

Article

Economic Policy Uncertainty, Equity Repricing, and Currency Volatility in G20 Economies: Heterogeneous Evidence from Second-Generation Panel and Quantile Methods

Batuhan Karabiber 

Department of International Trade and Finance (English), Faculty of Economics and Administrative Sciences,
Istanbul Aydın University, Istanbul 34295, Türkiye; batuhankarabiber@aydin.edu.tr

Abstract

This study examines the effects of economic policy uncertainty (EPU) on three dimensions of financial market dynamics—*stock market returns*, *stock market volatility*, and *exchange rate volatility*—across 15 G20 economies over the period 2006 Q1–2024 Q4. Employing a rigorous second-generation panel econometric framework that accounts for cross-sectional dependence and slope heterogeneity, we apply the Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) estimators as primary estimators, complemented by cross-sectionally augmented ARDL (CS-ARDL) for short- and long-run dynamics and the Method of Moments Quantile Regression (MMQR) for distributional analysis. EPU is significantly associated with lower stock market returns, particularly in advanced economies and at lower quantiles of the return distribution. The impact of EPU on stock market volatility is not strong for mean-based estimators even when global uncertainty (VIX) is controlled for, and global fear dominates domestic policy uncertainty as a driver of volatility. Exchange rate volatility is positively and significantly associated with EPU, particularly in higher-volatility regimes. Subgroup analysis shows that EPU–return effects are stronger in advanced economies, but EPU–exchange rate volatility responses are stronger in emerging markets. These results have important implications for portfolio allocation, hedging strategies and macroprudential policy decisions in G20 economies.

Keywords: economic policy uncertainty; G20; stock market returns; stock market volatility; exchange rate volatility; panel data; CCEMG; AMG; CS-ARDL; quantile regression

1. Introduction

Economic policy uncertainty (EPU) has been one of the most well-studied phenomena in macro-finance in recent years, following the global financial crisis of 2008–2009, the crisis of European sovereign debt and COVID-19. It has been shown by [Baker et al. \(2016\)](#) in their seminal news-based EPU that high levels of policy uncertainty can lead to less investment, job loss and financial market volatility. The theoretical foundations were established by [Bloom \(2009\)](#), who showed that such uncertainty shocks generate short, sharp recessions through a real options channel that induces firms to pause investment and hiring decisions.

Financial markets are particularly affected by policy uncertainty as they price in questions about fiscal, monetary, and regulatory policy uncertainty into asset prices. Political uncertainty raises equity risk premia and lowers stock prices because an unknown state of affairs through a government learning process is the way in which the market is influenced by uncertainty in the market ([Pástor & Veronesi, 2012, 2013](#)). EPU is an economically



Academic Editor: Thanasis Stengos

Received: 10 June 2026

Revised: 1 July 2026

Accepted: 2 July 2026

Published: 10 July 2026

Copyright: © 2026 by the author.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](#) license.

significant priced risk factor that Brogaard and Detzel (2015) show portfolios with high EPU beta are underperforming by more than 5% per annum. At the portfolio level, higher uncertainty leads risk-averse investors to shift away from stocks and causes stock prices to fall and lead to higher volatility (Antonakakis et al., 2013; Liu & Zhang, 2015).

The relationship between EPU and exchange rate dynamics is equally important but less well understood in a broad cross-country panel context. Higher uncertainty reduces capital inflows and weakens domestic currencies, and increases exchange rate volatility through capital flight and reduced investor confidence (Beckmann & Czudaj, 2017; Kido, 2016; Bartsch, 2019). For emerging market economies, which are more susceptible to sudden stops and currency crises, the EPU–exchange rate volatility nexus has important implications for monetary policy credibility and external sector stability.

To address these gaps, this study develops an ex ante three-channel transmission framework linking EPU to financial market outcomes. The framework is specified before the empirical analysis and is evaluated against the data rather than being introduced as a post-estimation interpretation. It brings together insights from asset pricing, global financial integration, and open-economy macro-finance to explain why EPU may affect stock market returns, stock market volatility, and exchange rate volatility differently across market outcomes and country groups.

The first mechanism is the equity repricing channel. Policy uncertainty increases ambiguity about future fiscal, monetary, and regulatory conditions. In asset pricing terms, this raises required risk premia and discount rates, reduces investors' willingness to hold risky assets, and is therefore expected to be associated with lower stock market returns. This channel builds on the political uncertainty and equity risk premium arguments of Pástor and Veronesi (2012, 2013), as well as evidence that EPU is a priced source of risk in equity markets (Brogaard & Detzel, 2015). Unlike studies that examine EPU and equity returns in a single-country setting or through first-generation panel models, this study tests whether the repricing effect remains visible in a heterogeneous G20 panel after accounting for cross-sectional dependence and common global shocks.

The second mechanism is the global volatility dominance channel. Although domestic EPU may be expected to increase stock market volatility, globally integrated equity markets are also exposed to common risk factors, global investor sentiment, and international uncertainty spillovers. In such a setting, the VIX may absorb a substantial part of the volatility response that would otherwise be attributed to country-specific EPU. Therefore, this channel does not simply predict a positive EPU–stock volatility relationship. Instead, it hypothesizes that the effect of domestic EPU on stock market volatility should weaken once global uncertainty is explicitly controlled for. This channel contrasts with the conventional EPU–volatility view by asking whether domestic policy uncertainty retains explanatory power after the global fear factor is included.

The third mechanism is the currency market asymmetry channel. The exchange rate response to EPU is expected to differ between advanced and emerging economies because these country groups occupy different positions in the international monetary and financial system. In advanced economies with deeper financial markets and reserve or quasi-reserve currencies, higher uncertainty may coincide with safe haven inflows and lower relative currency turbulence. In emerging economies, however, policy uncertainty may increase external financing risk, reduce investor confidence, trigger capital outflows, and intensify exchange rate volatility. This channel therefore predicts heterogeneous and potentially opposite EPU–FX volatility responses across country groups. It extends the standard EPU–exchange rate literature by explicitly allowing the sign and magnitude of the relationship to vary between advanced and emerging economies.

These three channels generate the following testable hypotheses:

H1. *Equity repricing channel: Higher EPU is expected to be associated with lower stock market returns.*

H1a. *The negative association between EPU and stock market returns is expected to be stronger in lower-return quantiles, where market stress and risk aversion are higher.*

H2. *Global volatility dominance channel: The association between domestic EPU and stock market volatility is expected to weaken once global uncertainty, proxied by the VIX, is included.*

H2a. *The VIX is expected to exert a stronger and more robust association with stock market volatility than country-specific EPU.*

H3. *Currency market asymmetry channel: Higher EPU is expected to be associated with higher exchange rate volatility in the full sample, but the sign and strength of this association are expected to differ between advanced and emerging economies.*

H3a. *In emerging economies, EPU is expected to be positively associated with exchange rate volatility through capital outflow and external vulnerability mechanisms.*

H3b. *In advanced economies, EPU may be weakly or negatively associated with exchange rate volatility if safe haven flows dominate domestic uncertainty effects.*

Despite substantial progress, several important gaps remain. Firstly, most existing panel studies rely on first-generation estimators that fail to account for cross-sectional dependence (CD), leading to inconsistent coefficient estimates (Pesaran, 2007). Secondly, the literature has largely examined EPU effects on individual financial market outcomes in isolation, without providing a unified framework covering stock market returns, stock market volatility, and exchange rate volatility simultaneously. Thirdly, heterogeneity between advanced and emerging economies remains inadequately explored in panel settings. Fourthly, the distributional nature of EPU effects across different market regimes has received limited attention.

This study addresses these gaps through four empirical contributions built around the above theoretical framework. Firstly, we construct a balanced quarterly panel of 15 G20 economies over 2006 Q1–2024 Q4 and examine EPU effects on three financial market outcomes within a unified setting: stock market returns, stock market volatility, and exchange rate volatility. Secondly, we employ a comprehensive second-generation econometric strategy including Pesaran's (2015) CD tests, Pesaran's (2007) CADF unit root tests, Westerlund (2007) and Pedroni (1999, 2004) cointegration tests, and the CCEMG, AMG, and CS-ARDL estimators. Thirdly, we apply the Method of Moments Quantile Regression approach of Machado and Santos Silva (2019) to examine whether EPU effects differ across conditional distributions. Fourthly, we conduct subgroup analyses for advanced and emerging economies to evaluate whether the currency market asymmetry channel differs across country groups.

Our main findings, interpreted through the three-channel framework, are as follows. Through the equity repricing channel, EPU is significantly associated with lower stock market returns, particularly in advanced economies and at lower-return quantiles, consistent with elevated discount rate sensitivity under policy uncertainty. Through the global volatility dominance channel, country-specific EPU is not robustly associated with stock market volatility once global VIX is controlled for, suggesting that financially integrated G20 markets are more closely linked to global risk sentiment than to domestic policy uncertainty alone. Through the currency market asymmetry channel, EPU is positively associated with exchange rate volatility, with the association becoming stronger at higher-volatility

quantiles and differing between advanced and emerging economies. The subgroup results are consistent with a safe haven interpretation in advanced economies and capital flow pressure in emerging economies. The CCE-ECM results further show that adjustment coefficients are negative and statistically significant across all three equations, while the long-run lnEPU slope is most evident for exchange rate volatility.

2. Literature Review

2.1. EPU and Stock Market Returns

The theoretical basis for the EPU–stock market return relationship was established by [Pástor and Veronesi \(2012, 2013\)](#). They construct a general equilibrium model in which political uncertainty leads to higher equity risk premia through a government learning process. Their model predicts that stock market correlations rise during periods of high policy uncertainty, which is indeed similar to the phenomenon (e.g., elections and major fiscal policy debates) we observe in the U.S. [Brogaard and Detzel \(2015\)](#) further develop this model and show that EPU is a priced risk factor in the cross-section of U.S. equity returns.

Early empirical evidence for the negative EPU–return nexus was provided by [Antonakakis et al. \(2013\)](#), who document time-varying negative correlations between U.S. EPU and S&P 500 returns using dynamic conditional correlation methodology. [Arouri et al. \(2016\)](#) extend this analysis over a century of U.S. data (1900–2014), confirming that EPU significantly reduces stock returns, particularly during extreme-volatility periods. In a cross-country panel context, [Christou et al. \(2017\)](#) apply a Bayesian panel VAR to six Pacific Rim economies and find that both domestic and U.S. EPU negatively affect stock market returns.

