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Common volatility analysis in emerging stock markets

Thi Ngan Nguyen*

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Abstract

This paper investigates whether emerging equity markets share a common volatility component and reexamines the major events that have most affected these markets over the past two decades. Common volatility is defined as the exposure of financial assets/markets to common shocks in volatility that simultaneously affect a broad range of these assets or markets. We measure regional COVOL as an indicator of regional common risk and its factor loadings for emerging markets. Our empirical results indicate that COVID-19, major geopolitical events (Brexit, the US tax policy in 2025, and the ongoing Russia-Ukraine war), and global economic events (the 2008 GFC and oil market-related shocks) exert the strongest influence on the co-movement of emerging markets. Countries in the Middle East exhibit the highest exposure to regional COVOL, suggesting that investment diversification in these markets is relatively less effective at the regional level. Meanwhile, China, South Africa, and Hungary exhibit lower sensitivity.

Keywords: common volatility, co-movement, emerging markets, interconnectedness

JEL: C51, C58, G15

* SGH Warsaw School of Economics, SGH Doctoral School; e-mail: nn114401@doktorant.sgh.waw.pl.

1. Introduction

International stock market co-movement constitutes a central topic in finance research due to its significant implications for asset allocation and risk management. In the context of globalization and digitization, news or events, can be transmitted instantaneously across the world. Over time, increasing interconnectedness between financial markets has significantly diminished the potential benefits of international diversification, or even triggered heightened volatility in stock markets. In light of this, market participants must continuously evaluate various types of risk and the effectiveness of their risk management strategies. Furthermore, in recent years, the top risks have evolved, in terms of significantly heightened global trade tensions in 2025 related to US tax policy, the US presidential election in 2024, geopolitical risk of the ongoing Russia–Ukraine war in 2022, the COVID-19 pandemic, and significant setbacks in global climate efforts in 2020 and so on. These events can significantly increase global market volatility, causing more uncertainty and negatively affecting investor expectations (Gudmundsson et al. 2022). As a result, this leads to spillovers and greater disagreement concerning macroeconomic variables, increasing domestic uncertainty (Montes, Marcelino 2022; Huang et al. 2022; Jiang et al. 2023). Conflicting perceptions among economic analysts further intensify these effects (Beckmann, Geiger 2025). Therefore, understanding common volatility patterns is essential for international investors, portfolio managers, and policymakers to plan strategically.

The co-movements of stock markets are more pronounced in advanced economies (Jordà, Schularick, Taylor 2020). Recently, emerging financial markets have been catching up rapidly, attributable to factors such as higher economic openness, technological advances, and more transparent legal framework (Inaba 2020). Although globalization serves as a catalyst for financial market integration, its implications manifest themselves differently across regions and markets. The distinct characteristics, including political instability, economic policy, and stage of market maturity, differentiate emerging markets from developed markets. Furthermore, emerging markets also present significant risks in addition to their potential for high returns (Hedström et al. 2020). As these markets become increasingly integrated into the global economy, their volatility can have far-reaching implications on a global scale. Therefore, it is essential to establish a volatility index that is specifically tailored to the unique features and dynamics of emerging markets. Such an indicator would more effectively capture evolving interconnectedness and provide a more accurate reflection of events that occur within the region. Through a comprehensive analysis, we can identify the events driving emerging market movements and potential predictions of market fluctuations. In this study, based on the approach of Engle and Campos-Martins (2023), we measure the regional common volatility (COVOL) designed for emerging markets. Our objective is to identify the major events that have ‘shaken’ the emerging markets by detecting the shocks that exerted the largest impact on these stock markets. In addition, we assess the extent of emerging markets’ exposure to the regional COVOL factor. Based on these findings, the paper provides practical implications for portfolio management as well as policy insights.

Our paper makes two contributions. Firstly, to the best of our knowledge, this paper is pioneering in measuring regional COVOL and its factor loadings within emerging markets applying Engle and Campos-Martins’ (2023) approach. This proposed approach allows us to identify the most influential shocks on asset returns across emerging markets over two decades. Secondly, the paper investigates the influence of regional COVOL on financial assets and factors, providing valuable insights for asset managers. The results enhance our understanding of dynamic interconnectedness in emerging markets. It also provides practical strategies for mitigating the risks linked to substantial volatility.

The remainder of the paper is organized as follows. Section 2 reviews the literature regarding financial market co-movements. Section 3 describes the methodology and data for measuring regional COVOL. Section 4 analyses the empirical results. Section 5 concludes.

2. Literature review

It is widely documented that asset return volatilities across different markets, sectors, or countries exhibit strong co-movement (see Bollerslev et al. 2014; Miranda-Agrippino, Rey 2020; Bekaert, Hoerova, Xu 2023; Engle, Campos-Martins 2023, among others). Given the integrated nature of financial markets across countries over the past few decades (see Jordà, Schularick, Taylor 2020), it is important to understand the mechanisms driving cross-border co-movements. Engle and Campos-Martins (2023) stated that if all assets or markets are concurrently exposed to shared factors, common variation can be observed. In the literature, a variety of factors, including financial crises, changes in policy and investor regulations, financial integration, and cross-sectional country characteristics, have been investigated to examine the dynamic co-movement between equity markets. Bekaert, Hoerova and Xu (2023) investigated the transmission of monetary policy shocks as well as risk shocks[1] to asset prices in Japan, the euro region, and the US from 2000 to 2017. For monetary policy shocks, they considered both traditional events regarding formal policy decision announcements and supplementary communication events, including minutes releases of central bank meetings or any key reports, press conferences, and public speeches. They showed a pronounced global common component in risk shocks among the US, the euro area, and Japan. This component is not driven by conventional US monetary policy. Their results also confirmed that changes in global risk aversion affect all financial markets. In parallel work, Cieslak and Schrimpf (2019) investigated the effects of central bank communication events across four major monetary authorities, including the European Central Bank, the Federal Reserve, the Bank of Japan and the Bank of England. Their results provided evidence of the effects of monetary policy communications on stock returns. Auer et al. (2023) confirmed evidence for the significant role of global value chains in driving the co-movement of global equity markets. Their findings showed that real integration remains a strong and robust determinant of global equity market co-movement. Using monthly data and a dynamic factor model, Miranda-Agrippino and Rey (2020) also documented that the Global Financial Cycle, induced by US monetary policy, which is presented in strong co-movements of financial asset prices across countries. This is consistent with Kalemli-Özcan (2019), who found that monetary policy in the US has strong spillover effects in emerging markets. Hausman and Wongswan (2011) also analysed the impact of unexpected US monetary policy announcements on global equity indices. Their results confirmed that global equity markets primarily react to target surprises. They defined target surprises as unexpected changes to the target federal funds rate. On average, an unanticipated 25-basis-point cut in the federal funds rate is associated with an approximate 1% increase in worldwide equity indices. Bekaert, Hoerova and Xu (2023) documented that on average communication and traditional monetary policy shocks have a nearly equivalent role in explaining the variation in stock returns. Jordà, Schularick and Taylor (2020) stated that the co-movement in equity prices across 17 advanced economies has reached historically high levels over the past three decades. Using data

[1] Bekaert, Hoerova and Xu (2023) utilized the VIX index for the US and similar implied volatility indexes on the STOXX50 for the euro region, and on the Nikkei225 for Japan.

from 37 developed and emerging markets, Inaba (2020) identified country-specific fixed effects and time-varying factors as the key drivers of global stock market co-movements over the period 2007–2015. Focusing on Latin American stocks, Marcet (2017) demonstrated that analyst coverage networks play a significant role in explaining stock return commonalities. Chuluun (2017) investigated the influence of cross-country financial connectedness on the co-movement of international equity markets. The results indicated that countries situated at central positions in the global portfolio investment network experience heightened synchronization of stock markets. Moreover, countries central in both financial and trade networks exhibit the highest co-movement levels. Meanwhile, Gomes and Taamouti (2016) showed that the covariances between asset returns are linear functions of risk factors. Their findings confirmed that these factors account for 50 to 60% of the variation in covariances among European stocks. If asset returns are linear functions of shared factors, then volatility naturally inherits this time-varying factor structure (see Merton 1973; Fama, French 1993; Ross 2013). The idiosyncratic returns, after removing shared factors, still exhibit correlated volatilities (see Herskovic et al. 2016; Engle, Campos-Martins 2023). Herskovic et al. (2016) showed a remarkable degree of co-movement among the idiosyncratic volatilities of more than 20 thousand individual stock from 1926 to 2010. Their results implied that any economic variable associated with the history of idiosyncratic shocks can help explain expected stock returns.

