

Dynamic Conditional Correlation Analysis of Post Election Volatility Spillovers Across Global Equity Markets: Evidence from the 2024 Super Election Year

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Abstract

With over 3.7 billion voters taking part in significant national elections across 72 nations, 2024 was dubbed a “super election year”. This study uses the DCC GARCH model to examine post election volatility spillovers from election origin stock markets (US, UK, India, Russia and Japan) to major global equity bourses. Over the course of 350 trading days following the election, the daily closing values of benchmark equity indices are assessed. As evidenced by statistically negligible DCC α_1 parameters for the majority of index pairs, the empirical results show that cross border volatility transmission is very noticeable, and statistically substantial DCC β_1 coefficients support ongoing cross market financial connectivity. These results have important ramifications for investors and regulators assessing the susceptibility of domestic markets to foreign political shocks during times of global upheaval.

Keywords

Super election year, volatility spillovers, election-bound stock markets, spillover Receipting markets, benchmark equity indices, DCC-GARCH model

Introduction

National elections, whether presidential or parliamentary, constitute major political events that profoundly impact domestic economies and international equity bourses. Elections provide an institutional framework through which the electorate selects a governing party whose ideological orientation directly shapes national, fiscal, monetary, trade, taxation and regulatory frameworks because financial policy direction relies heavily on electoral outcomes, national political transitions introduce significant policy uncertainty into equity markets, fundamentally altering investor behavior and asset price dynamics. It systemically important economies, election shocks generate spillover effects that spread beyond domestic boundaries, heightening global stock market volatility due to deep financial integration (Mnasri & Essaddam, 2021; Nguyen et al., 2023). Dubbed the “super election year,” 2024 saw nearly 3.7 billion voters across 72+ developed, emerging and frontier nations participate in the elections at all levels (Benjamin Plackett, 2024; UNDP, 2024). Major presidential and parliamentary contests occurred in key economies, including the United States, United Kingdom, India, France, Russia and Japan (John & Sen, 2024). Donald Trump secured a second non consecutive US presidential term, while Narendra Modi’s coalition retained power for a third term in India.

Conversely, Keir Starmer's Labour Party achieved a decisive victory in the UK, France faced a fragmented hung parliament under Emmanuel Macron, Vladimir Putin secured re election in Russia amid ongoing geopolitical conflict and Shigeru Ishiba led a minority government in Japan. The collective impact of this historical electoral cycle on the global market stability remains highly uncertain, requiring rigorous empirical investigation (*Chevallier, 2024*).

Electoral policy uncertainties directly influence business cycles, risk premiums, asset pricing model and portfolio diversification strategies (*Baker et al., 2016; Musah et al., 2023; Nordhas, 1975*). These political shifts trigger volatility spillovers – transmitting price instability and information shocks across international borders, particularly during structural policy transitions (*Aziz et al., 2020; Sethy & Tripthy, 2024; Agarwal et al., 2026; Roy & Gautam, 2026*). To model these dynamic cross border linkages effectively, empirical methodology must move beyond static correlations and capture time varying conditional co-movements. The DCC GARCH framework provides an optimal architecture for this analysis. Unlike traditional multivariate models constrained by the “curse of dimensionality” or Constant Conditional Correlation (CCC) assumptions, DCC GARCH models time varying correlations while maintaining computational tractability (*Engle, 2002*). By isolating univariate variances in the first stage and estimating dynamic conditional correlation matrices in the second stage, it precisely captures dynamic variance persistence, cross market shock transmissions and financial contagion during high uncertainty event windows (*Su et al., 2024*). Utilizing this framework is essential because anchor economies like US, UK, India, Japan, France and Russia represent a vast majority of global GDP and market capitalization. Post election realignments in these systemically vital bourses alter capital flows, trade regimes and monetary alignments, propagating volatility across the global financial architecture (*Ben Rejeb & Boughrara, 2015; Forbes & Rigobon, 2002*). Evaluating these dynamic correlation trajectories allows portfolio managers, regulators and central banks to distinguish between net shock transmitters and receivers, safeguard domestic systemic stability, and mitigate international market contagion (*Malhotra et al., 2024; Zhang et al., 2021*).