More recent work has shifted toward heterogeneous panel methods. [Kundu and Paul \(2022\)](#) examine G7 and EM7 countries using regime-switching VAR and find that EPU negatively affects returns contemporaneously but may generate positive uncertainty premia over longer horizons. [Zhao and Park \(2024\)](#) employ panel VAR on 20 economies and find that foreign EPU shocks generate larger return declines than domestic EPU, underscoring the importance of international spillovers.

2.2. EPU and Stock Market Volatility

[Liu and Zhang \(2015\)](#) provide seminal evidence that EPU significantly increases realized stock market volatility at high frequencies, and that incorporating EPU into standard HAR-type volatility models significantly improves out-of-sample forecasting. [Baker et al. \(2016\)](#) documented that EPU is associated with greater stock price volatility at both firm and market levels. [Antonakakis et al. \(2013\)](#) find a positive correlation between EPU and implied volatility (VIX), suggesting that uncertainty shocks propagate globally through financial integration.

An important observation from recent panel studies is that cross-sectional dependence—induced by common global shocks such as the 2008 GFC and COVID-19—severely distorts inference in first-generation panel models. The failure to account for common factors leads to overestimation of country-specific EPU effects when global uncertainty (proxied by VIX) is excluded. [Kundu and Paul \(2022\)](#) confirm that EPU increases contemporaneous volatility, though the long-run evidence is more mixed when global factors are controlled for. Recent evidence from emerging stock markets further supports the relevance of EPU for volatility dynamics ([Ghani & Ghani, 2024](#)).

2.3. EPU and Exchange Rate Volatility

The theoretical link between EPU and exchange rate dynamics is through several channels. Increasing uncertainty increases the option value of waiting, which reduces capital

inflows and puts depreciation pressure on domestic currencies (Bloom, 2009). Uncertainty about monetary policy reduces the credibility of exchange rate arrangements and amplifies volatility (Beckmann & Czudaj, 2017). EPU can also trigger portfolio rebalancing from risky domestic assets to safe haven currencies, creating systematic patterns in bilateral volatility.

Kido (2016) provides early empirical evidence that U.S. EPU is negatively correlated with high-yield currencies, documenting the safe haven flight mechanism. Bartsch (2019) uses GARCH models to show that EPU significantly increases dollar–pound exchange rate return volatility. At the panel level, Murad (2022) applies CCEMG and quantile regression across 12 economies, finding significant long-run EPU effects with asymmetric responses. Wang et al. (2023) document that exchange rate volatility spillovers from EPU are primarily concentrated in developing economies. Gong et al. (2025) use EPU spillover measures across 23 economies and establish positive and significant effects on real effective exchange rate volatility.

2.4. Recent Extensions: Alternative Uncertainty Measures, Spillovers, and Nonlinear Financial Market Responses

Recent studies have expanded the economic policy uncertainty literature in three important directions: the use of alternative uncertainty indicators, the analysis of international spillovers and financial connectedness, and the modeling of nonlinear or state-dependent financial market responses. These developments are particularly relevant for the present study because the effect of EPU on financial markets is unlikely to be homogeneous across countries, asset classes, and market regimes.

Firstly, a growing body of research shows that EPU belongs to a broader family of uncertainty indicators, including the World Uncertainty Index (WUI), the Global Economic Policy Uncertainty index (GEPU), geopolitical risk (GPR), climate policy uncertainty, and other global risk measures. The WUI, developed by Ahir et al. (2022), captures uncertainty using Economist Intelligence Unit country reports and has been associated with lower output, higher risk, and greater stock market volatility. Similarly, the GEPU index proposed by Davis (2016) aggregates national EPU indices into a global policy uncertainty measure, allowing researchers to examine uncertainty transmission at the international level. More recent studies also combine EPU with geopolitical and climate-related uncertainty measures. For example, Hu and Borjigin (2024) show that geopolitical risk, EPU, and climate risk amplify energy–stock market volatility spillovers across economic cycles. Choi (2024) further demonstrates that EPU and geopolitical risk generate asymmetric sectoral responses in the U.S. stock market, indicating that uncertainty shocks may affect financial markets unevenly across industries and volatility states. These studies suggest that country-specific EPU should be analyzed not in isolation, but within a wider global uncertainty environment.

Secondly, the recent literature has increasingly emphasized international spillovers and connectedness. This strand is important because financial markets are integrated across borders, and domestic asset prices may respond not only to domestic policy uncertainty but also to foreign and global uncertainty shocks. Zhao and Park (2024), using a panel VAR framework, examine the dynamic interrelationship between domestic and foreign EPU and stock market returns, showing that the response of equity markets depends on the source of policy uncertainty. Hong et al. (2024) provide global evidence from developed and emerging economies using a time-varying Granger causality approach and show that the EPU–stock market relationship changes over time, particularly around major international crises and country-specific events. Lean et al. (2024), using connectedness and copula approaches, examine the spillover effects of Chinese and U.S. EPU on ASEAN stock markets and document heterogeneous cross-country responses. These findings support the view that EPU transmission is not purely domestic; rather, it operates through international financial linkages, global investor sentiment, and common risk factors. Recent Latin

American evidence further documents dynamic spillovers and external-variable linkages associated with EPU (Marín-Rodríguez et al., 2025a, 2025b).

Thirdly, the exchange rate literature has also moved toward spillover and network-based approaches. Wang et al. (2023) analyze asymmetric spillovers between EPU and exchange rate volatility from a global network connectedness perspective and show that the interaction between uncertainty and currency market volatility differs across countries. Gong et al. (2025) examine the effect of EPU spillovers on real effective exchange rate volatility for 23 countries and find that EPU spillovers significantly increase subsequent exchange rate volatility, with stronger effects in emerging markets than in developed markets. These findings are directly related to the currency market asymmetry channel proposed in this study. In advanced economies, policy uncertainty may trigger safe haven flows and reduce relative currency turbulence, whereas in emerging economies, it may intensify capital flight, exchange rate pressure, and currency volatility. Therefore, a pooled estimate may conceal important heterogeneity between advanced and emerging market economies.

Fourthly, recent studies increasingly suggest that EPU effects are nonlinear and regime-dependent. Kundu and Paul (2022) show that the relationship between EPU, stock returns, and volatility varies across heterogeneous market conditions, implying that uncertainty shocks may be stronger in bear markets or periods of financial stress. Yu (2023) shows that the WUI improves the forecasting of sector-level stock market volatility in China, especially during high-volatility states. These findings are consistent with the idea that uncertainty does not affect tranquil and turbulent periods symmetrically. During low-return or high-volatility regimes, investors may become more sensitive to policy signals, liquidity may deteriorate, and risk premia may rise more sharply. This provides a strong rationale for complementing mean-based estimators with quantile-based methods.

Against this background, the present study contributes to the recent literature in four ways. Firstly, it examines three financial market outcomes—stock market returns, stock market volatility, and exchange rate volatility—within a unified G20 framework. Secondly, it explicitly accounts for cross-sectional dependence and slope heterogeneity using second-generation panel estimators. Thirdly, it incorporates global uncertainty through the VIX in order to distinguish domestic EPU effects from global risk sentiment. Fourthly, it applies the Method of Moments Quantile Regression approach to identify whether EPU effects differ across market regimes. In doing so, the study connects the EPU literature with the more recent literature on uncertainty spillovers, financial connectedness, and nonlinear market responses.

2.5. Control Variables and Macro-Financial Channels

The selection of control variables follows the macro-financial transmission channels commonly discussed in the uncertainty–finance literature. Inflation is included because changes in price dynamics may affect nominal discount rates, real returns, monetary policy expectations, and investor risk perceptions. Higher inflation can increase uncertainty about future policy responses and may therefore influence both stock market performance and exchange rate volatility.

The short-term interest rate captures the monetary policy stance and the opportunity cost of holding risky assets. Changes in interest rates affect equity valuation through discount rate channels and influence exchange rate dynamics through interest rate differentials and capital flow incentives. Therefore, controlling for interest rates helps isolate the association between EPU and financial market outcomes from conventional monetary policy effects.

Trade openness is included to capture exposure to international trade and external shocks. More open economies may be more sensitive to global demand conditions, supply

chain disruptions, and external policy uncertainty. At the same time, trade openness may also reflect deeper international integration, which can affect how uncertainty is transmitted to domestic asset prices and exchange rates.

The real effective exchange rate is included because it captures external competitiveness and relative price movements across trading partners. REER fluctuations are particularly relevant for exchange rate volatility, as real appreciation or depreciation may alter market expectations, trade balances, and external sector pressures. In this sense, REER helps control for currency market fundamentals beyond policy uncertainty.

Finally, the VIX is used as a proxy for global uncertainty and investor risk sentiment. This is important because G20 financial markets are highly integrated and may respond simultaneously to global risk shocks. Including the VIX allows the empirical analysis to distinguish country-specific EPU effects from common global uncertainty conditions. This distinction is central to the global volatility dominance channel, which predicts that domestic EPU may lose explanatory power for stock market volatility once global risk sentiment is explicitly controlled for.

2.6. Methodological Positioning

The existing literature exhibits several limitations that this study addresses. Firstly, most panel studies use first-generation estimators inconsistent under cross-sectional dependence (Pesaran, 2006; Bond & Eberhardt, 2009). Secondly, most studies focus on a single financial market outcome, precluding comparisons across different dimensions of financial risk. Thirdly, the distributional heterogeneity of EPU effects across market regimes has received insufficient attention in panel contexts. Fourthly, systematic differences between advanced and emerging economies have been studied primarily in time series settings. This study addresses all four limitations within a unified framework.

3. Data and Methodology

3.1. Data and Variables

Our sample consists of 15 G20 economies for which Baker et al.'s (2016) EPU indices are available over the period 2006 Q1–2024 Q4. The panel start date is determined by the availability of Turkey's EPU index (Kilic & Balli, 2024). The sample includes nine advanced economies (United States, United Kingdom, Canada, Japan, France, Germany, Italy, Australia, South Korea) and six emerging economies (China, India, Brazil, Russia, Mexico, Turkey), yielding a balanced panel of 1140 quarterly observations.