Another strand of the literature provides strong evidence of co-movement of financial markets and uncertainty (see Hedström et al. 2020; Bekaert, Hoerova, Xu 2023; Herskovic, Kind, Kung 2023; Beckmann, Geiger 2025). Uncertainty is a broad concept that poses significant challenges for empirical measurement. The term reflects uncertainty regarding future developments in various social, political, and economic spheres. Global uncertainty significantly undermines expectations and heightens domestic instability. Beckmann and Geiger (2025) suggested that uncertainty is largely driven by international factors, while country-specific dynamics plays a secondary role. In addition, adjustments in expectations in the aftermath of an uncertainty shock can amplify shocks on domestic variables. Herskovic, Kind and Kung (2023) confirmed that both micro- and macroeconomic uncertainty are related to long-term movements in the equity premium. The transmission of financial shocks across borders can be exacerbated by economic linkages and integrated.

Empirical evidence indicates the existence of a common global factor driving systematic variation in equity markets. Therefore, what events determine co-movement is a key question in international finance and has important implications for diversification strategy and risk management. Research grounded in the most current data is essential for comprehensive assessment. Additionally, given the rapidly evolving landscape in finance and geopolitics, evaluating the degree to which assets and markets are exposed to common volatility factors has become increasingly critical. Engle and Campos-Martins (2023) proposed a statistical framework for identifying global common volatility. In their research, the multivariate volatility model incorporates volatility shocks that are common to all assets. Their aim is to detect those events that impact volatilities of most markets, and assess all types of broad financial risk. They conducted several tests, confirming that the global COVOL outperforms existing geopolitical measures and economic sentiment indicators.

Meanwhile, in recent years, emerging markets have attracted considerable attention from both institutional and individual investors seeking to diversify their portfolios (Badhani et al. 2022). However, investments in these markets are susceptible to various risks, including both unsystematic and systematic risks. Arreola Hernandez and Al Janabi (2020), and Choi (2024) concluded that investment

risk in these markets is higher than in advanced markets. Amid complex geopolitical conditions, global markets are under considerable stress. This heightened tension is reflected in the pricing of risk, which appears to be elevated in emerging markets and European assets (Wilson, Chang 2022). Given this context, in this paper, we adopt the approach of Engle and Campos-Martins (2023), but focus on emerging markets by measuring regional COVOL, rather than global COVOL. Based on the literature, we propose two hypotheses to be addressed.

H1: There exists a common volatility factor that drives the systematic variation in emerging equity markets.

H2: Given the substantial heterogeneity in economic development, financial openness, and institutional frameworks across emerging markets, the degree of exposure to regional COVOL varies among these markets.

3. Methodology and data

3.1. Methodology

Basic definition of key variables

According to Engle and Campos-Martins (2023), global COVOL is defined as the exposure of global financial assets to common shocks in volatility that simultaneously affect a broad range of markets. The key feature of these shocks is their ability to move financial prices globally at the same time. They may originate from a variety of sources, including both financial and non-financial events.

Regional COVOL refers to common volatility that is confined to a specific geographic region or group of markets. These shocks primarily affect the countries within that region and may differ in magnitude and timing from global shocks due to regional economic conditions, institutional structures, or local market dynamics.

COVOL model

Engle and Campos-Martins (2023) proposed the global COVOL model in the cross-sectional context, given that the squared jointly standardized residuals of returns across assets exhibit positive correlation. Their framework considers that assets across various classes or markets tend to react simultaneously to significant news events. Using this approach, modelling multiplicative volatility factors through numerical methods becomes easier to implement, while simultaneously providing a measure of geopolitical and other major risks. Using exchange traded fund (ETF) data from markets across the world, Engle and Campos-Martins (2023) identified common volatility events that led to rising volatility in all markets and label this measure global COVOL. They further demonstrated that a COVOL measure can be constructed for any collection of asset returns, different classes or sectors. For illustrative purposes, their empirical implementation included a COVOL index for US asset class returns (USCOVOL). In subsequent work, Campos-Martins and Hendry (2024) also applied the model to a set of oil and gas stocks.

Let $\mathbf{y}_t = \left(y_{1t}, \cdots, y_{Nt}\right)'$ denote an $(N \times 1)$ vector of N returns at time t. $\mathbf{f}_t \in \mathrm{R}^{K \times 1}$ is a column vector of common factors where K denotes the number of factors and w is a $(N \times 1)$ vector of weights.

The standard asset pricing model can be expressed as a factor model of the form:

$$\boldsymbol{f}_t = \boldsymbol{w}'_{t-1}\boldsymbol{y}_t \tag{1}$$

$$\boldsymbol{y}_t = \boldsymbol{y}^f + \boldsymbol{\beta}\boldsymbol{f}_t + \text{diag}\left\{\sqrt{\boldsymbol{h}_t^i}\right\}\boldsymbol{e}_t^i \tag{2}$$

where $\boldsymbol{\beta}$ is an $(N \times K)$ matrix of factor loadings measuring the sensitivity of each asset to the K common factors $\boldsymbol{f}_t$ and vector $\boldsymbol{e}_t^i \equiv \left(e_{1t}^i, \ldots, e_{Nt}^i\right)'$ contains residuals from factors while $\boldsymbol{h}_t^i \equiv \left(h_{1t}^i, \ldots, h_{Nt}^i\right)'$ is the vector of conditional variances of these residuals. The operator diag{$\boldsymbol{a}$} forms a diagonal matrix with vector $\boldsymbol{a}$ on the diagonal and 0 elsewhere.

Engle and Campos-Martins (2023) assumed that the idiosyncratic residuals, e_t^i, are uncorrelated in both time series and cross section with unit conditional variances:

$$E_{t-1}\left(\boldsymbol{e}_t^i \boldsymbol{e}_t^{i'}\right) = I \tag{3}$$

The factors have a conditional mean $\boldsymbol{\mu}^f$ and conditional covariance matrix $\boldsymbol{H}_t^f$. The standardized factors residuals are defined as:

$$\boldsymbol{e}_t^f = \left(\boldsymbol{H}_t^f\right)^{-\frac{1}{2}}\left(\boldsymbol{f}_t - \boldsymbol{\mu}^f\right) \tag{4}$$

It is assumed that the factors residuals $\boldsymbol{e}_t^f$ are mutually uncorrelated and orthogonal to the idiosyncratic residuals $\boldsymbol{e}_t^i$:

$$E_{t-1}\left(\boldsymbol{e}_t^f \boldsymbol{e}_t^{f'}\right) = I, \qquad E_{t-1}\left(\boldsymbol{e}_t^f \boldsymbol{e}_t^{i'}\right) = 0 \tag{5}$$

Thus, the combined residual vector can be expressed as:

$$\boldsymbol{e}_t = \begin{pmatrix} \boldsymbol{e}_t^i \\ \boldsymbol{e}_t^f \end{pmatrix} \tag{6}$$

Assuming that:

$$E_{t-1}\left(\boldsymbol{e}_t \boldsymbol{e}_t'\right) = I \tag{7}$$

denote ι as the vector of ones; then the conditional covariance matrix of these squared residuals is defined as:

$$E_{t-1}\left[\left(\boldsymbol{e}_t^2 - \iota\right)\left(\boldsymbol{e}_t^2 - \iota\right)'\right] \equiv \Psi_t \tag{8}$$

If Ψ contains non-zero off-diagonal elements, it implies that multiple assets will experience high volatility shocks concurrently.

To estimate global COVOL, Engle and Campos-Martins (2023) denote the global COVOL by $\sqrt{x}$ with x being a latent $(T \times 1)$ vector of strictly positive variables. Its conditional expectation and variance are given by:

$$E_{t-1}\left(x_t\right)=1 \tag{9}$$

$$E_{t-1}\left(x_t-1\right)^2=v_t \tag{10}$$

They denote $\boldsymbol{s}$ as an $N\times 1$ vector of factor loadings $\boldsymbol{s}\in \mathrm{R}^{N\times 1}$ with $s_i\in[0,1]$, and ε_{it} as i.i.d. standard normal innovations, $\varepsilon_{it}\sim \text{i.i.n.}(0,1)$.

They define a data-generating function $g\left(s_i,x_t\right)$ for the random variable e_{it} from $x_t, s_i, \varepsilon_{it}$. They assume that $g\left(s_i,x_t\right)$ is non-negative with unit conditional expectation. Therefore, e_{it} satisfies Equation 7:

$$e_{it}=\sqrt{g\left(s_i,x_t\right)}\varepsilon_{it} \tag{11}$$

where $g\left(s_i,x_t\right)\equiv s_i x_t+1-s_i$.