Literature Review

The sensitivity of financial markets to political developments particularly national elections is a well established paradigm in empirical finance. Elections represent critical institutional events characterized by heightened policy uncertainty, which frequently amplifies asset price volatility and triggers rapid adjustments in market valuations (*Mlandu et al., 2026*). During electoral cycles, market participants reevaluate risk premiums in response to prospective shifts in fiscal, monetary, trade and regulatory policies. A substantial body of international literature provides evidence on the relationship between political events and stock market behavior. (*Nguyen et al., 2023*) examined the reaction of European Union stock markets to election shocks and policy uncertainties, documenting a significant increase in conditional equity volatility during both pre and post election windows. Similarly, (*Gayathri and Sophia, 2025*) evaluated the influence of the 2019 and 2024 Indian general elections on the volatility behavior of Indian equity markets, revealing pronounced volatility clustering and elevated variance surrounding key electoral phases. In the context of developed markets, (*Botta and Sakariyahu, 2025*) analyzed the effect of US presidential elections on volatility across multiple asset classes between 1992 and 2024, reporting evidence of heightened abnormal volatility around election periods. These empirical observations align with earlier findings by (*Mnasri and Essaddam, 2021*), who investigated the political uncertainty hypothesis across seven US presidential elections held between 1992 to 2016 and confirmed that electoral cycles consistently induce structural volatility shocks in equity bourses. Beyond domestic equity dynamics, major political outcomes frequently generate cross border volatility spillover that propagate across international bourses and non equity assets classes. evaluating cross asset transmission during major political shifts, (*Ampountolas, 2025*) examined volatility spillovers across global financial markets

including global stock indices, crude oil and cryptocurrencies during the 2024 US presidential election. Their findings confirmed that global asset classes exhibited acute sensitivity to election based policy uncertainty, which significantly intensified cross market volatility spillovers and altered dynamic interdependencies worldwide.

To model time varying variance structures and cross market risk transmissions accurately, empirical researchers extensively employ the DCC GARCH framework. Across various segments of global financial markets, the DCC GARCH specification has proven indispensable for capturing dynamic co-movements and differentiating between immediate short term news shocks and persistent long term variance linages. Evaluating inter market transmission across different development tiers, (*Bala and Takimoto, 2017*) assessed the impact of the Global Financial Crisis on volatility spillovers between emerging and developed stock markets using a DCC – MGARCH approach. their empirical results demonstrated profound volatility spillovers, with own market variance persistence being significantly larger than cross market spillovers in emerging bourses, while also exhibiting weaker shock transmission compared to developed equity markets. Focusing on Asian market linkages, (*Sainath et al., 2023*) investigated dynamic connectedness and volatility spillovers from the Indian stock market to seven major global equity bourses (US, UK, China, Japan, Australia, Taiwan and Germany) using DCC GARCH model from December 2021 to December 2022. Their analysis revealed a distinct structural pattern, an absence of statistically significant short run spillover effects, alongside highly significant long run volatility spillovers between Indian equity bourses and major international market. in a related study on cross border transmission channels, (*Yadav et al., 2023*) estimated volatility spillovers running from major Western bourses (NYSE, NASDAQ and Euro Stoxx 50) to the Indian equity market (Sensex) between 2012 to 2022 using DCC GARCH specification. Their findings confirmed strong, persistent long run volatility spillovers from the US and Eurozone markets to India, suggesting that emerging markets remain vulnerable to sustained external shocks from developed bourses over extended horizons. The applications of the DCC GARCH methodology has also yielded vital insights during global crisis events characterized by extreme market stress. (*Rai et al., 2022*) analyzed volatility transmissions among eight major global equity indices including the DAX 30, Nifty 50, FTSE 100, Nikkei 225, Hang Seng, MOEX, CAC 40 and NASDAQ 100 during the first two phases of the COVID 19 pandemic (January 2019 to July 2021). The results established that volatility transmitted by both the Nifty 50 (except to MOEX) and the NASDAQ 100 (except the Hang Seng) was statistically significant over long term horizons. Investigating emerging market linkages, (*Kumar and Gupta, 2025*) examined dynamic connectedness among stock, bond and currency markets across BRICS nations during the pandemic (December 2019 to April 2021), identifying severe stress spillovers where China and India acted as primary spreaders and receivers of systemic shocks. Extending this analysis to geopolitical crises, (*Agrawal et al., 2026*) explored volatility spillover phenomena among BRICS equity bourses across pre COVID 19, COVID 19 and Russia – Ukraine war periods using a multivariate DCC GARCH framework. The empirical results confirmed the absence of immediate short term shock transmission across market pairs, while verifying persistent long run spillover effects through all three stress periods. Concurrently, (*Gopal et al., 2025*) evaluated the volatility spillover effects of the Russia – Ukraine war across BRICS equity bourses, concluding that long term volatility memory exerted a far greater influence on dynamic correlation structures than immediate short term innovations.