The classification of countries into advanced and emerging economy groups follows the analytical country grouping used in the IMF World Economic Outlook (International Monetary Fund, 2025). This classification is appropriate for the present study because the EPU–financial market relationship is expected to differ across countries with different levels of income, financial depth, institutional credibility, external vulnerability, and integration into the global financial system. Advanced economies generally have deeper equity markets, more liquid currencies, stronger policy credibility, and greater capacity to absorb uncertainty shocks. Emerging economies, by contrast, are typically more exposed to capital flow reversals, exchange rate pressure, and external financing constraints. Therefore, separating the sample into advanced and emerging economy groups allows the empirical analysis to test whether EPU transmission differs across structurally distinct macro-financial environments.

Accordingly, the advanced economy group consists of the United States, United Kingdom, Canada, Japan, France, Germany, Italy, Australia, and South Korea. The emerging economy group consists of China, India, Brazil, Russia, Mexico, and Turkey. This clas-

sification is used only for subgroup analysis and does not affect the construction of the full-sample balanced panel.

The dependent variables are: (i) quarterly log stock market return (Return); (ii) realized stock market volatility (StockVol), computed as within-quarter standard deviation of daily returns; and (iii) realized exchange rate volatility (FXVol), computed from bilateral exchange rate daily data. Stock price index and bilateral exchange rate data are sourced from Investing.com, which aggregates real-time data from exchange feeds and is widely used in empirical panel finance research. To address potential data quality concerns, the U.S. S&P 500 return series was cross-checked against the Macrotrends historical database (Robert Shiller dataset), yielding a correlation of 1.000 with a maximum absolute quarterly discrepancy of 0.009 percentage points, confirming that the Investing.com series is virtually identical to established benchmark sources. The key explanatory variable is lnEPU, the natural logarithm of country-specific EPU. Control variables include: CPI inflation (IMF WEO), overnight interbank rate (OECD IRSTCI01, supplemented with CBRT official rates for two missing Turkey quarters), trade openness (World Bank, linearly interpolated from annual to quarterly frequency), and REER (BIS Broad Real EER). To assess whether linear interpolation of the annual trade openness series affects inference, we re-estimated all models using only end-of-year quarterly observations (Q4) as an alternative; the results were qualitatively unchanged, confirming that the interpolation does not drive our findings. Global uncertainty is captured by lnVIX (FRED). The variable definitions, data types, and sources are summarized in Table 1.

Data Validation and Variable Construction

Several steps were taken to enhance confidence in the financial market data and the construction of the volatility measures. Stock price indices and bilateral exchange rates were obtained from Investing.com, which provides historical series compiled from exchange and market data feeds. Because this source is widely used but may still raise comparability concerns in a multi-country panel setting, the data were subjected to additional validation checks. Firstly, the U.S. S&P 500 series obtained from Investing.com was cross-checked against the Macrotrends historical database based on the Robert Shiller dataset; the two quarterly return series were virtually identical, with a correlation of 1.000 and a maximum absolute quarterly discrepancy of 0.009 percentage points. Secondly, selected non-U.S. benchmark indices and exchange rate series were cross-checked against alternative public financial data sources where available. These checks were conducted to ensure that the Investing.com series were consistent with standard benchmark market data and that the empirical results were not driven by obvious data source inconsistencies.

To further address potential data source concerns, additional non-U.S. benchmark validation checks were conducted for Germany and Japan. The Investing.com-based German DAX and Japanese Nikkei 225 series were compared with independently downloaded benchmark series over the same quarterly sample. For Germany, the correlation between the master panel quarterly return series and the alternative DAX-based return series was 1.0000, while the corresponding correlation for realized stock market volatility was 0.9988. For Japan, the return correlation was 1.0000 and the realized volatility correlation was 0.9999. The mean absolute discrepancies were negligible in both countries. These additional checks, together with the S&P 500 validation, indicate that the Investing.com-based financial market variables are highly consistent with alternative benchmark data sources and that the empirical results are unlikely to be driven by obvious data source inconsistencies.

The dependent variables were constructed as follows. Quarterly stock market returns were computed using end-of-quarter national stock index prices:

$$Return_{it} = 100 \times \ln \left(\frac{P_{it}}{P_{i,t-1}} \right) \quad (1)$$

where P_{it} denotes the end-of-quarter closing value of the national stock market index for country i . Realized stock market volatility was calculated from daily log returns within each quarter:

$$r_{i,d} = 100 \times [\ln(P_{i,d}) - \ln(P_{i,d-1})] \quad (2)$$

$$StockVol_{it} = sd(r_{i,d}), d \in t \quad (3)$$

Similarly, realized exchange rate volatility was computed from daily log changes in the bilateral exchange rate, expressed as domestic currency per U.S. dollar:

$$fx_{i,d} = 100 \times [\ln(E_{i,d}) - \ln(E_{i,d-1})] \quad (4)$$

$$FXVol_{it} = sd(fx_{i,d}), d \in t \quad (5)$$

where $E_{i,d}$ denotes the daily bilateral exchange rate. This approach captures within-quarter realized variability rather than relying only on quarterly end-point changes, making it more suitable for assessing volatility dynamics.

Trade openness was obtained from the World Bank at annual frequency and converted to quarterly frequency using linear interpolation. This procedure is appropriate for trade openness because it is a slow-moving structural variable rather than a high-frequency financial indicator. To ensure that the interpolation did not mechanically drive the results, the models were also re-estimated using only end-of-year quarterly observations as a robustness check. The qualitative conclusions remained unchanged, indicating that the interpolation of trade openness is unlikely to be responsible for the main findings.

Table 1. Variable definitions, data types, and sources.

Variable	Abbreviation	Description	Frequency	Source
Dependent Variables				
Return	Stock Market Return	Quarterly log return of the national stock index (%). Computed as $\ln(P_t/P_{t-1}) \times 100$ where P_t is the end-of-quarter closing price.	Quarterly	Investing.com
StockVol	Realized Stock Market Volatility	Within-quarter standard deviation of daily log returns of the national stock index.	Quarterly	Investing.com
FXVol	Realized Exchange Rate Volatility	Within-quarter standard deviation of daily log changes in the bilateral exchange rate (domestic currency per USD).	Quarterly	Investing.com
Key Explanatory Variable				
EPU	Economic Policy Uncertainty Index	News-based EPU index constructed by Baker et al. (2016) based on newspaper coverage frequency of policy uncertainty. Turkey: Kilic and Balli (2024) ECSU index constructed using identical methodology.	Monthly to Quarterly	www.policyuncertainty.com
lnEPU	Log of EPU	Natural logarithm of EPU index. Used in all regressions to reduce skewness and allow percentage change interpretation of coefficients.	Quarterly	Derived

Table 1. Cont.

Variable	Abbreviation	Description	Frequency	Source
Control Variable				
Inflation	CPI Inflation Rate	Annual percentage change in consumer price index. Captures monetary conditions and cost push factors affecting financial markets.	Monthly to Quarterly	IMF World Economic Outlook
Interest	Short-Term Interest Rate	Overnight interbank rate (%). Proxies monetary policy stance. Turkey: CBRT official overnight lending rate for two missing quarters (2024 Q3–Q4).	Monthly to Quarterly	OECD MEI (IRSTCI01); CBRT (Turkey)
Open	Trade Openness	(Exports + Imports)/GDP × 100. Measures the degree of integration with global goods markets. Higher openness may amplify EPU transmission.	Annually to Quarterly	World Bank WDI
REER	Real Effective Exchange Rate	BIS Broad Real Effective Exchange Rate index (2020 = 100). An increase indicates real appreciation.	Monthly to Quarterly	BIS (Broad Real EER)
Global Uncertainty Control				
VIX	CBOE Volatility Index	Implied 30-day volatility of S&P 500 options. Identical value for all countries in each period (zero cross-sectional variation).	Daily to Quarterly	FRED
lnVIX	Log of VIX	Natural logarithm of VIX. Included in Models 2 and 3 to control for global uncertainty co-movement. Excluded from CCEMG cross-sectional averages due to zero cross-sectional variation.	Quarterly	Derived

Notes: Monthly to Quarterly = monthly series averaged or end-of-quarter aggregated to quarterly frequency depending on the variable structure; Annual to Quarterly = annual series linearly interpolated to quarterly frequency; Daily to Quarterly = daily observations transformed into daily log changes and then aggregated to quarterly realized volatility using the within-quarter standard deviation. Sample period: 2006 Q1–2024 Q4 (T = 76 quarters). N = 15 G20 economies. Stock index and bilateral exchange rate data were retrieved from Investing.com and subjected to selected benchmark validation checks. EPU indices are from Baker et al. (2016) for 14 countries and Kilic and Balli (2024) for Turkey. Selected benchmark validation checks were performed for the S&P 500, DAX, and Nikkei 225 series. The validation results showed near-perfect correlations between the Investing.com-based quarterly measures and alternative benchmark series for both returns and realized stock market volatility.

3.2. Econometric Methodology

3.2.1. Model Specification

The empirical analysis is based on a unified panel framework in which the dependent variable represents one of three financial market outcomes: stock market returns, stock market volatility, and exchange rate volatility. The baseline model is specified as follows:

$$Y_{it}^m = \alpha_i^m + \beta_i^m \ln EPU_{it} + \theta_i^{m'} X_{it} + \varepsilon_{it}^m \quad (6)$$

where Y_{it}^m denotes the dependent variable for country (i) in quarter (t), with ($m = 1, 2, 3$) referring respectively to (Return), (StockVol), and (FXVol). $\ln EPU_{it}$ is the natural logarithm of country-specific economic policy uncertainty, while X_{it} is the vector of control variables including inflation, short-term interest rate, trade openness, real effective exchange rate, and, where applicable, global uncertainty proxied by $\ln VIX_t$.

To account for cross-sectional dependence, the CCEMG specification augments the baseline model with cross-sectional averages:

$$Y_{it}^m = \alpha_i^m + \beta_i^m \ln EPU_{it} + \theta_i^{m'} X_{it} + \pi_i^{m'} \bar{Z}_t^m + u_{it}^m \quad (7)$$

where $\bar{Z}_t^m$ denotes the vector of cross-sectional averages of the dependent and explanatory variables. These averages proxy for unobserved common factors affecting G20 financial markets.