Consequently,

$$\begin{aligned} E_{t-1}\left[\left(e_{i,t}^2-1\right)\left(e_{j,t}^2-1\right)\right]\equiv\Psi_{ij,t}&=s_i s_j v_t, E_{t-1}\left[\left(e_{i,t}^2-1\right)^2\right]\\ &\equiv\Psi_{ii,t}=3s_i^2 v_t+2\end{aligned} \tag{12}$$

They construct sample covariance matrix Ψ, given by:

$$\begin{aligned}\Psi=\frac{1}{T}E\left[\sum_{t=1}^{T}\boldsymbol{e}_t^2\boldsymbol{e}_t^{2'}\right]=\frac{1}{T}\sum_{t=1}^{T}\Psi_t=\mathbf{s}\mathbf{s}'\overline{v}+D\\ D=\text{diag}\left\{3s_i^2\overline{v}+2\right\}\end{aligned} \tag{13}$$

with $\overline{v}=\frac{1}{T}\sum_{t=1}^{T}v_t$.

This decomposition reveals that Ψ is a factor structure with *x* as the common factor and *s* as the factor loadings. Applying principal component analysis to the empirical Ψ matrix yields estimates for *x* and *s*.

In this paper, we extend the work of Engle and Campos-Martins (2023) for regional COVOL in emerging markets. Substantial heterogeneity among emerging markets and between emerging and developed markets necessitates the construction of a regional COVOL measure and its corresponding factor loadings. The common volatility dynamics within these regions may diverge significantly from those captured by the global COVOL measure of Engle and Campos-Martins (2023). Motivated by these considerations, this study measures an emerging-market-specific COVOL index, derived from the squared standardized residuals of equity returns in these economies. Details regarding the data are provided in the following section.

3.2. Data

We employ daily adjusted closing prices of all emerging markets, spanning the period from 2 January 2005 to 25 April 2025. The emerging markets are provided by the Morgan Stanley Capital International

(MSCI) market classification (see Table 1). In addition, we also included Vietnam in our analysis. Stock index returns are measured in local currencies. Carvalhal and de Melo Mendes (2008) demonstrated that their results using volatility models are consistent for both local currency and US dollar returns. Table 2 presents the preliminary descriptive statistics, including sample mean, median, standard deviation, skewness, and kurtosis, and the Jarque-Bera test for emerging market returns.

Following Engle and Campos-Martins (2023), for each emerging market's return series, the mean equations are specified as AR(1) processes and incorporate two factors, namely the ACWI index and the first principal component. The ACWI index captures the performance of the global equity market and is provided by MSCI. For variance, a GARCH(1,1) specification is employed to capture the stylized heteroskedastic feature in financial time series. Standardized residuals for each emerging market are obtained after this process. Similarly, the two factors – ACWI and the first principal component – are modelled via AR(1)GARCH(1,1) with no external regressors included in their mean equations to derive standardized residuals for these factors. In accordance with Engle and Campos-Martins (2023), we assume that the model innovations follow a conditional normal distribution. The hybrid strategy is employed to optimize and estimate the parameters of the GARCH model through maximization of the likelihood function. Subsequently, the COVOL model is applied to all standardized residual series, capturing the common volatility dynamics across emerging markets.

The estimated residuals and volatilities for all returns are depicted in Figure 1. For comparison purposes, the lower panel of Figure 1 displays the average estimated volatilities across all emerging market returns alongside the estimated volatility of the ACWI. The daily cross-sectional mean volatility is calculated by $\sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}\hat{h}_{i,t}}$.

The 2008 global financial crisis (GFC), the European sovereign debt crisis in 2011, and the COVID-19 pandemic mark periods of very extreme shocks and very heightened volatility. According to Igan, Kutan and Mirzaei (2016), emerging markets experienced a remarkable surge in capital inflows between 2002 and 2007, leading to a robust bull market. These economies became increasingly sensitive and volatile when global economic instability emerged. Inflows dropped dramatically, accompanied by sudden capital outflows prior to the onset of the GFC in 2008. Consequently, emerging markets experienced increased volatility, largely driven by sudden and significant capital outflows. Along with shifts in global investor sentiment, market fluctuations were exacerbated.

An interesting observation for the Peruvian market is that the market experienced peak stock volatility between 2011 and 2012. This time frame coincides with the political event of the presidential election in July 2011. In addition to the widespread volatility observed during the 2008 GFC and the COVID-19 pandemic, the period of 2015–2016 witnessed significant turbulence in the Greek and Chinese stock markets. The Greek debt crisis had a profound impact on the country's stock market (Kchaou, Bellalah, Tahi 2021). In early 2016, China also experienced heightened economic volatility, marked by a sharp market sell-off (Wang et al. 2018; Ahmed, Huo 2019). It is also noteworthy that in early 2025, the ACWI index exhibited substantial volatility, coinciding with the US presidential election.

4. Empirical results

4.1. Findings

The COVOL model is now applied for the volatility standardized residuals of the 23 emerging equity return and the two factors. The averaged correlation of their squares, $\hat{\rho}_{\hat{\varepsilon}^2} = 0.052$. A statistical test assessing whether the average correlation of the squared standardized residuals differs significantly from zero is given by *t*-statistic value of $t = 15.23$. This suggests that the squared residuals are positively correlated. We perform principal component analysis and extract the loadings on the first principal component. Regional COVOL effects are then estimated using cross sectional heteroskedasticity regressions, while factor loadings are obtained from time-series heteroskedasticity regressions. The optimization algorithm converged after 18 iterations, for the sample under study, to obtain the final results of both regional COVOL and the regional COVOL factor loadings. The largest estimated values for regional COVOL are presented in Table 3. We also report the average returns across emerging market returns on the same day. A concise summary of the key events for each day is provided as well.

As shown in Table 3, emerging markets have been increasingly exposed to diverse shocks, encompassing geopolitical tension, political instability, COVID-19 pandemic, and trade war. Despite their differing origins, these events have exerted an influence on financial markets. Emerging markets are highly vulnerable, affected by both internal events and spillovers from developed markets. Previous studies show that, over time, emerging markets have transitioned from depending on regional 'bridge' markets to establishing more direct global connections, deepening their integration with the rest of the world (Chowdhury et al. 2018; Lee, Lee 2019).

Several COVID-19-related events rank among the most significant events of the past two decades. The pandemic has triggered substantial increases in emerging financial market volatility. On 26 November 2021, World Health Organization (WHO) officially announced the newly identified Omicron variant. Global stock markets subsequently experienced sharp declines due to concerns about the high transmissibility of Omicrons and its potential vaccine resistance. Consequently, emerging markets suffered significant losses in both equity and currency values, as investor risk appetite declined sharply under heightened concerns about economic disruption, renewed lockdowns, and vaccine effectiveness. On 15 March 2020, the US Federal Reserve announced an emergency interest rate reduction, lowering the federal funds rate to 0–0.25%, and launched a new round of quantitative easing (QE) in Treasury and mortgage-backed securities purchases. According to de Crescenzio and Lepers (2021), an unprecedented surge in monthly capital outflows from emerging markets was recorded in March 2020. The emergency policy measures announced on 15 March 2020 were intended to stabilize financial markets. However, they inadvertently heightened concerns regarding the severity of the global economic and financial crisis. In addition, emerging markets experienced rapid capital outflows, sharp currency depreciation, and significant declines in equity market on 16 March 2020. The CBOE Volatility Index (VIX) reached a closing value of 82.69 on 16 March, the highest level observed in its history (Davis, Liu, Sheng 2021). The Chilean stock market experienced the sharpest decline, followed by the Brazilian stock market, with corresponding decreases of 15.2% and 15%, respectively. Other emerging markets recorded more moderate losses, averaging approximately 5.8%. The Thailand stock market crash also generated major upheavals and spillover effects in other countries. On 19 December 2006, the Stock Exchange of Thailand (SET) witnessed a pronounced sell-off. The index declined by 14.84%,

triggering a temporary trading suspension – the first time such a halt occurred in its history. The panic spread regionally, with markets in Indonesia (2.85%), Malaysia (2%), Singapore (2.23%), Hong Kong, and India all suffering sharp losses (Li 2007). Another noteworthy observation is that emerging markets experienced a day of heightened trading volatility, coinciding with the immediate aftermath of the US government's enactment of sweeping tariffs on all trading partners on 2 April 2025 (CSIS 2025). The announcement intensified global market uncertainty and risk aversion. Investors were concerned about prolonged trade wars and supply chain disruptions. This induced a reallocation of capital from riskier emerging markets toward safe-haven assets. The event triggered a significant shock to emerging markets through reduced exports, capital outflows, inflation, and supply chain disruption. The overall effect resulted in heightened volatility and economic uncertainty for several emerging markets. The impact of this event persisted strongly for a week following its occurrence. Ignatenko et al. (2025) also highlighted the long-term macroeconomic consequences of these tariff policies. Their findings indicated that reciprocal retaliation leads to net welfare losses not only for the US economy, but also for the global economy as a whole. Under optimal foreign retaliation to the USTR tariff actions, US welfare is estimated to decline by up to 3.38%, while global employment is projected to contract by approximately 0.58%. Escalating trade tensions and retaliatory measures adversely affect the global economy. Similarly, Auclert, Rognlie and Straub (2025) confirmed that trade wars associated with tariffs exacerbate trade imbalances and deepen recessions.