The utility of the DCC GARCH model extends beyond pure equity to equity connections to encompass cross asset volatility spillovers between stock markets, digital assets and physical commodity markets. In cryptocurrency literature, (*Bhatia and Bedi, 2022*) conducted a bivariate DCC GARCH volatility spillover analysis between fourteen Nifty sectoral indices and the Crypto 30 (CCI30) index from 2015 to 2019. Their results showed an absence of short run spillovers across all sectors, but confirmed statistically significant long run spillovers for a majority of sectoral indices. Similarly, (*Ibrahim et al., 2024*) studied Bitcoin volatility spillovers to six major global stock markets (US, UK,

Japan, China, Germany and France) across pre pandemic and pandemic periods using the DCC GARCH technique, documenting a consistent absence of short run spillovers alongside robust, statistically significant long run conditional dependencies. In commodity markets (*Nguyen, 2023*) analyzed volatility transmissions between crude oil prices (WTI spot) and six emerging ASEAN stock indices using DCC GARCH modeling, demonstrating positive volatility spillovers from energy markets to ASEAN equities. (*Abuzayed and Al – Fayoumi, 2021*) examined crude oil spillovers to six Gulf Cooperation Council (GCC) equity bourses during COVID 19 pandemic, finding significant short term spillovers in most markets and persistent long term spillovers across all GCC bourses. Furthermore, (*Malhotra et al., 2024*) empirically evaluated agricultural commodity spillovers from wheat futures to equity indices of ten major importing nations during Russia Ukraine conflict, demonstrating that the DCC GARCH framework effectively isolated short term dynamic linkages in select markets while confirming widespread long run spillovers to major equity indices. Econometrically, early specifications such as the full Vector VEC model by (*Bollerslev et al., 1998*), Diagonal VEC and Constant Conditional Correlation (CCC-MGARCH) by (*Bollerslev, 1990*), BEKK-GARCH by (*Engle and Kroner, 1995*) and time varying conditional correlation (TVCC-MGARCH) by (*Tse and Tsui, 2002*) exhibited severe limitations, including the “curse of dimensionality” or restrictive constant correlation assumptions. The DCC GARCH model proposed by (*Engle, 2002*) overcomes these structural bottlenecks. By decomposing the conditional covariance matrix into univariate conditional variance and a time varying conditional correlation matrix, the DCC GARCH model provides a flexible, parsimonious and computationally robust estimation process (*Rai et al., 2022; Yadav et al., 2024*). It allows conditional correlations to evolve dynamically over time while preserving parameter tractability, effectively capturing bidirectional volatility spillovers, dynamic conditional covariances and asymmetry across international financial markets (*Chittedi, 2015; Fiszeder et al., 2019; Malhotra & Sinha, 2024*). Consequently the DCC GARCH approach represents the optimal econometric methodology for evaluating dynamic cross border volatility transmissions and financial connectedness surrounding the 2024 Super Election Year.

Data Description

The study analyzes dynamic volatility transmission effects using daily historical closing prices of recipient global stock markets and benchmark equity indices from election based nations. Five significant national elections USA, UK, India, France and Japan that took place during the 2024 “super election year” are included in the sample. Each election bound market is assessed using a DCC GARCH framework to model its dynamic variance persistence, cross market conditional correlations and post election volatility spillover across a subset of global equity market each pairwise estimation does not include the domestic market.

Period of the Study

Using a DCC GARCH model, daily benchmark index closing prices from Bloomberg are examined over a 350 trading day period after each election result in order to investigate post election volatility spillovers. This timeline captures time varying variance persistence and cross border conditional co-movements across recipient equity markets during short term and long term adaptation periods.

Empirical Results

The empirical results are presented in this section under three main subsections: the bivariate DCC GARCH results capturing cross market volatility transmissions from election origin countries to major global equity bourses, the univariate GARCH(1,1) estimates examining conditional variance persistence, and the pairwise transmission plots showing time varying conditional correlations over the post election period.