The AMG estimator is specified as follows:

$$Y_{it}^m = \alpha_i^m + \beta_i^m \ln EPU_{it} + \theta_i^{m'} X_{it} + \phi_i^m CD\hat{P}_t + u_{it}^m \quad (8)$$

where $CD\hat{P}_t$ is the estimated common dynamic process obtained from a first-difference pooled regression with time dummies.

The dynamic specification is reported in its cross-sectionally augmented error correction form:

$$\Delta Y_{it}^m = \delta_i^m + \mu_i^{m'} \Delta W_{it} + \lambda_i^m Y_{i,t-1}^m + \varphi_i^{m'} W_{i,t-1} + \rho_i^{m'} \bar{Z}_t^m + \varepsilon_{it}^m \quad (9)$$

where $W_{it} = [\ln EPU_{it}, X_{it}]$. ΔW_{it} captures short-run changes, while $W_{i,t-1}$ contains the lagged-level regressors used to derive long-run coefficients. The coefficient λ_i^m is the error correction or adjustment coefficient and is reported as $ECM(-1)$. A negative and statistically significant λ_i^m indicates adjustment toward the long-run equilibrium.

The long-run coefficient of each explanatory variable is computed as follows:

$$LR_x^m = -\frac{\varphi_x^m}{\lambda_i^m} \quad (10)$$

where φ_x^m is the coefficient of the lagged level of explanatory variable x , and λ_i^m is the adjustment coefficient on the lagged dependent variable. Therefore, long-run coefficients are obtained by normalizing the lagged-level coefficient of each explanatory variable by the error correction coefficient.

Finally, the MMQR specification is used to examine whether the EPU–financial market relationship differs across conditional quantiles:

$$Q_{\tau(Y_{it}^m|W_{it})} = \alpha_i^m(\tau) + \beta^m(\tau) \ln EPU_{it} + \theta^m(\tau)' X_{it} + \varepsilon_{it}^m(\tau) \quad (11)$$

where $Q_{\tau(Y_{it}^m|W_{it})}$ denotes the conditional quantile of Y_{it}^m at quantile τ . The analysis is conducted at the 25th, 50th, and 75th quantiles to capture lower-tail, median, and upper-tail market regimes.

3.2.2. Cross-Sectional Dependence and Unit Root Tests

Lag selection was determined by the quarterly frequency of the data, the time dimension of the panel, and the need to preserve degrees of freedom in heterogeneous second-generation panel estimators. For the CADF unit root tests, a maximum lag length of four quarters was allowed in order to capture up to one year of persistence in the variables. This choice is consistent with the quarterly structure of the dataset and provides a balance between dynamic flexibility and estimation efficiency.

For the cross-sectionally augmented dynamic specification, the baseline CCE-ECM/CS-ARDL model includes one lag of the dependent variable in levels, lagged-level regressors, and contemporaneous first differences of the explanatory variables. This specification allows the model to distinguish short-run changes, long-run equilibrium relationships, and the error correction adjustment coefficient while avoiding over-parameterization in a panel with 15 countries and 76 quarterly observations. The cross-sectional averages are included contemporaneously, following the standard implementation of the cross-sectionally augmented estimator. As a robustness check, the main findings were compared with alternative lag structures where feasible, and the qualitative interpretation of the EPU coefficients remained unchanged.

After specifying the lag structure, we begin with the [Pesaran \(2015\)](#) cross-sectional dependence (CD) test applied to individual variables and fixed-effects residuals of each model. The CD statistic follows $N(0,1)$ under the null of cross-sectional independence. Given strong CD evidence, we apply the [Pesaran \(2007\)](#) CADF unit root test, which augments individual ADF regressions with cross-section averages to control for unobserved common factors.

3.2.3. Cointegration Tests

We employ two complementary cointegration approaches. Firstly, [Westerlund's \(2007\)](#) error correction-based panel cointegration tests (Gt, Ga, Pt, Pa) with bootstrap p -values (400 replications) to ensure robustness to CD. Secondly, [Pedroni's \(1999, 2004\)](#) residual-based tests after cross-sectional demeaning and trend inclusion provide panel and group mean statistics.

3.2.4. Mean-Based Estimation: CCEMG and AMG

The CCEMG estimator of [Pesaran \(2006\)](#) augments individual country regressions with cross-sectional averages of all variables, filtering unobserved common factors, and averages slope coefficients across countries. The AMG estimator of [Bond and Eberhardt \(2009\)](#) and [Eberhardt and Teal \(2010\)](#) extracts a common dynamic process from a pooled first-difference regression and augments country-level regressions with it. Both estimators are consistent under slope heterogeneity, nonstationarity, and cross-sectional dependence. Since lnVIX has zero cross-sectional variation, it is excluded from CCEMG cross-sectional averages but retained as a regressor in AMG, consistent with [Pesaran \(2006\)](#).

3.2.5. CS-ARDL Estimation

The CS-ARDL framework of [Chudik and Pesaran \(2015\)](#), implemented via `xtdcce2` ([Ditzen, 2018](#)), is employed to examine short-run dynamics and long-run equilibrium relationships while accounting for cross-sectional dependence. To address the interpretation of dynamic adjustment explicitly, we report the cross-sectionally augmented error correction representation of the model.

In this representation, the dependent variable enters in first differences, while the lagged level of the dependent variable identifies the error correction or loading coefficient. The estimated model can be written as follows:

$$\Delta Y_{it} = \alpha_i + \lambda_i Y_{i,t-1} + \theta_i X_{i,t-1} + \sum_j \beta_{ij} \Delta X_{i,t-j} + \sum_j \delta_{ij} \bar{Z}_{t-j} + \varepsilon_{it} \quad (12)$$

where $Y_{i,t}$ denotes stock market returns, stock market volatility, or exchange rate volatility; $X_{i,t}$ includes lnEPU and the control variables; $\bar{Z}_{t-j}$ represents cross-sectional averages; and λ_i is the error correction/loading coefficient. A negative and statistically significant λ_i , reported as $ECM(-1)$, indicates adjustment toward the long-run equilibrium. Long-run coefficients are computed as $-\frac{\theta_i}{\lambda_i}$. Therefore, the long-run slopes are conceptually distinct from the error correction coefficient and are reported separately in the empirical results.

3.2.6. Quantile Analysis: MMQR

The MMQR estimator of [Machado and Santos Silva \(2019\)](#) estimates quantile effects by combining a location-scale panel model with individual fixed effects through method of moments. Applied at the 25th, 50th, and 75th quantiles, MMQR reveals whether EPU effects vary across different market states, a question that mean-based estimators cannot address.

Although the econometric framework controls for cross-sectional dependence, slope heterogeneity, common global factors, and distributional heterogeneity, the empirical

design is based on observational panel data. Therefore, the results should be interpreted as robust conditional associations rather than definitive causal effects.

4. Empirical Results and Discussion

4.1. Preliminary Diagnostics

Table 2 presents the descriptive statistics. The average EPU level of 162.11 masks substantial cross-country heterogeneity (standard deviation 104.77; range 17.57–983.77). The Pesaran (2015) CD test indicates cross-sectional dependence in all nine variables, with CD statistics from 10.50 (REER) to 89.33 (lnVIX) and all p -values below 0.001. The average absolute cross-sectional correlations range from 0.451 (lnEPU) to 1.000 (lnVIX), confirming deep financial integration across G20 economies. The model-level CD tests on fixed-effects residuals yield CD statistics of 51.68, 41.93, and 30.42 for Models 1–3, confirming that first-generation estimators would produce inconsistent results.

Table 2. Descriptive statistics and cross-sectional dependence.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	CD Stat.	Avg. Corr.
Full Sample (N = 15, T = 76)							
EPU	1140	162.11	104.77	17.57	983.77	37.964	0.451
lnEPU	1140	4.923	0.569	2.866	6.891	37.964	0.451
Return	1140	1.417	10.627	−53.443	54.953	56.229	0.629
StockVol	1140	1.232	0.690	0.303	7.478	64.646	0.724
FXVol	1140	0.599	0.402	0.027	5.548	42.370	0.496
Inflation	1140	4.323	6.848	−1.331	72.309	39.777	0.481
Interest	1140	3.967	4.933	−0.584	47.000	45.335	0.528
Open	1140	53.343	17.136	22.110	101.681	17.371	0.459
REER	1140	108.567	19.149	68.087	183.250	10.498	0.489
lnVIX	1140	2.908	0.334	2.333	4.071	89.331	1.000
Advanced Economies (N = 9, T = 76)							
EPU	684	169.17	104.99	30.344	983.773	32.917	0.629
lnEPU	684	4.990	0.512	3.413	6.891	32.917	0.629
Return	684	−0.938	8.957	−32.107	21.434	41.037	0.785
StockVol	684	1.130	0.606	0.303	4.907	44.508	0.851
FXVol	684	0.549	0.253	0.198	3.178	42.053	0.804
Inflation	684	2.166	1.799	−1.331	9.067	41.198	0.788
Interest	684	1.477	1.830	−0.584	7.250	42.327	0.809
Open	684	56.525	18.054	23.402	101.681	19.844	0.444
REER	684	103.599	10.641	69.790	134.703	10.559	0.464
lnVIX	684	2.908	0.334	2.333	4.071	89.331	1.000
Emerging Economies (N = 6, T = 76)							
EPU	456	151.509	103.665	17.571	705.992	5.305	0.233
lnEPU	456	4.822	0.631	2.866	6.560	5.305	0.233

Table 2. Cont.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	CD Stat.	Avg. Corr.
Emerging Economies (N = 6, T = 76)							
Return	456	2.135	12.695	−53.443	54.953	15.900	0.471
StockVol	456	1.385	0.775	0.418	7.478	20.453	0.606
FXVol	456	0.675	0.547	0.027	5.548	6.312	0.255
Inflation	456	7.561	9.748	−0.692	72.309	3.248	0.222
Interest	456	7.702	5.709	1.500	47.000	6.066	0.269
Open	456	48.571	14.422	22.110	88.798	−0.930 *	0.508
REER	456	116.020	25.595	68.087	183.250	−0.643 *	0.508
lnVIX	456	2.908	0.334	2.333	4.071	89.331	1.000

Notes: CD Stat. = [Pesaran \(2015\)](#) CD statistic. All CD statistics significant at 1% ($p < 0.001$) except * ($p > 0.05$). lnVIX excluded from Panels B and C (zero cross-sectional variation).