In addition, emerging markets reacted to the announcement and launched the BRICS Development Bank on 30 November 2009. However, the impact of this event is mixed. While most Asian markets recovered after the GFC, the Dubai stock market experienced its largest one-day drop of the year, plunging approximately 8.7% on that day. The Gulf emirate of Dubai sparked global concern about its state-owned conglomerate, Dubai World, to meet its debt obligations. Consequently, the equity markets of the United Arab Emirates (UAE) experienced a marked decline. The Russian-Ukraine war exerted a pronounced adverse impact on the market. As both countries are key global suppliers, the Russian--Ukraine war precipitated a sharp surge in commodity prices, particularly in the energy and agricultural sectors. Global risk sentiment deteriorated, triggering capital outflows from emerging markets as investors sought safer assets. Sanctions on Russia led to financial volatility, particularly for countries with economic links to Russia. The 2008 GFC originating in the US similarly exerted substantial adverse spillovers to emerging markets. Escalating trade war concerns on 11 October 2018 triggered pronounced volatility and capital sell-offs in emerging markets, particularly in economies closely linked to China or heavily dependent on exports. The oil price war also had a pronounced negative impact. On 9 March 2020, Saudi Arabia and Russia failed to reach an agreement to cut oil production, triggering a sharp plunge in oil prices. Crude oil prices dropped by nearly 30% in a single day – the largest drop since the 1991 Gulf War. The plunge in oil prices caused severe shocks across global financial markets. Combined with growing fears of the COVID-19 pandemic, it triggered the Black Monday stock market collapse on 9 March 2020. Table 3 further illustrates the average returns on days characterized by high regional COVOL. The majority of these returns are negative, indicating large volatility is predominantly associated with adverse news in all emerging markets.

Figure 2 illustrates how the regional COVOL index fluctuates over time. This index reflects the common volatility of emerging markets in response to various events. Notably, as observed in Figure 2, the regional COVOL index exhibits occasional sharp spikes, reflecting episodes of synchronized volatility across multiple emerging markets. However, the periods of heightened

common volatility among these markets are typically short-term, resulting in a rapid decline of the index shortly thereafter. This observation is reasonable. In reality, emerging markets are highly heterogeneous in terms of economic structures, political environments, financial market depth, and monetary policies. As a result, they are subject to distinct risk profiles and idiosyncratic shocks. They often do not move in a synchronous manner. Consequently, when one market experiences substantial volatility, others may remain relatively stable, leading to a low level of group-level common volatility.

During significant global financial events – such as the US tax policies in April 2025, the outcome of US 2024 elections, or the COVID-19 pandemic – emerging markets tend to exhibit greater co-movement. These events increase the variance of the common factor, resulting in pronounced spikes in common volatility among emerging markets. Once markets absorb the information and adjust to the new conditions, the responses across different emerging markets disperse, causing the common volatility to decline rapidly. Furthermore, government interventions and policy responses differ significantly across countries (Reuters 2025; Chang, Feng, Zheng 2021). To stabilize the domestic financial market, their governments may implement a range of measures, including monetary easing, capital flow restrictions, or fiscal support. Such country-specific policy actions further reduce the degree of synchronized volatility across markets.

It is worth highlighting that a low level of regional COVOL should not be misinterpreted as indicating low overall volatility in emerging markets. This index reflects the synchronized volatility across these heterogeneous markets. Individual markets may still experience substantial idiosyncratic volatility, even when the aggregate measure of common volatility is low.

Figure 2 also incorporates the VIX index for comparison with the regional COVOL index. Periods of pronounced spikes in both the regional COVOL and VIX indices are highlighted using an orange background. The VIX index exhibits a smoother trajectory, which can be explained by the fact that the VIX measures the expected volatility of the US equity market only, whereas the regional COVOL index captures the degree of co-movement among several heteroskedastic emerging markets. Nevertheless, during episodes of extreme market shocks, both indices exhibit dramatic increases.

Interestingly, during the 2008 GFC, although both indices recorded substantial spikes, the timing of these peaks did not align perfectly. Emerging markets experienced heightened volatility even prior to the official onset of the GFC in the US. The Thai stock market crash in late 2006 had already exerted a significant impact on emerging markets, especially in Asia. Prior to 2008, emerging markets benefited from growth and investment. However, they remained highly vulnerable due to weak financial systems, deficiencies in governance, and dependence on volatile foreign capital. These underlying fragilities contributed to episodes of financial instability across emerging markets well before the GFC fully materialized. Historical evidence indicates that countries with weak corporate governance are prone to more severe declines in asset prices (Johnson et al. 2000). Emerging markets inherently face structural weaknesses and are highly sensitive to external shocks. Kaminsky and Reinhart (1999) suggested that crises occur as the economy enters a recession, following a prolonged boom in economic activity that was fuelled by credit and capital inflows. Gaytan and Rancière (2003), and Aghion, Bacchetta and Banerjee (2004) emphasized that 'middle income' economies or countries at 'an intermediate level of financial development' are most vulnerable. Furthermore, Igan, Kutan and Mirzaei (2016) state that a substantial outflow of capital from emerging markets occurred in 2007, preceding the formal outbreak of the GFC in the US. This sequence of events accounts for the observed temporal misalignment between the two indices.

In contrast, more recent geopolitical events – including Brexit, the US-China trade tensions, the COVID-19 pandemic, the Russia–Ukraine war, the 2024 US presidential election, and the 2025 US tax policy – appear to have affected both the VIX and the regional COVOL index almost simultaneously, leading to nearly concurrent spikes in these measures of volatility.

Lastly, the estimated factor loadings and variance weighted loadings for the analysed countries are reported in Table 4, ranked in descending order. By assumption, the factor is uncorrelated with other idiosyncratic shocks. The results reveal that the Gulf Cooperation Council countries – namely the UAE, Saudi Arabia, and Qatar – have higher loadings on the regional volatility factor. This suggests that these markets demonstrate more sensitive to regional COVOL shocks. Interestingly, all three countries are located in the Middle East, a region highly sensitive to geopolitical developments and oil market fluctuations. On the other hand, markets with lower factor loadings such as China, South Africa or Hungary appear comparatively less sensitive. It is noteworthy that China ranks among the countries least affected by regional COVOL, which may be explained by the isolation of its stock market from the rest of the world. In our opinion, this finding is aligned with expectations, given geopolitical differences, capital controls and regulations, and restrictions on foreign investors in China (see Chen et al. 2010; Kenett et al. 2012; Zhang 2022). The substantial governmental interventions and restrictions have contributed to the observed decoupling of the Chinese market from the rest of the world. In the context of asset allocation, portfolio managers and international investors consider the potential benefits of diversification within and across countries. To diversify and reduce the impact of regional COVOL on portfolio variance, markets with smaller loadings on the regional COVOL should be assigned higher weights, whereas markets with larger loadings should receive lower weights.

From columns 4–9 of Table 4, we re-estimate the COVOL model separately for each subregion Americas, EMEA, and APAC – to obtain regional COVOL loadings individually for each region. As expected, the magnitude of the loading parameters tends to increase when the number of time series included in the estimation decreases. The assumption, which requires the sum of squared loadings to equal one, implies that expanding the cross-section naturally reduces the average loading. Our findings indicate that the relative ordering of countries based on their regional COVOL loadings remains highly stable across regions. It implies that the ranking is robust to changes in cross-sectional dimension.

Focusing on the EMEA region, the dispersion in regional COVOL loadings is particularly pronounced, ranging from approximately 20% to 36%. The Gulf Cooperation Council countries exhibit substantially higher loadings compared with emerging European markets. This implies that these countries are more exposed to regional volatility shocks. This pattern is consistent with the findings for the full emerging-market sample. Two main reasons may account for this heightened exposure. We argue that the region is highly sensitive to political shocks and oil price shocks. Al Refai, Zeitun and Eissa (2022) confirmed that the GCC is highly sensitive to global oil market shocks during the pandemic. Umar, Trabelsi and Zaremba (2021) also found that demand shock and risk shock are the main contributors to the connectedness between equity markets and oil shocks in the GCC. These factors contribute to a consistently stronger responsiveness of Middle Eastern emerging markets to common volatility movements.