The ADF test was used to assess stationarity across all daily log return series prior to estimating the dynamic correlation structures. For all chosen benchmark equity indices, the ADF test produces p-values of 0.0000, indicating that all return series are stationary at level [1(0)] and appropriate for conditional heteroskedasticity modeling.

Strong ARCH (α) and GARCH (β) parameters are revealed by the first stage univariate GARCH (1,1) estimations, suggesting significant volatility clustering and enduring conditional variances in both election bound and recipient equity markets. Building on these variance assumptions, the second stage DCC GARCH model establishes that shock transmissions and cross border co-movements are significantly time-varying rather than constant, confirming statistically dynamic conditional correlation parameters (α and β). election uncertainty dramatically modifies international risk transmission, resulting in increased volatility spillovers during political changes, according to time varying correlation trajectories

The empirical results of the volatility dynamics analysis conducted by employing a GARCH (1,1) model on the stock market indices across the selected elections are presented in Tables 1-5.

Table 1: DCC GARCH results for USA elections

INDICES	CONDITIONAL VARIANCE	
	α_1	β_1
S&P 500	0.1317*** (3.6059)	0.8071*** (16.6408)
FTSE 100	0.3893*** (4.2098)	0.2926** (2.4812)
NIFTY 50	0.0824*** (3.0718)	0.9100*** (36.1376)
MOEX	0.0810*** (9.1785)	0.9104*** (29.0305)
DAX 40	0.1828*** (3.5416)	0.6659*** (7.6637)
NIKKEI 225	0.3071*** (3.5479)	0.5009*** (4.7677)
SSE	0.0000 (0.0000)	0.9939*** (281.4963)

Source: Author's own estimates.

Notes: t-statistics values in parenthesis. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 2: DCC GARCH results for UK elections

INDICES	CONDITIONAL VARIANCE	
	α_1	β_1
FTSE 100	0.3686*** (4.3480)	0.2566** (2.3942)
S&P 500	0.1346*** (3.5610)	0.7980*** (15.2526)
NIFTY 50	0.0498*** (2.6160)	0.9395*** (39.3355)
MOEX	0.0000 (0.0000)	0.9989*** (7606.5507)
DAX 40	0.1918*** (3.7044)	0.6323*** (6.7599)
NIKKEI 225	0.3925*** (4.5886)	0.3499*** (0.1049)
SSE	0.1953** (2.3958)	0.3783* (1.8418)

Source: Author's own estimates.

Notes: t-statistics values in parenthesis. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 3: DCC GARCH results for Indian elections

INDICES	CONDITIONAL VARIANCE	
	α_1	β_1
NIFTY 50	0.0681** (2.4646)	0.9050*** (23.9773)
S&P 500	0.1600*** (3.6890)	0.7703*** (14.3541)
FTSE 100	0.3727*** (4.3660)	0.2123** (2.0436)
MOEX	0.0000	0.9990***

	(0.0000)	(5553.96)
DAX 40	0.1890***	0.6263***
	(3.6102)	(6.1998)
NIKKEI 225	0.4143***	0.3192***
	(4.4553)	(2.5919)
SSE	0.2006**	0.3887*
	(2.2924)	(1.8241)

Source: Author's own estimates.

Notes: t-statistics values in parenthesis. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 4: DCC GARCH results for Russian elections

INDICES	CONDITIONAL VARIANCE	
	α_1	β_1
MOEX	0.1364**	0.8625***
	(2.3823)	(14.4009)
S&P 500	0.1573***	0.7949***
	(3.9333)	(18.0186)
FTSE 100	0.3533***	0.2292*
	(4.0233)	(1.7437)
NIFTY 50	0.3020***	0.2446**
	(3.6573)	(1.9769)
DAX 40	0.2021***	0.6589***
	(3.9406)	(8.2752)
NIKKIE225	0.3488***	0.3816***
	(4.4021)	(3.2207)
SSE	0.2089**	0.3850*
	(2.3805)	(1.9075)

Source: Author's own estimates.