Table 3 reports the CADF unit root results. The mixed integration order—lnEPU, Interest, and Open being I(1); Return, StockVol, and FXVol being I(0); Inflation and REER showing mixed evidence—is the primary motivation for the CS-ARDL approach, which accommodates I(0)/I(1) mixed-order regressors. lnVIX is excluded from unit root tests due to zero cross-sectional variation.

Table 3. Panel unit root test results (Pesaran CADF).

Variable	t-bar (C)	p (C)	t-bar (T)	p (T)	t-bar (D)	p (D)	Order
lnEPU	−2.124	0.071	−2.367	0.468	−4.561	0.000	I(1)
Return	−3.718	0.000	−3.943	0.000	−5.597	0.000	I(0)
StockVol	−2.553	0.000	−2.688	0.060	−4.852	0.000	I(0)
FXVol	−2.480	0.001	−3.145	0.000	−5.006	0.000	I(0)
Inflation	−2.012	0.162	−2.723	0.043	−4.121	0.000	Mixed
Interest	−1.945	0.241	−2.618	0.108	−3.476	0.000	I(1)
Open	−1.409	0.943	−2.063	0.907	−3.400	0.000	I(1)
REER	−2.327	0.010	−2.441	0.338	−3.911	0.000	Mixed
lnVIX	—	—	—	—	—	—	—

Notes: CADF = Cross-Sectionally Augmented Dickey–Fuller ([Pesaran, 2007](#)). Lag length = 4. Critical values (constant): 1% = −2.420, 5% = −2.250, 10% = −2.150. Critical values (trend): 1% = −2.920, 5% = −2.750. lnVIX excluded (zero cross-sectional variation).

4.2. Cointegration Tests

Table 4 presents the cointegration results. The [Westerlund \(2007\)](#) tests indicate cointegration for Models 1 and 3: for Model 1, the Gt statistic (robust $p = 0.015$) and Pt statistic (robust $p = 0.065$) reject the null; for Model 3, three of the four statistics are significant at the 5% level with bootstrap p -values, indicating strong cointegration between EPU and exchange rate volatility. Model 2 shows no significant Westerlund statistics, suggesting the EPU–stock volatility relationship is primarily short-run.

The Pedroni tests strongly support cointegration in all three models: the rho, t, and adf statistics for both panel and group dimensions are large and negative, exceeding critical values at the 1% level. The PDOLS long-run estimates confirm a significant positive effect of lnEPU on StockVol ($\beta = 0.477$, $t = 6.45$) and FXVol ($\beta = 0.091$, $t = 2.36$), but an insignificant

effect on Returns ($\beta = 0.488$, $t = 0.40$). The overestimation in PDOLS reflects its inability to account for cross-sectional dependence.

Table 4. Cointegration test results: Westerlund and Pedroni tests.

Westerlund ECB Tests				
Statistic	Value	Z-Value	<i>p</i> -Value	Robust <i>p</i>
EPU → Return				
Gt	−3.102	−1.854	0.032	0.015 **
Ga	−8.236	3.167	0.999	0.923
Pt	−9.653	−0.428	0.335	0.065 *
Pa	−6.969	2.020	0.978	0.715
EPU → StockVol				
Gt	−2.428	1.644	0.950	0.613
Ga	−0.299	7.302	1.000	0.910
Pt	−4.115	5.447	1.000	0.295
Pa	−0.195	5.646	1.000	0.895
EPU → FXVol				
Gt	−2.612	0.901	0.816	0.165
Ga	−0.317	7.294	1.000	0.033 **
Pt	−6.703	3.043	0.999	0.000 ***
Pa	−0.349	5.580	1.000	0.040 **
Pedroni Cointegration Tests				
Statistic	Panel		Group	
EPU → Return				
v	2.07		—	
rho	−17.79		−17.4	
t	−29.87		−33.31	
adf	−22.32		−22.67	
EPU → StockVol				
v	1.40		—	
rho	−10.45		−9.767	
t	−14.9		−16.22	
adf	−8.546		−7.407	
EPU → FXVol				
v	1.417		—	
rho	−9.158		−8.532	
t	−14.03		−15.09	
adf	−11.91		−11.9	

Notes: [Westerlund \(2007\)](#) bootstrap p-values based on 400 replications. Gt, Ga: group mean statistics; Pt, Pa: panel statistics. Pedroni statistics distributed $N(0,1)$ under null of no cointegration (diverge to negative infinity except panel v). *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

4.3. Mean-Based Estimation Results

Table 5 reports the CCEMG and AMG results. For Model 1 (Return), both estimators deliver consistent findings: lnEPU is significantly associated with lower stock market returns (CCEMG: $\beta = -2.517$, $p = 0.016$; AMG: $\beta = -2.042$, $p = 0.000$). A one standard deviation increase in lnEPU is associated with approximately two percentage points lower quarterly returns, economically meaningful given the sample mean of 1.42%. The common dynamic process in AMG ($\beta = 1.004$, $p = 0.000$) confirms that global common factors are important drivers.

Table 5. Main estimation results: CCEMG and AMG.

Analyses		CCEMG			AMG	
Variable	Model 1 Return	Model 2 StockVol	Model 3 FXVol	Model 1 Return	Model 2 StockVol	Model 3 FXVol
lnEPU SE	−2.517 ** (1.044)	0.117 * (0.060)	0.065 ** (0.030)	−2.042 *** (0.481)	0.093 (0.057)	0.054 (0.043)
Inflation SE	−0.011 (0.220)	−0.001 (0.020)	0.009 (0.008)	0.059 (0.185)	−0.018 (0.010)	−0.025 ** (0.011)
Interest SE	−1.256 (1.088)	0.020 (0.076)	0.007 (0.017)	−2.098 (1.127)	0.111 (0.068)	0.055 ** (0.025)
Open SE	−0.156 (0.218)	−0.004 (0.014)	−0.014 *** (0.005)	0.067 (0.110)	−0.022 *** (0.006)	−0.023 *** (0.005)
REER SE	−0.060 (0.057)	−0.011 (0.007)	−0.014 *** (0.003)	−0.033 (0.058)	−0.017 *** (0.006)	−0.020 *** (0.004)
lnVIX SE	—	—	—	—	1.846 *** (0.137)	0.680 *** (0.094)
CDP SE	—	—	—	1.004 *** (0.039)	0.964 *** (0.094)	0.794 *** (0.160)
R ² (MG)	0.63	0.82	0.73	0.63	0.82	0.74
CD Statistic	−3.38 ***	−2.98 ***	1.93	−3.38 ***	−3.44 ***	1.93

Notes: CCEMG = Common Correlated Effects Mean Group (Pesaran, 2006); AMG = Augmented Mean Group (Bond & Eberhardt, 2009). Standard errors in parentheses. CDP = Common Dynamic Process (AMG). lnVIX excluded from CCEMG (zero cross-sectional variation). *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

For Model 2 (StockVol), the lnEPU coefficient is weakly significant under CCEMG ($\beta = 0.117$, $p = 0.050$) but statistically insignificant under AMG ($\beta = 0.093$, $p = 0.105$) once global uncertainty (VIX) is controlled for. The effect is therefore not robust across estimators, and its economic relevance is limited compared with the dominant role of the global fear factor. The lnVIX coefficient in AMG is large and highly significant ($\beta = 1.846$, $p = 0.000$), confirming that global fear—not domestic policy uncertainty—is the dominant cross-country volatility driver.

For Model 3 (FXVol), CCEMG yields $\beta = 0.065$ ($p = 0.032$) and AMG yields $\beta = 0.054$ ($p = 0.179$) for lnEPU. The AMG result becomes insignificant once lnVIX ($\beta = 0.680$, $p = 0.000$) is included, suggesting partial mediation through the global uncertainty channel. The REER coefficient is significant and negative (AMG: $\beta = -0.020$, $p = 0.000$), consistent with real exchange rate appreciation reducing FX volatility. AMG successfully eliminates residual CD in all three models, reinforcing its choice as the preferred mean estimator.

The limited statistical significance of several domestic control variables should be interpreted in light of the estimator structure and the nature of quarterly financial market dynamics. Both CCEMG and AMG explicitly account for unobserved common factors and cross-sectional dependence, which may absorb a large portion of the variation that

would otherwise be attributed to domestic macroeconomic controls. In highly integrated G20 financial markets, short-run movements in returns and volatility may be more closely associated with global risk sentiment, liquidity conditions, and common shocks than with slow-moving domestic macroeconomic variables. This is particularly relevant for trade openness and REER, which are structural indicators and may affect financial markets gradually rather than through immediate quarterly adjustments. Similarly, inflation and short-term interest rates may influence asset prices through expectations and policy regimes, but their direct average effects may become weaker once country heterogeneity and common global factors are controlled for. Therefore, the insignificance of several control variables does not necessarily indicate model weakness; rather, it suggests that their marginal explanatory power is limited after accounting for EPU, global uncertainty, heterogeneous slopes, and cross-sectional dependence.

4.4. CS-ARDL Results

Table 6 reports the cross-sectionally augmented error correction results. To avoid ambiguity, the table separates short-run coefficients, the error correction term, and long-run estimates. The coefficient labeled $ECM(-1)$ denotes the adjustment or loading coefficient and is measured by the coefficient on the lagged dependent variable in each model. It should therefore not be confused with the long-run coefficient of $\ln EPU$ or any other explanatory variable.

Table 6. Cross-sectionally augmented error correction results.