In contrast, markets such as Turkey, Poland, Hungary, and South Africa display much lower regional COVOL loadings. Therefore, these markets are less sensitive to contemporaneous regional volatility factor. In recent years, the Polish equity market has emerged as one of the best-performing markets in Europe, with the WIG index rising by more than 40% and nearly tripling from its

2022 trough (The Economist 2025). In addition, Gunay and Can (2022) confirmed that the extent of stress exposure in Turkey remains relatively low. Agyei (2023) also found that Turkish stocks possess significant diversification potential for investors. Our results suggest that investors may benefit from diversification across countries with less sensitivities to regional COVOL.

A similar degree of dispersion in COVOL loadings is observed within the APAC region. Taiwan, Indonesia, and Thailand display relatively high sensitivity to regional COVOL, indicating greater vulnerability to common regional volatility shocks. Interestingly, the results again highlight the distinct behaviour of the Chinese equity market. Compared to other markets, China remains relatively insulated from the regional COVOL index despite being the region's largest economy. By contrast, the sensitivity to regional COVOL among emerging markets in the Americas appears more homogeneous, with most countries exhibiting similar loadings. This suggests that regional volatility shocks in the Americas may be more broadly distributed across markets.

4.2. Practical implications

Firstly, equity markets are highly sensitive to fluctuations in different states of global and regional uncertainty (Kirci Altinkeski et al. 2024). These states may also have a significant impact on the linkages among individual markets. Furthermore, Caldara and Iacoviello (2017) documented that increases in geopolitical risk depress economic activity and stock returns and increase capital outflows in emerging countries. In light of this context, the regional COVOL index can be incorporated into a cross-quantilogram framework to investigate the quantile dependence among emerging equity markets under different states of regional volatility. By focusing on emerging markets, employing regional COVOL – alongside other uncertainty indicators, including the VIX, Economic Policy Uncertainty (EPU), and the Geopolitical Risk Index (GPR) – offers a more context-appropriate representation of the risk environment faced by these emerging markets. For instance, Kiss, Alipanah and Sallai (2024) confirmed that these Central-Eastern European stock markets exhibited strong intra-regional interactions and were significantly affected by shocks from major Western European stock markets (Germany, Austria, France, and the Netherlands). Therefore, these measures provide a comprehensive view of the underlying cross-market dependence across the emerging markets.

Secondly, the most extreme events typically tend to affect all assets and markets simultaneously, exerting a substantial impact on investment portfolios. These extreme events are inherently unpredictable. Meanwhile, conventional diversification does not reduce their impact (Engle, Campos--Martins 2023). Therefore, recognizing that certain assets and markets are more exposed to such shocks than others provides a valuable tool for reducing risk of portfolio. To mitigate negative impacts, when assets or markets exhibit the same variance and expected return, portfolio managers can overweight those that are less sensitive to extreme events, thereby enhancing portfolio optimization. To illustrate, consider a simple scenario involving two uncorrelated assets (asset 1 and asset 2) that exhibit identical variances and expected returns. Only asset 1 is subject to exposure from regional COVOL. We have:

$$y_{1,t} = \sqrt{x_t}\varepsilon_{1,t} \quad \text{and} \quad y_{2,t} = \varepsilon_{2,t}; \text{ where } \varepsilon_{1,t},\ \varepsilon_{2,t} \sim N\left(0,\ \sigma^2\right) \quad \text{and} \quad x_t \sim D\left(1, k\right)$$
$$\text{Var}\left(y_{1,t}\right) = \text{Var}\left(\sqrt{x}\varepsilon_{1,t}\right) = E\left(x_t\right)\text{Var}\left(\varepsilon_{1,t}\right) = \sigma^2 \tag{14}$$

with the assumption $E(x_t)=1$.

$$\mathrm{Var}(y_{2,t})=\mathrm{Var}(\varepsilon_{2,t})=\sigma^2 \tag{15}$$

The variance of the portfolio can be derived as follows:

$$\sigma_p^2=w_1^2\sigma^2+w_2^2\sigma^2+2w_1w_2\mathrm{Cov}_{12}=\ w_1^2\sigma^2+w_2^2\sigma^2 \tag{16}$$

with the assumption $\mathrm{Cov}_{12}=0$.

Within the framework of Markowitz's mean-variance model, to construct a portfolio with a minimum variance portfolio, we have: σ_p^2 min $\Leftrightarrow$ $\sigma_p^2=\sigma^2/2$ at $w_1=w_2=½$.

The expected return of the portfolio can be obtained:

$$E(y_{p,t})=\frac{1}{2}y_{1,t}+\frac{1}{2}y_{2,t}=\frac{1}{2}\sqrt{x_t}\varepsilon_{1,t}+\varepsilon_{2,t} \tag{17}$$

Markowitz's model focuses on the first two moments of the return distribution (mean and variance). Samuelson (1970) emphasized the importance of incorporating higher-order moments to more accurately capture the stock market behaviour. The study of portfolio selection models involving the skewness and kurtosis has emerged as a significant direction (see Joanes, Gill 1998; Li, Zhang 2019; Mandal, Thakur 2024). Incorporating kurtosis, we extend our portfolio analysis to account for the fourth central moment of the portfolio return distribution. Kurtosis measures the degree of presence of outliers and infers about the heavy-tailed or light-tailed behaviour of the portfolio return distribution. The kurtosis of portfolio – denoted by $K[y_p]$ – is defined as: $K[y_p]=E\left[\left(y_p-E[y_p]\right)^4\right]$.

Given the aforementioned assumptions, we have:

$$\begin{aligned}K[y_p]&=\left(\frac{1}{2}\right)^4 E\ \ (y_1)^4+\left(\frac{1}{2}\right)^4 E\ \ (y_2)^4+6\left(\frac{1}{2}\right)^2\left(\frac{1}{2}\right)^2\mathrm{Var}(y_1)\mathrm{Var}(y_2)=\\&=\frac{3\sigma^4(1+k)+3\sigma^4+6\sigma^4}{16}=\frac{3\sigma^4(4+k)}{16}\end{aligned} \tag{18}$$

Therefore,

$$\frac{K[y_p]}{\mathrm{Var}(y_p)}=\frac{3\sigma^4(4+k)}{16}\cdot\frac{4}{\sigma^4}=\frac{3}{4}(k+4) \tag{19}$$

A large kurtosis value implies that the portfolio is subject to a high probability of having extreme returns on both sides. In our case, asset 1 exposed to regional COVOL carries an additional source of systematic volatility specific to the region. Consequently, this exposure amplifies its contribution to overall portfolio risk relative to asset 2, which is not exposed. This illustration highlights the importance of accounting for regional volatility factors into portfolio construction, particularly within markets where regional shocks exert a significant impact.

Thirdly, our results can provide valuable guidance for policy-making. Countercyclical capital buffers are important instruments within the macroprudential tools, proposed by the Basel Committee on Banking Supervision. They are designed to mitigate the amplification of economic shocks by ensuring that banks maintain additional capital to absorb potential losses during periods of stress. Based on the observed sensitivity of specific markets to the regional COVOL, policymakers may adjust regulatory capital requirements accordingly. In particular, for countries that are especially exposed to such shocks, higher countercyclical capital buffers should be considered during stress periods. Implementing these measures would strengthen the resilience of financial institutions and enhance the capacity of markets to withstand extreme events.

5. Conclusion

Global financial markets have become increasingly interconnected, with cross-border linkages amplifying the transmission of shocks and risks. This heightened interconnectedness is attributable to both structural and technological developments. Such trends have increased the vulnerability of global markets, underscoring the need for robust risk management. The effectiveness of international diversification is fundamentally contingent upon the degree of correlation among global equity markets. Diversification strategies are most effective when inter-market correlations are low. However, these correlations tend to rise during period of crises, limiting the potential benefits of diversification. As emerging markets become more deeply integrated into the global system, understanding the dynamics of volatility is essential. Following Engle and Campos-Martins (2023), this paper provides a systematic analysis of regional risks affecting 23 emerging markets by utilizing regional COVOL measurement. When squared standardized residuals for a broad range of markets are high, regional COVOL tends to be large. Therefore, the COVOL indicator can measure the magnitude of shocks to volatility that are common across all markets in the portfolio. Our empirical results identify regional COVOL effects stemming from the COVID-19 pandemic as well as global economic, financial, and political events. Shocks associated with the COVID-19 pandemic exert the most pronounced impact on the co-movement of emerging markets. The pandemic not only triggered unprecedented disruptions in global trade, capital flows, and supply chains, but also heightened market uncertainty and volatility across countries. Additionally, as the world's largest economy, the US tariff policies implemented in April 2025 (J.P. Morgan Global Research 2025) significantly influenced investor sentiment, fostering higher co-movement among emerging markets. Other major events, such as the 2008 GFC and geopolitical events – including the Russia-Ukraine war and Brexit – have also substantially shaped common volatility in these markets.

