stock market volatilities due to the unprecedented equity market response to the COVID-19 pandemic (Baker et al. 2020). Likewise, the infectious disease volatility index Granger-causes the stock market volatility of Latin American countries (Coronado, Martinez, and Romero-Meza 2022). The literature also uses implied volatility as an uncertainty measure (Shu and Chang 2019, Fameliti and Skintzi 2024). The VSTOXX volatility index significantly affects the returns of international stock markets (Shu and Chang 2019). It is based on the Euro Stoxx 50 index, which includes 50 blue-chip companies operating in 11 countries over the Eurozone.

As a result, this study uses two control variables in dynamic regression analysis along with economic policy uncertainty in Germany and the US. The first one is infectious disease equity market volatility

Figure 6. Time series plots of the indices



(IDEMV) based on the study of Baker et al. (2020), and it quantifies uncertainty in equity markets caused by infectious diseases like COVID-19. The second one is the VSTOXX volatility index as a proxy for uncertainty in the Eurozone. Figure 6 gives time series plots of the monthly economic policy uncertainty indices for Germany and the US, the VSTOXX volatility index, and the infectious disease equity market volatility.

This study estimates ARDL models for each stock market in the second stage to investigate dynamic relationships between economic policy uncertainty and long-run stock market volatility. Table 3 provides the descriptive statistics for the variables used to estimate ARDL models. As stated earlier, in the first stage, the long-run stock market volatility (LRV) is estimated by the GARCH-MIDAS model for each stock market. This study receives the data on economic policy uncertainty indices and the IDEMV index from the following website: https://www.policyuncertainty.com. Besides, the implied volatility of Eurozone stock markets (VSTOXX) is obtained from the Datastream database. The dataset covers 137 monthly observations from June 2009 to October 2020. Those monthly variables have positively skewed and leptokurtic distributions. Harrison and Moore (2011) suggest that the nonlinearity in CEE stock markets should be considered to avoid misleading inferences. Accordingly, the natural logarithm of all variables except IDEMV is used in regression models.

Before embarking on a dynamic regression analysis, this study investigates time series specifications of the variables. For this purpose, it conducts the ADF and the PP unit root tests with an intercept and with a trend and an intercept. The PP unit root tests are conducted by using four lags for the Newey-West standard errors. The number of lags is computed in accordance with the Newey-West suggestion. Table A.2 gives the results of unit root tests for the variables. According to the results of the unit root tests with an intercept, the null hypothesis of a unit root is rejected in all cases. Besides, the unit root tests with a trend and an intercept reject the null hypothesis of a unit root for all variables except the LRVs. Thus, those unit root tests are also carried out on the first differences of long-run stock market volatility. The latter tests reject the null hypothesis of non-stationarity for the first differences of the LRVs. It is possible to get a stationary variable by extracting the effects of the deterministic components from a trend stationary variable (Hill, Griffiths, and Lim 2011).

Equation (8) specifies the ARDL model used in the second stage of the empirical analysis. One can directly include a constant term and a trend term in a regression model rather than utilizing the de-trended data for estimation (Hill, Griffiths, and Lim 2011); therefore, this study includes those terms in dynamic regression equations. The dependent variables are the log values of long-run volatility in CEE-3 stock markets. The optimal lag orders p (for the regressand) and q (for the regressors) are determined by using the Bayesian information criterion (BIC) because the BIC tends to choose parsimonious models (Kripfganz and Schneider 2023). The maximum admissible lag lengths for the dependent and independent variables are also restricted to four to ensure sufficient degrees of freedom for estimating the models.