Variable	Model 1—Return	Model 2—StockVol	Model 3—FXVol
Short-Run Estimates			
$\Delta \ln EPU$	−2.984 *** (0.854)	0.083 (0.069)	0.081 ** (0.037)
$\Delta Inflation$	0.054 (0.359)	0.016 (0.016)	0.007 (0.008)
$\Delta Interest$	−1.094 (1.422)	−0.094 (0.140)	−0.083 (0.062)
$\Delta Open$	0.262 (0.277)	−0.012 (0.013)	−0.019 *** (0.008)
$\Delta \ln VIX$	-	0.007 (0.163)	0.065 (0.050)
$\Delta REER$	−0.184 (0.166)	−0.010 (0.006)	−0.019 *** (0.004)
Error Correction Coefficient			
$ECM(-1)$	−1.221 *** (0.039)	−0.866 *** (0.040)	−0.901 *** (0.044)
Long-Run Estimates			
Long-run $\ln EPU$	−0.928 (0.813)	0.078 (0.092)	0.115 * (0.065)
Long-run Inflation	−0.009 (0.231)	−0.011 (0.028)	0.003 (0.009)
Long-run Interest	−1.616 (1.004)	0.038 (0.078)	0.024 (0.019)
Long-run Open	−0.207 (0.174)	0.007 (0.016)	−0.011 * (0.006)
Long-run REER	−0.031 (0.055)	−0.011 (0.009)	−0.011 *** (0.003)
Observations	1125	1125	1125
R^2 (MG)	0.82	0.86	0.82
CD Statistic	−2.41 **	−3.28 ***	2.79 ***

Notes: The table reports the cross-sectionally augmented error correction representation estimated using `xtdcce2`. $ECM(-1)$ denotes the adjustment/loading coefficient, measured by the coefficient on the lagged dependent variable in each model. A negative and statistically significant $ECM(-1)$ indicates adjustment toward the long-run equilibrium. Short-run coefficients are first-difference effects. Long-run coefficients are computed as $-\beta_L X / \beta_L Y$, where $\beta_L Y$ is the coefficient on the lagged dependent variable and $\beta_L X$ is the coefficient on the lagged level of each explanatory variable. Standard errors are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

The ECM(−1) coefficient is negative and statistically significant in all three models. It is −1.221 for the stock return model, −0.866 for the stock market volatility model, and −0.901 for the exchange rate volatility model. These findings indicate adjustment toward the long-run equilibrium. The return equation displays rapid adjustment with some degree of overshooting, as its adjustment coefficient is below −1. By contrast, the stock market volatility and exchange rate volatility equations show large but monotonic adjustment speeds, since their ECM(−1) coefficients lie between −1 and 0.

The short-run estimates show that changes in lnEPU are negatively and significantly associated with stock market returns. This finding is consistent with the equity repricing channel, according to which increases in policy uncertainty are associated with weaker equity market performance. By contrast, the short-run lnEPU coefficient in the stock market volatility model is positive but statistically insignificant, supporting the view that domestic EPU does not robustly explain stock market volatility once common factors and global risk conditions are accounted for.

For exchange rate volatility, the short-run lnEPU coefficient is positive and statistically significant. This indicates that increases in policy uncertainty are associated with higher exchange rate volatility in the short run. The long-run lnEPU coefficient is also positive and weakly significant at the 10% level, suggesting that the EPU–exchange rate volatility relationship has both short-run and longer-run components. Among the long-run control variables, trade openness and REER are negatively associated with exchange rate volatility, indicating that external sector structure and real exchange rate conditions matter for currency market dynamics. The significance of trade openness and REER in the exchange rate volatility equation further indicates that external sector structure matters more directly for currency market dynamics than for equity market outcomes. This is consistent with the view that exchange rates are more sensitive to trade exposure, external competitiveness, and real exchange rate conditions, whereas stock market returns and stock volatility are more strongly shaped by risk premia, investor sentiment, and common financial shocks.

Overall, the CCE-ECM results support the main empirical interpretation of the paper: EPU is most clearly associated with lower stock returns and higher exchange rate volatility, whereas its association with stock market volatility is weaker and less robust.

4.5. MMQR Results

Table 7 presents the MMQR results. For Model 1 (Return), the lnEPU effect is negative and significant across all quantiles but declines monotonically: Q25 ($\beta = -3.001$, $p = 0.000$), Q50 ($\beta = -2.030$, $p = 0.000$), Q75 ($\beta = -1.209$, $p = 0.026$). The negative association is strongest when markets are already in distress—at low-return quantiles, the negative association is approximately 2.5 times larger than at high-return quantiles, consistent with regime-dependent EPU amplification documented by [Kundu and Paul \(2022\)](#).

The stronger negative association between EPU and stock market returns at the lower quantiles has a clear economic interpretation. Lower-return quantiles correspond to market stress states in which investor risk aversion is higher, liquidity is weaker, and downside risk is more salient. Under these conditions, policy uncertainty is more likely to be incorporated into asset prices through higher required risk premia and stronger discount rate effects. Investors may also react more asymmetrically to policy-related news during downturns, because uncertainty about future fiscal, monetary, or regulatory conditions increases the value of waiting and reduces willingness to hold risky assets. Therefore, the larger EPU coefficient at the lower tail of the return distribution is consistent with a state-dependent repricing mechanism: policy uncertainty is not uniformly priced across all market conditions, but becomes more strongly associated with returns when markets are already under stress.

For Model 2 (StockVol), lnEPU remains insignificant across all quantiles, confirming the AMG finding. The lnVIX coefficient increases monotonically from Q25 (1.000) to Q75 (1.531), indicating that the global uncertainty–volatility nexus intensifies during high-volatility regimes. For Model 3 (FXVol), lnEPU shows the opposite pattern to Model 1: the coefficient increases from Q25 ($\beta = 0.044$, $p = 0.007$) to Q75 ($\beta = 0.132$, $p = 0.009$), suggesting that the EPU–exchange rate volatility association becomes stronger during already elevated currency market turbulence.

Table 7. MMQR estimation results (full sample).

Variable	Q25	Q50	Q75
EPU → Return			
lnEPU	−3.001 *** (0.682)	−2.030 *** (0.540)	−1.209 ** (0.541)
Inflation	0.119 (0.158)	0.250 ** (0.125)	0.360 *** (0.126)
Interest	−0.160 (0.183)	−0.147 (0.145)	−0.137 (0.145)
Open	−0.010 (0.023)	−0.032 * (0.018)	−0.051 *** (0.018)
REER	−0.032 (0.025)	−0.029 (0.020)	−0.026 (0.020)
EPU → StockVol			
lnEPU	−0.019 (0.017)	−0.023 (0.023)	−0.029 (0.039)
Inflation	0.002 (0.003)	0.002 (0.004)	0.003 (0.007)
Interest	0.015 *** (0.004)	0.022 *** (0.005)	0.033 *** (0.009)
Open	−0.001 ** (0.001)	−0.002 *** (0.001)	−0.003 ** (0.001)
REER	0.002 *** (0.001)	0.001 * (0.001)	0.000 (0.001)
lnVIX	1.000 *** (0.041)	1.217 *** (0.054)	1.531 *** (0.095)
EPU → FXVol			
lnEPU	0.044 *** (0.016)	0.080 *** (0.025)	0.132 *** (0.050)
Inflation	−0.006 * (0.003)	−0.007 (0.005)	−0.007 (0.010)
Interest	0.009 (0.006)	0.024 *** (0.009)	0.046 *** (0.017)
Open	0.001 ** (0.001)	0.001 (0.001)	0.000 (0.002)
REER	0.005 *** (0.001)	0.003 *** (0.001)	0.001 (0.002)
lnVIX	0.322 *** (0.033)	0.412 *** (0.052)	0.540 *** (0.101)

Notes: MMQR = Method of Moments Quantile Regression (Machado & Santos Silva, 2019). Q25, Q50, Q75 = 25th, 50th, 75th quantiles. Standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

4.6. Subgroup Analysis: Advanced vs. Emerging Economies

Table 8 reports the AMG subgroup estimates, while Table 9 provides additional distributional evidence from the MMQR subgroup analysis. For Model 1 (Return), lnEPU is negatively and significantly associated with stock market returns in advanced economies, whereas the association is weaker and statistically insignificant in emerging economies under the AMG specification. This finding may reflect the greater depth, liquidity, and informational efficiency of advanced financial markets, where policy-related uncertainty is more rapidly incorporated into equity prices.

The MMQR subgroup results provide further nuance. In emerging economies, lnEPU is negatively associated with returns across all quantiles, whereas in advanced economies, the association is concentrated mainly in lower-return quantiles. This pattern suggests that EPU-related equity repricing is state-dependent in advanced markets, becoming more visible during downturns, while emerging market returns display a more uniform negative association across market states.

Table 8. Subgroup analysis: advanced vs. emerging economies (AMG).

Variable	Advanced			Emerging		
	Model 1 Return	Model 2 StockVol	Model 3 FXVol	Model 1 Return	Model 2 StockVol	Model 3 FXVol
lnEPU	−3.045 ***	0.062	0.082 *	−1.131	0.038	0.071
SE	(0.709)	(0.047)	(0.042)	(1.207)	(0.162)	(0.058)
Inflation	0.814 ***	−0.018 *	0.002	−0.100	−0.021	−0.016
SE	(0.158)	(0.012)	(0.004)	(0.292)	(0.016)	(0.017)
Interest	0.343	0.145 *	0.027	−2.412	0.185	0.029
SE	(0.312)	(0.087)	(0.025)	(1.711)	(0.164)	(0.017)
Open	−0.002	−0.010	−0.002	−0.013	−0.044 ***	−0.038 ***
SE	(0.095)	(0.007)	(0.003)	(0.218)	(0.007)	(0.014)
REER	−0.039	−0.005	−0.009 ***	−0.049	−0.016 **	−0.021 ***
SE	(0.068)	(0.003)	(0.003)	(0.139)	(0.006)	(0.006)
lnVIX	—	1.959 ***	0.653 ***	—	1.720 ***	0.703 ***
SE		(0.087)	(0.062)		(0.342)	(0.217)
CDP	0.997 ***	0.992 ***	0.952 ***	1.011 ***	0.860 ***	0.641 **
SE	(0.054)	(0.059)	(0.094)	(0.083)	(0.226)	(0.246)
Wald chi2	140.71	607.87	140.16	1590.68	495.78	47.37

Notes: AMG = Augmented Mean Group estimator. Advanced: U.S., UK, Canada, Japan, France, Germany, Italy, Australia, Korea (N = 9). Emerging: China, India, Brazil, Russia, Mexico, Turkey (N = 6). Standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 9. MMQR subgroup analysis: advanced vs. emerging economies.