Notes: t-statistics values in parenthesis. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 5: DCC GARCH results for Japanese elections

INDICES	CONDITIONAL VARIANCE	
	α_1	β_1
NIKKEI 225	0.2851*** (3.8114)	0.5605*** (5.9694)
S&P 500	0.1203*** (3.6693)	0.8064*** (16.6725)
FTSE 100	0.3894*** (4.4780)	0.3009*** (2.6374)
NIFTY 50	0.0893*** (3.7464)	0.9096*** (39.8573)
MOEX	0.0677*** (3.1955)	0.9312*** (46.1562)
DAX 40	0.1980*** (3.6285)	0.6623*** (6.9896)
SSE	0.0000 (0.0000)	0.9897*** (3199.7911)

Source: Author's own estimates.

Notes: t-statistics values in parenthesis. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Prior to the modeling cross market conditional dependencies, the univariate GARCH (1,1) specification in the first stage of the DCC GRACH framework assesses the conditional variance parameters, namely the baseline variance (μ), the ARCH coefficient (α) (capturing short term innovation shocks) and the GARCH coefficient (β) (capturing volatility memory).

The degree of volatility persistence in the returns is measured by the sum of the ARCH and GARCH parameters ($\alpha + \beta$). The GARCH coefficient (β) is statistically significant for all benchmark equity indices throughout the five elections under consideration, indicating that historical variance has a significant, long term impact on contemporary conditional volatility in global markets.

All stock indexes show strong short term volatility persistence, with the exception of the SSE index after the elections in the United States and Japan and the Russia after the election in the UK and India, where the short term shock coefficient (α) is statistically negligible. The estimated parameter pairs of ($\alpha = 0.0000$) and ($\beta = 0.99$) for the SSE index (post US and Japan elections) and the Russia (post UK and Indian elections) show that long term structural persistence rather than immediate post election news shocks dominated volatility in these markets, indicating a delayed or muted immediate reaction to international electoral outcomes.

When the variance shocks dissipate slowly over time when the sum of the parameters ($\alpha + \beta$) falls between 0.90 and 1.00, suggesting very high volatility persistence (Tissaoui et al., 2024). The S & P 500, Nifty 50, MOEX and SSE indices show high volatility persistence ($0.90 - 0.995$) after the US and Japanese elections, whereas the FTSE 100 and DAX 40 show moderate to high persistence. The Nikkei 225, DAX 40 and SSE show moderate to high level after the UK and Indian elections, but the S & P 500, Nifty 50 and MOEX continue to show significant persistence. Finally, the MOEX and S & P 500 exhibit considerable volatility persistence over the post Russian election period, while the other indexes have moderate to high variance persistence. In the second stage of the DCC GARCH Model, the univariate conditional variance structures lay the ground work for estimating time varying dynamic correlations.

Conclusion

This study investigated post election volatility spillovers across major global equity bourses after the 2024 “super election year” by analyzing five crucial national elections – the US, UK, India, Russia and Japan across a 350 trading day post election window using a DCC GARCH model, synthesizing the dynamic conditional correlation framework and empirical findings. According to the bivariate DCC GARCH estimations, cross border volatility transmission is very prominent over long term horizons DCC β_1 , although it is mainly muted in the short run DCC α_1 . In particular, US based post election volatility. All chosen recipient bourses (FTSE 100, Nifty 50, DAX 40, Nikkei 225 and SSE Composite) show statistically significant long run conditional correlations with the S & P 500. This highlights the systemic importance of US equity markets in global price discovery, where US political policy realignments serve as the main net transmitters of global variance shocks, while emerging and non US markets primarily serve as volatility receivers (Bala & Takimoto, 2017). In contrast, market asymmetry is demonstrated by the lack of bidirectional volatility transmission from India’s Nifty 50 to the US S & P 500. This is because stocks originating in emerging bourses have a negligible feedback effect on highly developed, liquid US markets due to differences in market depth, capital controls and time-zone differences (Yadav et al., 2023). This presents significant portfolio diversification opportunities for international institutional investors looking for uncorrelated asset exposure in emerging markets. These findings provide useful information for both market players and regulatory bodies: investors should use tactical risk mitigation strategies, such as holding period adjustments and derivative based hedging (index futures and options), to protect against long lasting post election spillovers, while keeping a close eye on Foreign Institutional Investor (FII) flows as demonstrated by FII’s net selling record 12,436 crore in Indian equities on the day of the 2024 election results. At the same time, market regulators must implement dynamic circuit breakers and liquidity safeguards to absorb external volatility transmissions from major anchor economies.

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