This study estimates four distinct ARDL models for each stock market. It uses the Newey-West estimator to obtain heteroskedasticity and autocorrelation consistent (HAC) standard errors. The least squares

Table 3. Descriptive statistics for the variables

	GER EPU	US EPU	VSTOXX	IDEMV	LRVBET	LRVPX	LRVWIG
Mean	179.78	137.89	22.504	0.465	0.1745	0.1132	0.1138
Median	165.86	130.22	21.545	0.349	0.1315	0.0851	0.0950
Maximum	498.05	350.45	44.890	5.8495	0.5194	0.5168	0.3564
Minimum	59.587	71.26	13.211	0.0747	0.0955	0.0496	0.0749
Std. Dev.	79.06	46.87	6.478	0.543	0.0929	0.0781	0.0509
Skewness	1.528	1.612	0.808	7.427	1.855	2.557	2.482
Kurtosis	5.904	6.661	3.489	72.361	6.113	10.934	9.732
Observations	137	137	137	137	137	137	137

will be biased if there is a serial correlation problem in the errors (Hill, Griffiths, and Lim 2011). For this reason, this study conducts the Breusch-Godfrey test for higher-order serial correlation in residuals for all estimated models. This autocorrelation test is a Lagrange multiplier (LM) test of the null hypothesis of no autocorrelation up to a predefined order. The null hypothesis of no serial correlation up to orders one and twenty cannot be rejected at a 5% significance level in any estimated ARDL model.

Table 4, Table 5, and Table 6 provide the parameter estimates of the ARDL models for the stock market

Table 4. Parameter estimates for the Hungary stock market

$L\eta_t$	Model 1	Model 2	Model 3	Model 4
$L\eta_{t-1}$	1.66712***	1.40985***	1.39299***	1.54139***
	(0.1671)	(0.0984)	(0.0987)	(0.0893)
$L\eta_{t-2}$	-1.04120***	-0.44484***	-0.43415***	-0.85780***
	(0.2990)	(0.0934)	(0.0938)	(0.1393)
$L\eta_{t-3}$	0.50520**			0.40200***
	(0.2419)			(0.1191)
$L\eta_{t-4}$	-0.17515*			-0.13877**
	(0.0917)			(0.0565)
$LGEREPU_t$	0.02780*	0.00078	-0.00477	0.00426
	(0.0157)	(0.0094)	(0.0101)	(0.0109)
$LGEREPU_{t-1}$	0.04451*		0.02053*	
	(0.0260)		(0.0115)	
$LGEREPU_{t-2}$	-0.04293*			
	(0.0228)			
$LUSEPU_t$				-0.03269*
				(0.0177)
$LUSEPU_{t-1}$				0.05459***
				(0.0191)
$LVSTOXX_t$		0.15529***	0.15904***	0.17772***
		(0.0403)	(0.0371)	(0.0415)
$LVSTOXX_{t-1}$		0.13463**	0.13438**	0.09259*
		(0.0638)	(0.0635)	(0.0488)
$LVSTOXX_{t-2}$		-0.24595***	-0.25121***	-0.25383***
		(0.0803)	(0.0780)	(0.0892)
$LVSTOXX_{t-3}$				0.08450*
				(0.0477)
$LVSTOXX_{t-4}$				-0.05986**
				(0.0265)
$IDEMV_t$			-0.00811**	-0.00804**
			(0.0037)	(0.0033)
$IDEMV_{t-1}$			0.00339	0.00487**
			(0.0026)	(0.0023)
$IDEMV_{t-3}$			0.01776**	0.01700**
			(0.0068)	(0.0066)
Constant	-0.22091*	-0.21403***	-0.29400***	-0.35666***
	(0.1200)	(0.0768)	(0.0819)	(0.1158)
Trend	-0.00021	-0.00017	0.000004	-0.00005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Adjusted R^2	0.98207	0.99206	0.99161	0.99208
LM test prob[a]	0.5608	0.2175	0.0792	0.6868
LM test prob[b]	0.7940	0.2021	0.1560	0.3148
BIC	-2.84139	-3.57746	-3.45791	-3.37521
LLF	210.959	261.099	264.184	270.910

Note: The numbers in the parentheses are Newey-West HAC standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. [a] and [b] indicate p-values for the Breusch-Godfrey serial correlation LM test for one lag and twelve lags, respectively. BIC is the Bayesian information criterion. LLF indicates the optimal log-likelihood function value.

of Hungary (the BET index), the stock market of the Czech Republic (the PX index), and the stock market of Poland (the WIG index), respectively. The empirical results are pretty similar for the stock markets of CEE-3 countries; therefore, it is preferred to holistically interpret the findings rather than individual stock markets to avoid monotonic interpretation. According to all estimated models, positive and statistically significant relationships exist between the long-run stock market volatility of CEE-3 countries and their first lags.