Variable	Advanced			Emerging		
	Q25	Q50	Q75	Q25	Q50	Q75
Panel A: Model 1—EPU → Stock Market Return						
lnEPU	−3.171 ***	−1.292 *	0.235	−3.834 ***	−3.430 ***	−3.014 ***
SE	(1.009)	(0.763)	(0.735)	(1.269)	(1.043)	(1.063)
Inflation	−0.361	−0.477 **	−0.572 ***	0.216	0.326 **	0.440 ***
SE	(0.267)	(0.204)	(0.197)	(0.171)	(0.141)	(0.144)
Interest	−0.143	−0.165	−0.181	−0.290	−0.261	−0.230
SE	(0.346)	(0.264)	(0.253)	(0.250)	(0.206)	(0.210)
Open	−0.005	−0.011	−0.016	0.002	−0.006	−0.014
SE	(0.016)	(0.012)	(0.012)	(0.034)	(0.028)	(0.028)
REER	−0.013	−0.018	−0.022	−0.004	−0.022	−0.040
SE	(0.021)	(0.016)	(0.015)	(0.050)	(0.041)	(0.042)
Obs.	684	684	684	456	456	456
Panel B: Model 2—EPU → Stock Market Volatility						
lnEPU	−0.080 ***	−0.093 ***	−0.116 **	0.006	−0.014	−0.041
SE	(0.023)	(0.029)	(0.051)	(0.033)	(0.045)	(0.079)
Interest	0.007	0.009	0.013	0.021 ***	0.033 ***	0.053 ***
SE	(0.005)	(0.006)	(0.011)	(0.007)	(0.010)	(0.018)
lnVIX	1.093 ***	1.323 ***	1.729 ***	0.883 ***	1.124 ***	1.466 ***
SE	(0.053)	(0.067)	(0.120)	(0.074)	(0.102)	(0.179)
Obs.	684	684	684	456	456	456

Table 9. Cont.

Variable	Advanced			Emerging		
	Q25	Q50	Q75	Q25	Q50	Q75
Panel C: Model 3—EPU → Exchange Rate Volatility						
lnEPU	−0.067 ***	−0.048 ***	−0.028	0.135	0.229 *	0.362
SE	(0.016)	(0.017)	(0.024)	(0.129)	(0.137)	(0.262)
Interest	0.000	0.007	0.016 *	0.014	0.031	0.060
SE	(0.003)	(0.005)	(0.010)	(0.022)	(0.030)	(0.055)
lnVIX	0.383 ***	0.473 ***	0.572 ***	0.259	0.361	0.507
SE	(0.028)	(0.032)	(0.043)	(0.245)	(0.259)	(0.496)
Obs.	684	684	684	456	456	456

Notes: MMQR = Method of Moments Quantile Regression (Machado & Santos Silva, 2019). Q25, Q50, and Q75 denote the 25th, 50th, and 75th quantiles, respectively. Selected variables are reported for brevity; full controls are included in all specifications. Standard errors are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

For Model 3 (FXVol), the subgroup results reveal a clear asymmetry between advanced and emerging economies. In advanced economies, lnEPU is negatively associated with exchange rate volatility, whereas in emerging economies, the association is positive. The negative coefficient in advanced economies is consistent with a safe haven interpretation, whereby uncertainty may coincide with stronger demand for reserve or quasi-reserve currencies. In emerging economies, the positive coefficient is consistent with capital flow pressure and external vulnerability mechanisms. This heterogeneity indicates that pooled full-sample estimates can mask economically important differences in EPU transmission. Additional country-specific estimates are reported in Appendix A.

4.7. Robustness Checks

To assess the sensitivity of our main findings to crisis periods and potential endogeneity, we conduct three sets of robustness checks. Firstly, we add a COVID-19 dummy variable (2020 Q1–2021 Q4 = 1) to each model and separately re-estimate excluding the pandemic period entirely. Secondly, we exclude the global financial crisis quarters (2008 Q3–2009 Q2). Thirdly, we replace contemporaneous lnEPU with its one-quarter lag (L.lnEPU) to address potential reverse causality from financial market conditions to measured EPU. The results are reported in Tables 10 and 11.

Table 10. Robustness checks: crisis period sensitivity.

Specification	Model 1: Return		Model 2: StockVol		Model 3: FXVol	
	β	SE	β	SE	β	SE
Baseline (AMG)	−2.042 ***	(0.481)	0.093	(0.057)	0.054	(0.043)
COVID-19 Robustness						
(R1a) COVID dummy included	−2.867 ***	(1.080)	0.078	(0.060)	0.070 *	(0.039)
(R1b) COVID period excluded (N = 948)	−3.309 ***	(1.095)	0.110	(0.060)	0.058 *	(0.031)
Global Financial Crisis Robustness						
(R2) GFC excluded (N = 1080)	−2.454 **	(1.075)	0.091 *	(0.055)	0.072 **	(0.036)

Notes: Baseline reproduces the AMG estimate from Table 5 for reference. Robustness specifications (R1a, R1b, R2) are estimated via CCEMG (Pesaran, 2006) with cross-sectional averages. The close correspondence between AMG baseline and CCEMG robustness results confirms estimator robustness. Standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table 11. Robustness check: lagged EPU—endogeneity control.

Variable	Model 1—Return	Model 2—StockVol	Model 3—FXVol
L.lnEPU	2.116 ***	−0.028	0.034 *
SE	(0.478)	(0.032)	(0.020)
Inflation	0.023	−0.002	0.009
Interest	−1.191	0.019	0.006
Open	−0.151	−0.004	−0.014 ***
REER	−0.058	−0.011	−0.014 ***
Observations	1125	1125	1125
R ² (MG)	0.61	0.82	0.72

Notes: L.lnEPU = one-quarter lag of log EPU index. One observation per country lost due to lagging (N = 1125). All specifications estimated via CCEMG (Pesaran, 2006) with cross-sectional averages. The positive coefficient on L.lnEPU in Model 1 warrants careful interpretation. One explanation, consistent with Brogaard and Detzel (2015), is an uncertainty risk premium: investors demand higher future returns as compensation for bearing policy risk, producing a positive lagged EPU–return relationship. An alternative explanation is mean reversion: EPU-driven price declines in period *t*, creating a mechanical positive return in *t* + 1 as prices partially recover. Both mechanisms predict a positive lagged coefficient; disentangling them requires higher-frequency data beyond the scope of this study. *** *p* < 0.01; * *p* < 0.10.

Table 10 presents the crisis period sensitivity results. The negative and significant effect of EPU on stock market returns (Model 1) is robust across all specifications: the coefficient remains significant at the 5% level when the COVID dummy is included ($\beta = -2.867$, $p < 0.05$) and strengthens when the COVID period is excluded ($\beta = -3.309$, $p < 0.01$), confirming that the baseline finding is not driven by pandemic-era extreme observations. Excluding the GFC period similarly yields a significant negative coefficient ($\beta = -2.454$, $p < 0.05$). For Model 3 (FXVol), the positive EPU effect on exchange rate volatility persists with marginal significance ($p < 0.10$) across all crisis exclusion specifications. Model 2 (StockVol) remains statistically insignificant throughout, reinforcing our conclusion that EPU does not robustly drive stock market volatility once global uncertainty is controlled for.

Table 11 addresses endogeneity issues by replacing contemporaneous EPU with its one-quarter lag. For Model 1, L.lnEPU has a positive and very significant coefficient ($\beta = 2.116$, $p < 0.01$). This sign reversal from the contemporaneous negative effect is not surprising since Brogaard and Detzel (2015) found that higher EPU decreases stock prices through a discount rate channel, but generates an uncertainty risk premium that leads to higher future returns as a result of bearing policy risk. For Model 3, the lag effect is positive ($\beta = 0.034$, $p < 0.10$), which is consistent with the baseline. Model 2, however, is not significant. Combined, the robustness checks indicate that our three core findings are not artefacts of crisis periods or reverse causality.

5. Conclusions

This study provides a comprehensive examination of the association between economic policy uncertainty and financial market dynamics in G20 economies, organized around three asymmetric transmission channels. The findings support the equity repricing channel: EPU is significantly associated with lower stock market returns, with the effect being stronger in advanced economies and at lower-return quantiles. This suggests that policy uncertainty is priced more strongly during market downturns, when risk aversion and discount rate sensitivity are higher. The robustness checks confirm that this result is not driven by the COVID-19 period, the global financial crisis, or contemporaneous feedback from financial markets to EPU.

The results also qualify the conventional EPU–volatility narrative. Through the global volatility dominance channel, country-specific EPU is not robustly associated with stock

market volatility once global uncertainty is accounted for. The weak CCEMG coefficient and insignificant AMG and quantile results indicate that, in financially integrated G20 markets, stock market volatility is more closely linked to global risk sentiment, proxied by the VIX, than to domestic policy uncertainty alone. This does not imply that domestic EPU is irrelevant, but rather that its volatility effect is largely absorbed by common global risk factors.

The currency market asymmetry channel receives stronger support. EPU is positively associated with exchange rate volatility in the full sample, and the effect becomes more pronounced at higher-volatility quantiles. The subgroup evidence suggests that this relationship differs between advanced and emerging economies. In advanced economies, the findings are consistent with a safe haven interpretation, whereas in emerging economies, they are consistent with capital flow pressure and external vulnerability mechanisms. Therefore, pooled estimates can mask important heterogeneity in the way policy uncertainty is transmitted to currency markets.

The CCE-ECM results provide additional evidence on dynamic adjustment. The error correction coefficient is negative and statistically significant in all three equations, confirming adjustment toward long-run equilibrium. The return equation displays rapid adjustment with some degree of overshooting, whereas the stock market volatility and exchange rate volatility equations exhibit large but monotonic adjustment speeds. Importantly, the long-run lnEPU coefficient is statistically evident only for exchange rate volatility at the 10% level. This suggests that the EPU–exchange rate volatility relationship contains both short-run and longer-run components, while the EPU–return relationship is more clearly reflected in short-run repricing and distributional effects.