Finally, empirical results reveal that emerging markets exhibit heterogeneous exposure to regional volatility factors. Countries in the Middle East demonstrate the highest exposures to regional shocks. In contrast, China, South Africa, Hungary, and Turkey are among the least affected. Incorporating regional COVOL as an additional criterion in portfolio optimization can reduce extreme risks. From the portfolio managers and investors' perspective, this provides a more comprehensive understanding of risks and opportunities. For policymakers, such insights help to design effective policy responses to mitigate global adverse effects and maintain financial stability and economic growth.

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Appendix

Table 1
Emerging markets under investigation

Latin Americas	EMEA	APAC
Brazil	Czech Republic	China
Chile	Egypt	India
Mexico	Greece	Indonesia
Peru	Hungary	Korea
	Poland	Malaysia
	Qatar	Philippines
	Saudi Arabia	Taiwan
	South Africa, Turkey, UAE	Thailand

Notes: EMEA – Europe, Middle East, and Africa, APAC – Asia Pacific.

Source: Morgan Stanley Capital International (MSCI). MSCI classifies markets according to three criteria: economic development, market size and liquidity, and the degree of market accessibility.

Table 2
Descriptive statistics

Markets	Median	Mean	Std. dev.	Skewness	Kurtosis	JB	ADF
Brazil	0.0007	0.0002	0.0170	-0.3406	7.8975	11,751***	-19.0275***
Chile	0.0004	0.0004	0.0110	-0.2676	13.6418	34,853***	-18.2561***
Mexico	0.0006	0.0004	0.0117	-0.0610	6.2138	7,224***	-16.8772***
Peru	0.0005	0.0004	0.0141	-0.5358	11.1028	23,267***	-13.6752***
Europe, Middle East, and Africa (EMEA)							
Czech Republic	0.0006	0.0002	0.0129	-0.6631	17.1585	60,206***	-20.7254***
Poland	0.0005	0.0003	0.0124	-0.7262	7.6469	12,307***	-36.8294***
Greece	0.0008	-0.0001	0.0185	-0.5384	8.2873	14,065***	-12.7841***
Hungary	0.0006	0.0004	0.0148	-0.4166	8.4730	14,692***	-18.726***
Turkey	0.0010	0.0007	0.0179	-0.2685	3.4856	2,516***	-24.8376***
UAE	0.0003	0.0003	0.0113	-0.2179	11.2819	21,134***	-16.3539***
Qatar	0.0003	0.0002	0.0129	-0.3944	8.5746	12,010***	-25.5806***
Saudi Arabia	0.0010	0.0002	0.0143	-0.9401	11.3231	19,246***	-15.4621***
Egypt	0.0011	0.0006	0.0159	-0.9522	8.5651	12,101***	-11.0245***
South Africa	0.0008	0.0004	0.0130	-0.1786	4.9443	4,984***	-19.9093***
Asia Pacific (APAC)							
China	0.0006	0.0003	0.0163	-0.4717	4.222	3,486***	-42.2605***
India	0.0009	0.0005	0.0135	-0.2094	11.8659	26,915***	-10.7456***
Indonesia	0.0010	0.0004	0.0125	-0.5690	8.5788	14,121***	-13.5285***
Korea	0.0006	0.0002	0.0122	-0.4510	8.6923	14,566***	-13.3002***
Malaysia	0.0002	0.0001	0.0073	-0.8255	13.0541	32,909***	-32.5201***
Philippines	0.0006	0.0003	0.0129	-0.9269	10.4125	21,179***	-13.6986***
Taiwan	0.0007	0.0002	0.0113	-0.4565	4.2176	3,501***	-14.0132***
Thailand	0.0005	0.0002	0.0117	-1.2395	18.9331	68,434***	-16.8486***
Vietnam	0.0008	0.0003	0.0141	-0.3595	2.1276	971***	-22.4822***

Notes:
JB denotes the Jarque-Bera normality test statistic, and ADF is the Augmented Dickey-Fuller test statistic.
The optimal lag structure for the ADF test was selected based on the AIC.
Symbol *** indicates statistical significance at the 1% level.

Table 3
Largest values of the estimated squared regional COVOL and the corresponding dates

Date	Regional COVOL	$\overline{r}_t^{EM}$	Events
26 November 2021	106.6103	-2.083	Omicron variant sparks global market turmoil
19 December 2006	49.8910	-1.7869	Thailand Stock Market crash and emergency controls
23 January 2008	28.7354	0.3493	MSCI Barra announced and opened consultations on changes to how countries are classified in the MSCI Equity Indices
7 April 2025	28.3386	-2.8317	Historic global equity market crash after the US government enacted sweeping tariffs
5 August 2024	27.2233	-3.4107	July 2024 US jobs report and unwinding of yen-funded carry trades
30 November 2009	26.3936	0.0624	Launch of the BRICs Development Bank (the New Development Bank)
24 February 2022	23.3532	-3.0564	Russia's invasion of Ukraine
3 April 2025	22.5815	-1.5199	First day after the US government enacted sweeping tariffs
9 March 2020	21.2568	-6.9514	Black Monday due to coronavirus fears
28 February 2007	18.5643	-1.1665	US market falls after Chinese sell-off
8 April 2025	17.8120	0.1616	One week after the US government enacted sweeping tariffs
11 October 2018	17.6805	-2.1061	US-China trade tensions
17 February 2009	17.3749	-3.1032	The American Recovery and Reinvestment Act of 2009 (Recovery Act) was signed into law by President Obama
27 October 2008	16.0715	-3.6404	Global stock market turmoil
30 January 2020	15.2979	-0.7489	WHO declared the novel coronavirus (COVID-19) outbreak a Public Health Emergency of International Concern (PHEIC)
16 March 2020	14.6678	-6.6805	Black Monday II related to COVID-19 pandemic
3 June 2024	14.6271	0.554	OPEC+ announced plans to phase out voluntary production cuts. Announcement of the first-ever female president in Mexico
27 June 2016	14.3897	-0.5963	Brexit-induced chaos and pound plunge
12 March 2020	14.2285	-7.71	Black Thursday due to COVID-19 pandemic and the European Central Bank decided not to cut interest rates, despite market expectations
10 March 2008	14.0741	-1.8138	Concerns about Bear Stearns' liquidity crisis

Notes:
The average return of emerging markets (r_t^{EM}) on the same day is also shown in third column. A brief description of the key events for each day is also provided.

Table 4
Estimated regional COVOL loading $\hat{s}_i$ and variance weighted loading $\hat{s}_i\hat{\sigma}_i$ for each emerging market

EMs/factors	All EMs		America		EMEA		APAC	
	$\hat{s}_i$	$\hat{s}_i\hat{\sigma}_i$	$\hat{s}_i$	$\hat{s}_i\hat{\sigma}_i$	$\hat{s}_i$	$\hat{s}_i\hat{\sigma}_i$	$\hat{s}_i$	$\hat{s}_i\hat{\sigma}_i$
PC1	0.2837	0.8725	0.4528	1.8718	0.3665	2.5754	0.3708	2.1065
UAE	0.2511	0.2210	–	1	0.3395	0.8569	–	–
Saudi Arabia	0.2475	0.2418	–	–	0.3121	0.9330	–	–
Taiwan	0.2438	0.2008	–	–	–	–	0.3392	0.6977
Qatar	0.2389	0.2429	–	–	0.3447	0.9941	–	–
Malaysia	0.2342	0.1286	–	–	–	–	0.2857	0.4857
Indonesia	0.2326	0.2083	–	–	–	–	0.3328	0.7899
Thailand	0.2297	0.1968	–	–	–	–	0.3241	0.7839
Mexico	0.2227	0.1959	0.4024	0.6406	–	–	–	–
Czech	0.2116	0.1694	–	–	0.2767	0.7259	–	–
Peru	0.2109	0.2163	0.4087	0.8945	–	–	–	–
India	0.1934	0.1796	–	–	–	–	0.2653	0.9054
ACWI	0.1892	0.2011	0.4002	1.0632	0.2563	1.0631	0.2887	1.0631
Chile	0.1881	0.1580	0.4055	0.6755	–	–	–	–
Korea	0.1778	0.1462	–	–	–	–	0.2851	0.7076
Greece	0.1764	0.2447	–	–	0.2871	1.2968	–	–
Brazil	0.1691	0.2120	0.3757	0.8805	–	–	–	–
Poland	0.1665	0.1379	–	–	0.2572	0.7666	–	–
Philippines	0.1643	0.1639	–	–	–	–	0.2851	0.9255
Vietnam	0.1591	0.1922	–	–	–	–	0.2303	1.1929
Egypt	0.1523	0.2049	–	–	0.2933	1.3120	–	–
Turkey	0.1509	0.2166	–	–	0.2576	1.3688	–	–
Hungary	0.1433	0.1505	–	–	0.2198	0.9609	–	–
South Africa	0.1318	0.1121	–	–	0.2059	0.8531	–	–
China	0.1202	0.1671	–	–	–	–	0.2835	1.3314