Table 5. Parameter estimates for the Czech Republic stock market

$L\eta_t$	Model 1	Model 2	Model 3	Model 4
$L\eta_{t-1}$	1.64933***	1.47246***	1.45911***	1.48032***
	(0.1528)	(0.0978)	(0.1002)	(0.0936)
$L\eta_{t-2}$	-1.12365***	-0.93578***	-0.92207***	-0.97550***
	(0.2740)	(0.1590)	(0.1648)	(0.1512)
$L\eta_{t-3}$	0.57356***	0.50878***	0.49823***	0.56371***
	(0.1945)	(0.1192)	(0.1208)	(0.1178)
$L\eta_{t-4}$	-0.18587***	-0.13550***	-0.12193**	-0.15599***
	(0.0632)	(0.0462)	(0.0471)	(0.0467)
$LGEREPU_t$	0.05162**	0.00074	-0.00554	0.01598
	(0.0258)	(0.0143)	(0.0151)	(0.0176)
$LGEREPU_{t-1}$	0.09112**	0.04329**	0.05620***	0.02969*
	(0.0381)	(0.0181)	(0.0168)	(0.0156)
$LGEREPU_{t-2}$	-0.06084*			
	(0.0347)			
$LUSEPU_t$				-0.08399***
				(0.0309)
$LUSEPU_{t-1}$				0.09402***
				(0.0274)
$LVSTOXX_t$		0.28429***	0.29523***	0.32345***
		(0.0498)	(0.0424)	(0.0488)
$LVSTOXX_{t-1}$		0.17900**	0.17842**	0.15422**
		(0.0720)	(0.0790)	(0.0706)
$LVSTOXX_{t-2}$		-0.36978***	-0.37740***	-0.38727***
		(0.1265)	(0.1221)	(0.1126)
$LVSTOXX_{t-3}$		0.16097*	0.16143**	0.17097**
		(0.0833)	(0.0796)	(0.0734)
$LVSTOXX_{t-4}$		-0.15403***	-0.15706***	-0.16830***
		(0.0463)	(0.0450)	(0.0440)
$IDEMV_t$			-0.01809***	-0.01496***
			(0.0057)	(0.0055)
$IDEMV_{t-2}$			-0.01935***	-0.01888***
			(0.0056)	(0.0063)
$IDEMV_{t-3}$			0.02136***	0.02157***
			(0.0073)	(0.0069)
Constant	-0.57948***	-0.73830***	-0.76422***	-0.76548***
	(0.2067)	(0.1548)	(0.1556)	(0.1693)
Trend	-0.00070**	-0.00017	-0.00014	-0.00015
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Adjusted R^2	0.96365	0.98473	0.98560	0.98670
LM test prob[a]	0.3299	0.2216	0.2719	0.4530
LM test prob[b]	0.6363	0.1279	0.1846	0.1234
BIC	-1.79409	-2.54710	-2.46497	-2.48813
LLF	141.314	201.170	207.933	214.364

Note: The numbers in the parentheses are Newey-West HAC standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. a and b indicate p-values for the Breusch-Godfrey serial correlation LM test for one lag and twelve lags, respectively. BIC is the Bayesian information criterion. LLF indicates the optimal log-likelihood function value.

This finding is consistent with the study of Yang and Jiang (2016) and indicates the appropriateness of using the autoregressive model. In contrast, the parameter estimates are negative and statistically significant for the second lags of the long-run stock market volatility. This finding confirms the evidence from Zeng et al. (2024), which indicates the time-varying effects of policy uncertainty on stock market volatility.