These findings have several channel-specific policy implications. Firstly, governments and central banks should reduce avoidable policy ambiguity by strengthening forward guidance, fiscal communication, and regulatory transparency, particularly during periods of market stress. Secondly, because stock market volatility is more strongly associated with global risk conditions than with domestic EPU alone, macroprudential authorities should incorporate global uncertainty indicators such as the VIX into financial stability monitoring frameworks. Thirdly, emerging market policymakers should treat policy uncertainty as a potential currency market vulnerability and strengthen foreign exchange liquidity buffers, reserve adequacy, and contingency arrangements such as swap lines. Fourthly, the stronger effects observed in lower-return quantiles and higher exchange rate volatility quantiles imply that uncertainty management should be state-contingent rather than uniform across tranquil and stressed market regimes.

The study is subject to several limitations. Firstly, although the Turkish uncertainty index is constructed to capture domestic policy uncertainty, its source structure differs from the Baker, Bloom, and Davis EPU indices used for most other countries, which may introduce some measurement heterogeneity. Secondly, the quarterly frequency is appropriate for macro-financial panel analysis but does not capture high-frequency market reactions or intraday trading dynamics. Thirdly, the sample is limited to G20 economies with available EPU indices, which improves comparability but leaves small, frontier, and low-income economies outside the analysis. Future research could extend this framework by using dynamic factor models to separate domestic and global uncertainty components, applying threshold or regime-switching models around crisis episodes, and incorporating institutional quality, exchange rate regimes, and financial development as moderators of the currency market asymmetry channel.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: EPU indices from www.policyuncertainty.com; stock market and exchange rate data from Investing.com; inflation from IMF WEO; interest rates from OECD; trade openness from World Bank; REER from BIS; VIX from FRED. Stata 18.0 (StataCorp LLC, College Station, TX, USA) do-files available upon request from the corresponding author. All statistical analyses were conducted using Stata 18.0 (StataCorp LLC, College Station, TX, USA).

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

AMG	Augmented Mean Group estimator
CADF	Cross-sectionally augmented Dickey–Fuller
CCEMG	Common Correlated Effects Mean Group estimator
CD	Cross-sectional dependence
CS-ARDL	Cross-Sectionally augmented ARDL
EPU	Economic policy uncertainty
FXVol	Realized exchange rate volatility
GFC	Global financial crisis
G20	Group of Twenty
MMQR	Method of Moments Quantile Regression
PDOLS	Panel Dynamic OLS
REER	Real effective exchange rate
StockVol	Realized stock market volatility
VIX	CBOE Volatility Index

Appendix A

Table A1 presents country-specific OLS estimates of the lnEPU coefficient for all 15 G20 economies. These results are illustrative and complement the panel estimates in Tables 6–8.

Table A1. Country-specific lnEPU coefficients (OLS estimates).

Country	Model 1		Model 2		Model 3	
	β	<i>p</i> Value	β	<i>p</i> Value	β	<i>p</i> Value
Advanced Economies						
Australia	−6.727	0.002	0.158	0.141	0.179	0.036
Canada	−4.723	0.051	−0.095	0.414	−0.129	0.002
France	−12.104	0.004	0.105	0.544	−0.010	0.899
Germany	−4.311	0.182	−0.315	0.005	−0.246	0.000
Italy	−4.381	0.393	0.187	0.368	−0.087	0.187
Japan	−12.440	0.014	0.335	0.308	0.251	0.046
Korea	−4.413	0.149	0.003	0.982	−0.141	0.124
UK	−2.600	0.344	0.045	0.695	0.241	0.000
US	−3.137	0.362	−0.047	0.763	−0.186	0.000
Emerging Economies						
Brazil	−5.121	0.206	0.303	0.080	0.239	0.003
China	−3.365	0.441	−0.605	0.001	0.110	0.000
India	−5.836	0.133	0.046	0.809	0.035	0.462
Mexico	−5.307	0.103	0.087	0.505	−0.060	0.567
Russia	−10.435	0.006	0.259	0.282	0.497	0.004
Turkey	−7.005	0.124	0.180	0.238	0.216	0.020

Notes: Country-specific OLS estimates of lnEPU coefficient with inflation, interest, open, and REER as controls. M2 and M3 additionally include lnVIX. T = 76 observations per country. Presented for illustrative purposes to document heterogeneity. Bold *p*-values indicate significance at 10%.

References

- Ahir, H., Bloom, N., & Furceri, D. (2022). *The world uncertainty index* (NBER Working Paper No. 29763). NBER. [CrossRef]
- Antonakakis, N., Chatziantoniou, I., & Filis, G. (2013). Dynamic co-movements of stock market returns, implied volatility and policy uncertainty. *Economics Letters*, 120, 87–92. [CrossRef]
- Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. *Finance Research Letters*, 18, 136–141. [CrossRef]
- Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics*, 131, 1593–1636. [CrossRef]
- Bartsch, Z. (2019). Economic policy uncertainty and dollar-pound exchange rate return volatility. *Journal of International Money and Finance*, 98, 102067. [CrossRef]
- Beckmann, J., & Czudaj, R. (2017). Exchange rate expectations and economic policy uncertainty. *European Journal of Political Economy*, 47, 148–162. [CrossRef]
- Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77, 623–685. [CrossRef]
- Bond, S., & Eberhardt, M. (2009). *Cross-section dependence in nonstationary panel models: A novel estimator* (MPRA Paper 17692). University Library of Munich. Available online: <https://mpra.ub.uni-muenchen.de/17692/> (accessed on 9 June 2026).
- Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, 61, 3–18. [CrossRef]
- Choi, S.-Y. (2024). Sectoral responses to economic policy uncertainty and geopolitical risk in the US stock market. *Journal of Multinational Financial Management*, 76, 100874. [CrossRef]
- Christou, C., Cunado, J., Gupta, R., & Hassapis, C. (2017). Economic policy uncertainty and stock market returns in Pacific-Rim countries: Evidence based on a Bayesian panel VAR model. *Journal of Multinational Financial Management*, 40, 92–102. [CrossRef]
- Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188, 393–420. [CrossRef]
- Davis, S. J. (2016). *An index of global economic policy uncertainty* (NBER Working Paper No. 22740). NBER. [CrossRef]
- Ditzen, J. (2018). Estimating dynamic common-correlated effects in Stata. *Stata Journal*, 18, 585–617. [CrossRef]
- Eberhardt, M., & Teal, F. (2010). *Productivity analysis in global manufacturing production* (Discussion Paper 515). Department of Economics, University of Oxford. Available online: <https://ora.ox.ac.uk/objects/uuid:f9d91b40-d8b7-402d-95eb-75a9cbdc000> (accessed on 9 June 2026).
- Ghani, M., & Ghani, U. (2024). Economic Policy Uncertainty and emerging stock market volatility. *Asia-Pacific Financial Markets*, 31, 165–181. [CrossRef]
- Gong, Y., He, Z., & Xue, W. (2025). EPU spillovers and exchange rate volatility. *International Review of Financial Analysis*, 97, 103824. [CrossRef]
- Hong, Y., Zhang, R., & Zhang, F. (2024). Time-varying causality impact of economic policy uncertainty on stock market returns: Global evidence from developed and emerging countries. *International Review of Financial Analysis*, 91, 102991. [CrossRef]
- Hu, Z., & Borjigin, S. (2024). The amplifying role of geopolitical risks, economic policy uncertainty, and climate risks on energy-stock market volatility spillover across economic cycles. *The North American Journal of Economics and Finance*, 71, 102114. [CrossRef]
- International Monetary Fund. (2025). *World economic outlook: Frequently asked questions*. International Monetary Fund. Available online: <https://www.imf.org/en/publications/weo/frequently-asked-questions> (accessed on 9 June 2026).
- Kido, Y. (2016). On the link between the US economic policy uncertainty and exchange rates. *Economics Letters*, 144, 49–52. [CrossRef]
- Kilic, I., & Balli, F. (2024). Measuring economic country-specific uncertainty in Türkiye. *Empirical Economics*, 67, 1649–1689. [CrossRef]
- Kundu, S., & Paul, A. (2022). Effect of economic policy uncertainty on stock market return and volatility under heterogeneous market characteristics. *International Review of Economics & Finance*, 80, 597–612. [CrossRef]
- Lean, H. H., Alkhazali, O. M., Gleason, K., & Yeap, X. W. (2024). Connectedness and economic policy uncertainty spillovers to the ASEAN stock markets. *International Review of Economics & Finance*, 90, 167–186. [CrossRef]
- Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. *Finance Research Letters*, 15, 99–105. [CrossRef]
- Machado, J. A. F., & Santos Silva, J. M. C. (2019). Quantiles via moments. *Journal of Econometrics*, 213, 145–173. [CrossRef]
- Marín-Rodríguez, N. J., González-Ruiz, J. D., & Botero, S. (2025a). Dynamic linkages between economic policy uncertainty and external variables in Latin America: Wavelet analysis. *Economies*, 13(2), 22. [CrossRef]
- Marín-Rodríguez, N. J., González-Ruiz, J. D., & Botero, S. (2025b). Dynamic spillovers of economic policy uncertainty: A TVP-VAR analysis of Latin American and global EPU indices. *Economies*, 13(1), 11. [CrossRef]
- Murad, S. M. W. (2022). The role of domestic and foreign economic uncertainties in determining the foreign exchange rates: An extended monetary approach. *Journal of Economics and Finance*, 46, 666–677. [CrossRef]
- Pástor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *Journal of Finance*, 67, 1219–1264. [CrossRef]
- Pástor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110, 520–545. [CrossRef]

- Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics*, 61, 653–670. [\[CrossRef\]](#)
- Pedroni, P. (2004). Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory*, 20, 597–625. [\[CrossRef\]](#)
- Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74, 967–1012. [\[CrossRef\]](#)
- Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, 265–312. [\[CrossRef\]](#)
- Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, 34, 1089–1117. [\[CrossRef\]](#)
- Wang, P., Li, Y., & Liu, X. (2023). Asymmetric spillover between economic policy uncertainty and exchange rate volatility: A global network connectedness perspective. *PLoS ONE*, 18(1), e0279729. [\[CrossRef\]](#) [\[PubMed\]](#)
- Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, 69, 709–748. [\[CrossRef\]](#)
- Yu, M. (2023). Forecasting sector-level stock market volatility: The role of world uncertainty index. *Finance Research Letters*, 58, 104568. [\[CrossRef\]](#)
- Zhao, M., & Park, H. (2024). Research on the dynamic interrelationship between economic policy uncertainty and stock market returns. *Journal of Risk and Financial Management*, 17(8), 347. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.