Figure 1
Volatility of emerging markets

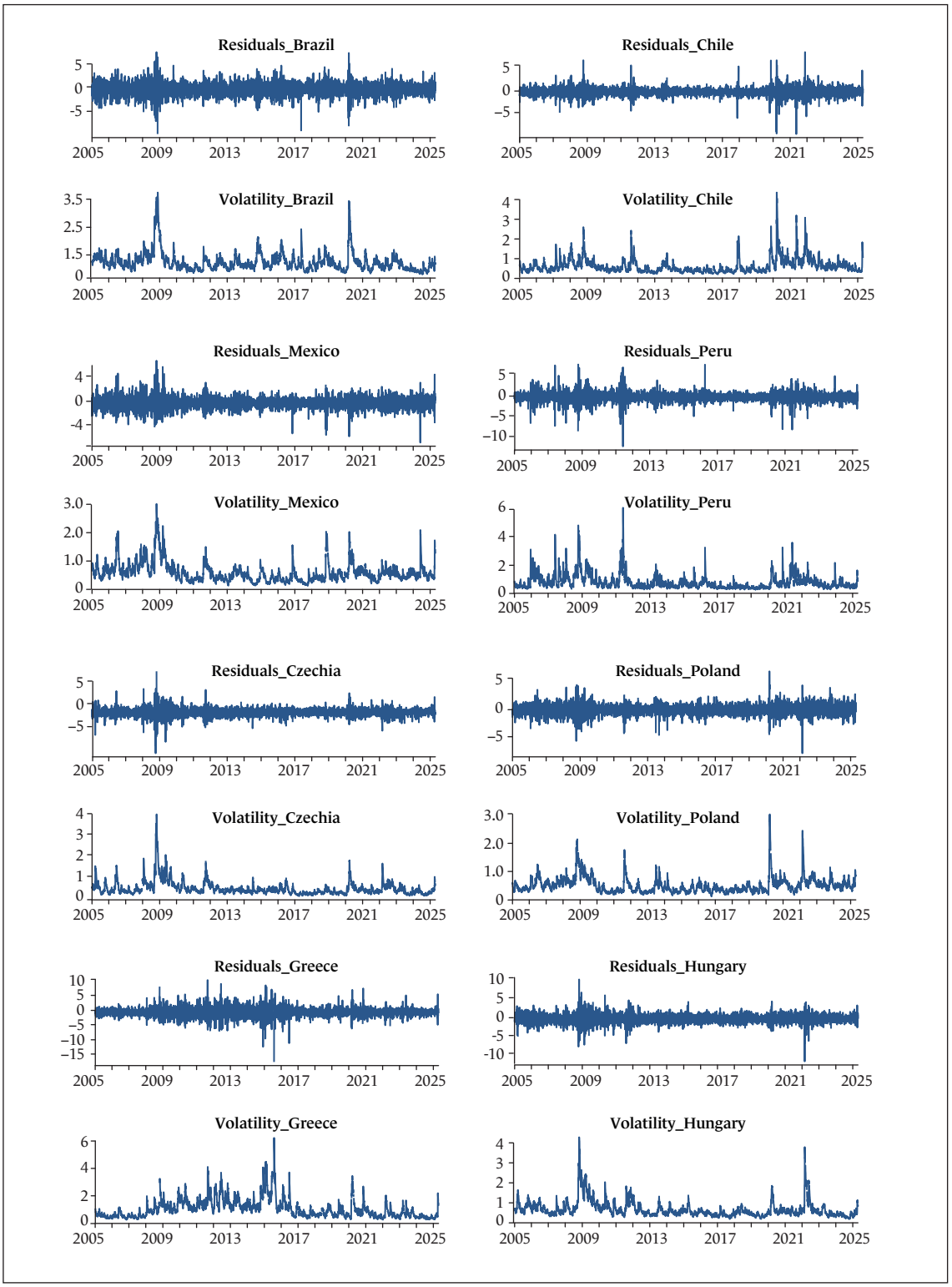


Figure 1, cont'd

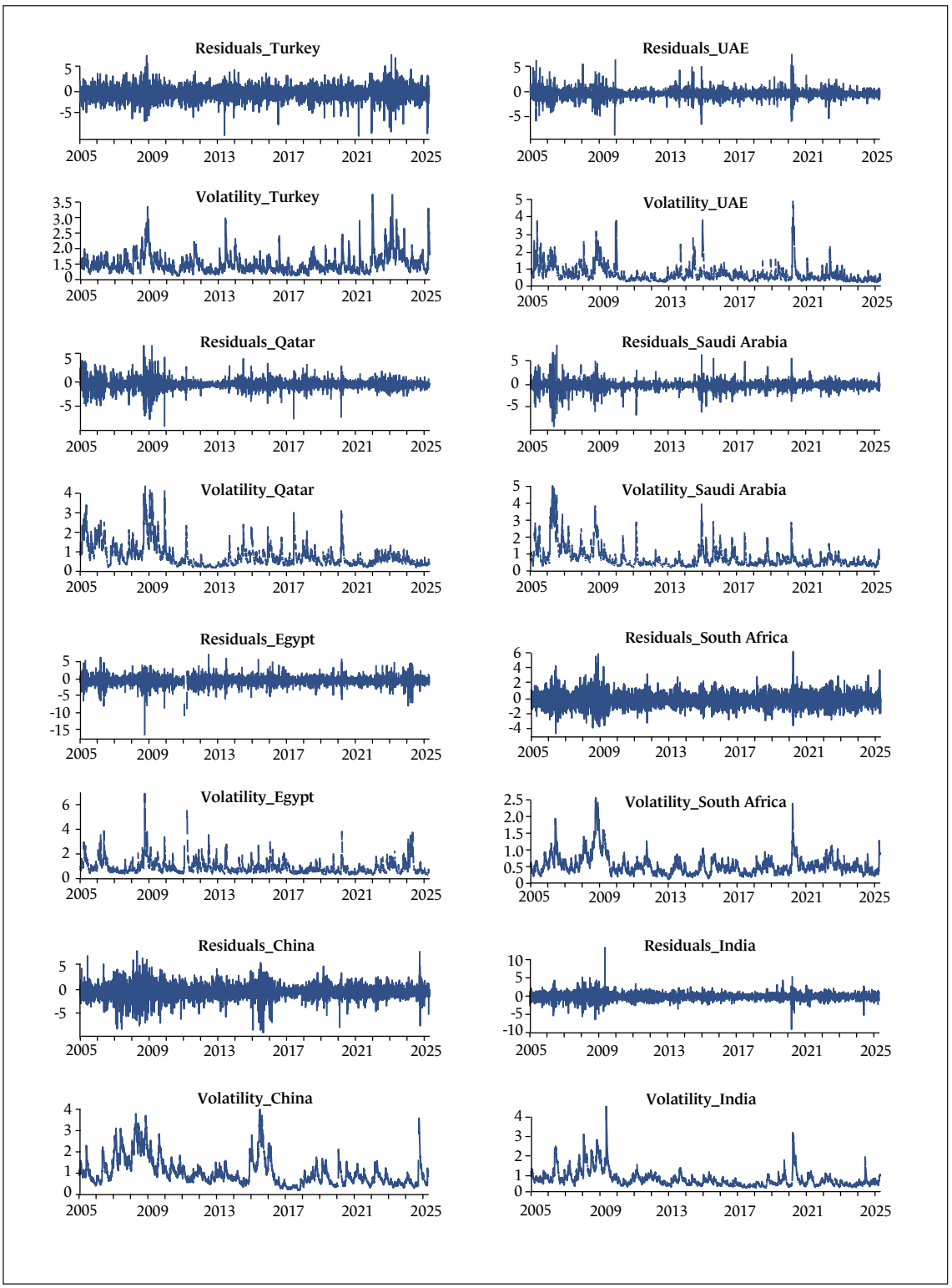


Figure 1, cont'd

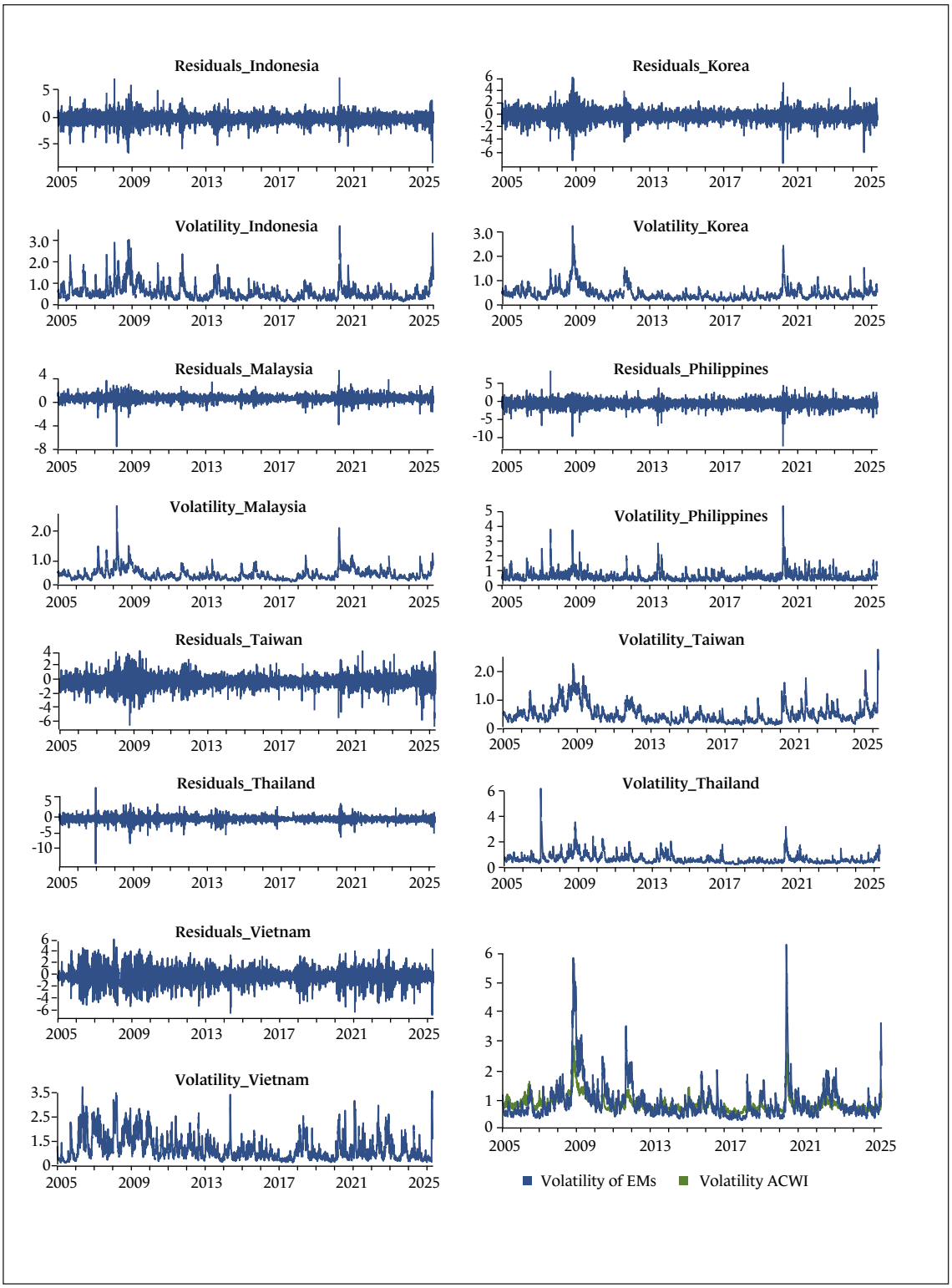
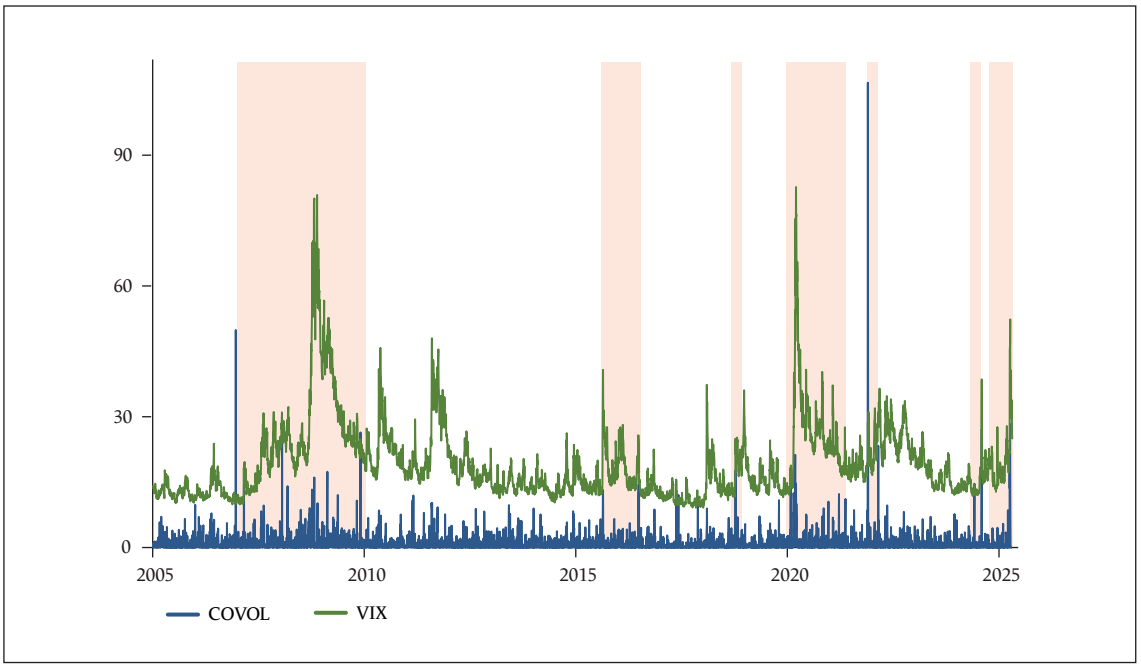


Figure 2
Comparing regional COVOL versus VIX



Analiza wspólnego komponentu zmienności na wschodzących rynkach akcji

Streszczenie

Wspólny komponent zmienności (COVOL) odgrywa kluczową rolę w zarządzaniu ryzykiem systemowym oraz w utrzymaniu globalnej stabilności finansowej. Zmienność kursów akcji jest ściśle powiązana z kanałem transmisji, za pomocą którego na rynek giełdowy dochodzą sygnały wywołane globalnymi szokami zewnętrznymi. Badania empiryczne wskazują, że w długim okresie na globalnych rynkach finansowych rynki akcji zachowują się symetrycznie, tzn. współzależność między nimi wywołuje zmiany kursów idące w tym samym kierunku (*co-movement*). Z tego względu można mówić o wspólnym komponencie zmienności. Engle i Campos-Martins (2023) zaproponowali globalny model COVOL w ujęciu przekrojowym. W swojej koncepcji wyszli z założenia, że aktywa z różnych klas oraz różnych rynków mają tendencję do jednoczesnej i symetrycznej kierunkowo reakcji w odpowiedzi na globalne szoki zewnętrzne lub istotne wydarzenia informacyjne.