The evidence on the immediate effects of economic policy uncertainties on long-run stock market volatilities is mixed. The parameter estimates of the first lag of the US economic policy uncertainty are positive and statistically significant. It means that a rise in economic policy uncertainty in the US leads to an increase in the long-run stock market volatility of CEE-3 countries after one period. Similarly, the

Table 6. Parameter estimates for the Poland stock market

$L\eta_t$	Model 1	Model 2	Model 3	Model 4
$L\eta_{t-1}$	1.32979***	1.17970***	1.14106***	1.15198***
	(0.1728)	(0.0781)	(0.0769)	(0.0727)
$L\eta_{t-2}$	-0.63914***	-0.30144***	-0.28547***	-0.32219***
	(0.2203)	(0.0643)	(0.0674)	(0.0586)
$L\eta_{t-3}$	0.16898*			
	(0.0944)			
$LGEREPU_t$	0.01012**	0.00264	0.00272	0.00501
	(0.0051)	(0.0029)	(0.0030)	(0.0033)
$LGEREPU_{t-1}$	0.01691	0.00561**	0.00739**	
	(0.0106)	(0.0028)	(0.0031)	
$LGEREPU_{t-2}$	-0.00733**		-0.00648**	
	(0.0032)		(0.0029)	
$LUSEPU_t$				-0.00897
				(0.0057)
$LUSEPU_{t-1}$				0.01768***
				(0.0063)
$LVSTOXX_t$		0.04047***	0.04189***	0.04309***
		(0.0068)	(0.0064)	(0.0064)
$LVSTOXX_{t-1}$		0.05871**	0.06116**	0.06142**
		(0.0297)	(0.0286)	(0.0287)
$LVSTOXX_{t-2}$		-0.09473***	-0.09300***	-0.09564***
		(0.0317)	(0.0302)	(0.0296)
$IDEMV_t$			-0.00055	-0.00017
			(0.0009)	(0.0009)
$IDEMV_{t-1}$			-0.00117	-0.00150
			(0.0012)	(0.0011)
$IDEMV_{t-3}$			0.00704***	0.00701***
			(0.0024)	(0.0024)
Constant	-0.03766	-0.04069*	-0.05306**	-0.07912***
	(0.0343)	(0.0212)	(0.02127)	(0.0268)
Trend	-0.00002	-0.00002	0.00001	0.00002
	(0.00005)	(0.00004)	(0.00004)	(0.00004)
Adjusted R^2	0.86842	0.94449	0.94642	0.94863
LM test prob[a]	0.8427	0.6357	0.7145	0.7302
LM test prob[b]	0.4342	0.1839	0.2331	0.1122
BIC	-5.00489	-5.83993	-5.73055	-5.80088
LLF	357.368	416.269	420.204	422.436

Note: The numbers in the parentheses are Newey-West HAC standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. a and b indicate p-values for the Breusch-Godfrey serial correlation LM test for one lag and twelve lags, respectively. BIC is the Bayesian information criterion. LLF indicates the optimal log-likelihood function value.

empirical results show a positive one-period lagged effect of economic policy uncertainty in Germany on the long-run stock market volatility of CEE-3 countries. Overall, these results suggest that changes in economic policy uncertainty either in Germany or the US have a distributed lag effect on the long-run stock market volatility of CEE-3 countries. This result is consistent with the study of Chiang (2019), which found a positive effect of lagged uncertainty on stock market volatility, and with the findings of Yu and Song (2018), which showed a significant effect of uncertainty on one-ahead-step volatility.

The one-period lagged impact of economic policy uncertainty in the US on the long-run stock market volatility of CEE-3 countries is larger than the effect of economic policy uncertainty in Germany. This result suggests that the long-run stock market volatility of CEE-3 countries is more vulnerable to economic developments in the US, although those countries are economically embedded in the economic processes of European countries. This evidence confirms the findings of Bai et al. (2019), Shi and Wang (2023).

Turning to the empirical evidence on the control variables, the estimates indicate that the effects of the VSTOXX volatility are dynamically more complex. Its immediate and one-period lagged effects are positive and statistically significant. It can be said that an increase in the European stock market volatility positively affects the long-run stock volatility of CEE-3 countries, both in the current and one period later. Finally, the relationships between the infectious disease equity market volatility and the long-run stock market volatility of CEE-3 countries differ by stock markets and time lags. The estimates of the impact multipliers are negative for all stock markets; however, those estimates are statistically significant except for the Poland stock market. This evidence suggests that a rise in the infectious disease equity market volatility leads to a decline in the long-run volatility of CEE-3 stock markets at the current period.

4. Conclusion

This study examines dynamic associations between economic policy uncertainty in developed countries (Germany and the US) and long-run stock market volatility in CEE-3 countries. For this purpose, this study carries out empirical analysis in two stages. First, it obtains long-run stock market volatilities. Then, it estimates dynamic regression models. Empirical evidence suggests a distributed lag effect of economic policy uncertainty on long-run stock market volatility. The findings show that economic policy uncertainty has a positive and significant one-period lagged impact on long-run stock market volatility. On the other hand, this study provides mixed empirical evidence of economic policy uncertainties' immediate effects on long-run stock market volatilities.

This study includes two uncertainty measures as control variables in dynamic regression models. The implied volatility of Eurozone stock markets has positive and significant effects on long-run stock market volatility in CEE-3 countries. Further, the immediate impact of infectious disease equity market volatility is negative. The empirical results are limited to CEE-3 stock markets; however, covering other emerging stock markets in Europe would be interesting. Further research might use firm- or sectoral-level data instead of aggregate stock market indices. The findings will benefit global investors, hedgers, portfolio managers, regulators, and policymakers seeking to comprehend how the uncertainty measures affect the CEE-3 stock market volatility over time.

APPENDICES

Table A 1. Unit root tests for stock market returns

	Intercept in test equation				
	ADF Test		*PP Test*		
Stock market index	Z(t)	p-value	*Z(rho)*	*Z(t)*	p-value
BET	-50.441	0.000	-2587.601	-50.448	0.000
PX	-47.974	0.000	-2314.113	-47.902	0.000
WIG	-48.052	0.000	2523.863	-48.168	0.000
	Trend and intercept in test equation				
	ADF Test		*PP Test*		
Stock market index	*Z(t)*	p-value	*Z(rho)*	*Z(t)*	p-value
BET	-50.441	0.000	-2586.483	-50.447	0.000
PX	-47.971	0.000	-2313.328	-47.899	0.000
WIG	-48.051	0.000	-2523.379	-48.165	0.000

Table A 2. Unit root tests for the variables

	Intercept in test equation				
	ADF Test		PP Test		
Variables	Z(t)	p-value	*Z(rho)*	*Z(t)*	p-value
GER EPU	-5.521	0.000	-51.907	-5.460	0.000
IDEMV	-8.605	0.000	-103.272	-8.753	0.000
US EPU	-3.932	0.001	-24.127	-3.519	0.007
VSTOXX	-3.174	0.021	-17.294	-3.099	0.026
LRVBET	-2.942	0.040	-7.342	-2.731	0.068
LRVPX	-3.278	0.015	-12.110	-3.254	0.017
LRVWIG	-2.880	0.047	-19.096	-3.387	0.011
	Trend and intercept in test equation				
	ADF Test		*PP Test*		
Variables	*Z(t)*	p-value	*Z(rho)*	*Z(t)*	p-value
GER EPU	-6.624	0.000	-72.192	-6.728	0.000
IDEMV	-8.683	0.000	-103.776	-8.809	0.000
US EPU	-3.901	0.012	-23.888	-3.475	0.042
VSTOXX	-3.389	0.052	-23.147	-3.399	0.051
LRVBET	-0.860	0.960	-5.218	-1.472	0.838
ΔLRVBET	-6.241	0.000	-57.892	-6.094	0.000
LRVPX	-2.132	0.528	-11.998	-2.616	0.272
ΔLRVPX	-6.198	0.000	-55.036	-5.953	0.000
LRVWIG	-2.643	0.260	-18.021	-3.190	0.086
ΔLRVWIG	-6.341	0.000	-56.149	-6.078	0.000

Note: This table provides the results of unit root tests for the natural logarithm of the variables except IDEMV. Δ denotes the first difference of a time series.

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