W niniejszym artykule, wykorzystując ogólną koncepcję Engle'a i Campos-Martinsa (2023), wyliczamy regionalne wskaźniki COVOL jako wyznaczniki wspólnego ryzyka typowego dla danego regionu oraz łącznie dla grupy rynków wschodzących. Empiryczne wyniki wskazują, że takie czynniki jak pandemia COVID-19, ważne wydarzenia polityczne (np. brexit, polityka podatkowa USA w 2025 r. oraz trwająca wojna rosyjsko-ukraińska), a także globalne wydarzenia gospodarcze (np. światowy kryzys finansowy z 2008 r. i wstrząsy związane z rynkiem ropy naftowej) wywierają najsilniejszy wpływ na wspólny komponent zmienności na wschodzących rynkach akcji. Ponadto kraje Bliskiego Wschodu wykazują największą ekspozycję na regionalny indeks COVOL z uwagi na to, że ich gospodarki są ściśle związane ze wspólnym czynnikiem rozwojowym, jakim jest eksport ropy naftowej. Może to sugerować, że na poziomie regionalnym dywersyfikacja inwestycji portfelowych na tych rynkach jest mniej efektywna. Warto również zauważyć, że Chiny plasują się wśród krajów najmniej dotkniętych regionalnym wskaźnikiem COVOL, mimo że są drugą co do wielkości gospodarką świata. Wynik ten można wyjaśnić izolacją chińskiego rynku akcji od reszty świata. Regionalne modele COVOL są źródłem informacji dla inwestorów i decydentów politycznych.

Słowa kluczowe: COVOL, współzmienność, rynki wschodzące, współzależność