5 FROM PANDEMIC TO WAR: SYSTEMIC RISK SPILLOVERS ACROSS GLOBAL CRISES FROM THE PERSPECTIVE OF INTRADAY VOLATILITY DYNAMICS

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Abstract

The paper examines the dynamics of financial market volatility and systemic risk during major crisis episodes over the period 2019-2025 using high-frequency intraday data for a broad set of international stock market indices, and proposes a high-frequency, volatility-based indicator designed to signal the emergence of systemic risk. Covering major global and regional stress episodes - including the COVID-19 crisis, the Russia - Ukraine war, and the subsequent energy and inflation shocks - and using five-minute data, the analysis employs a parametric Realized GARCH framework and shows that high-frequency estimates of conditional volatility and volatility shocks provide timely and informative insights into the onset, severity, and cross-market transmission of financial stress. Empirical results reveal that major crises, notably the COVID-19 pandemic and the Russia-Ukraine war, are associated with sharp and persistent increases in volatility across global equity markets, underscoring the suitability of high-frequency volatility for real-time stress monitoring. The paper also proposes a systemic risk indicator designed to detect the early stages of turbulent periods that may evolve into financial crises. The empirical results show that volatility estimated from high-frequency data exhibits pronounced and timely responses to major international shocks and that certain benchmark and regional indices consistently act as leading indicators. In particular, increases in conditional volatility in major global markets and in neighboring countries precede similar developments in small open economies, highlighting the dominant role of international spillovers in shaping domestic financial stress. The findings suggest that the proposed volatility-based systemic risk indicator can provide valuable early warning signals for policymakers and market participants, enabling more timely and informed responses to emerging systemic risks for better systemic risk monitoring and macroprudential policy analysis.

Keywords: *Financial Crises; Volatility; High Frequency; Realized GARCH; Systemic Risk; Spillovers; COVID-19; Russia-Ukraine; Inflation Shock; Energy Crisis*

JEL Classification: C5, C10; C22, F3, G1

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1. Introduction

The research on financial stress and stress-induced shifts in the fundamental properties of financial market data has spurred considerable attention among policymakers, practitioners, and researchers. It has been a long debated topic that evolved along the years, aiming to better estimate and forecast crises and capital flights, for a better timely response at the policy level. A comprehensive understanding of these dynamics is essential for strengthening resilience to the amplitude and frequency of crisis episodes, during which established hedging relationships may break down, contagion effects transmit volatility across markets beyond conventional expectations, and uncertainty regarding the near-term economic trajectory is markedly elevated.

The existing literature demonstrates that financial market data can function as a critical instrument for identifying and anticipating periods of crisis, systemic risk, and economic recession, while also providing insight into their underlying determinants and interrelations with other salient economic and financial phenomena. Some authors utilize equity market data to model systemic risk with an emphasis on the directionality of connectedness, whereas others examine the extent to which such connectedness contributes to the erosion of systemic capitalisation.

The objective of this paper is to investigate a list of important features of volatility during 2019-2025 period for a number of relevant stock indices, covering as well the COVID-19 crisis and Russia - Ukraine war, also to document a tool that allows to model the start of a turbulent period that frequently identifies the early stage of a financial crisis, allowing regulators and managers build necessary tools to alleviate adverse effects of the crisis. By using the statistical properties of a volatility parametric method, we compound a sensitivity indicator that shows markedly changing statistical properties when stress mounts, as compared to calm periods. This systemic risk indicator may thus suggest that the start of a crisis may be modelled and thus recognized in a timely manner and that ultimately financial stress that characterizes such crisis may source useful patterns to anticipate when a crisis starts.

The proposed method aims to estimate conditional volatility and volatility shocks, evaluate their systemic properties, relevance (the extent to which these methods can provide relevant answers from the point of view of systemic risks), and match to relevant events, by capturing them in real time, almost instantly upon their occurrence. To achieve the objective of monitoring systemic risk in real time, the literature uses high frequency data, sampled at intervals of less than a day (usually 1 to 5 minutes, but can be also 1, 5 or 10 second recordings), the frequency being able to go to intervals as small as seconds or even data sampled with each transaction carried out, for very liquid ones the sampling interval being able to represent fractions of a second. The data that can be used are therefore data obtained from quantifications/valuations of assets that are sufficiently liquid so that they can be sampled at intervals of seconds or minutes, such as exchange rates or stock prices or certain commodities (such as a barrel of Brent oil).

The choice of high frequency data models is therefore motivated by the fact that the construction of a systemic risk indicator that provides the necessary signals for timely monetary policy decisions to reduce the effects of a particular shock or an ongoing crisis in the shortest possible time requires the construction with data that are produced and published in the shortest possible time. The use of low frequency data (daily, weekly, monthly, quarterly or annual) has several disadvantages, among which the most important are those related to the fact that at the date of their obtaining or calculation, the shock will have already produced its effects and the economic consequences will already be transmitted throughout the economy, with sometimes significant damage. Another disadvantage of these low-frequency data is that their sampling at long time intervals does not include the best information on latent phenomena, such as volatility, information that occurs in the interval between the two samplings and which is therefore not included in the modeling, which can lead to poor estimation of latent variables that can change much more often, at very short time intervals, so in this case the rarely sampled data would not include useful information that would escape a less frequent sampling.

Therefore, a model that produces useful signals on volatility and systemic risk shocks, such as volatility shocks, needs to be built from data sampled at as short time intervals as possible. However, these have a number of disadvantages, as follows. The first is that data sampled at short time intervals contain microstructure noise that distorts the estimation of latent phenomena. This is particularly a problem for exchange rate price series, as documented by Lyons (1995), King *et al*. (2013), Evans and Lyons (2002), and Daníelsson and Love (2006). The second shortcoming is that the list of data series that can be used is short and will only consider time series that refer to assets that are sufficiently liquid so that prices change at sufficiently short time intervals. The time series used will mainly be financial, which means that shocks transmitted through the financial channel, through prices, will be taken into account. Third, the applicability of these models is restricted to markets and countries that have such data, illiquidity representing both a problem of transmission of systemic risks and their detection.

Thus, each choice, in favor of models that use rarely sampled (low frequency) data or those that use frequently sampled (high frequency) data, involves a set of advantages and disadvantages. The question that arises, therefore, in this context, is: which are the most appropriate models for composing a universal indicator of systemic risk, in particular one for Romania and Europe, those that use high-frequency data or those that use low-frequency data (the frequency being defined by the step with which they are sampled)? The answer is given by the fact that in recent years the specialized literature has developed in the sense of improving volatility modeling by perfecting models that use high frequency data, which indicates that the literature has reached a consensus regarding the superiority of models that use this type of data. This was also based on the numerous empirical studies that studied the error functions obtained following the application of both methods, concluding in favor of high frequency data models. Empirically, models with such data have produced smaller errors than models with sparsely sampled data, and attention has recently focused on improving the former. The advantages of these (high frequency) models far outweigh their disadvantages, primarily in that their use represents a better estimate of risk, especially given that microstructure noise has been significantly reduced from the data by econometric methods that can be applied during the preprocessing stage of the data prior to their actual use in specially created models. Thus, the shortcomings of frequently sampled data series due to microstructure noise can be removed by applying econometric cleaning techniques, such as that proposed by Hansen and Lunde (2006) or Barndorff-Nielsen *et al*. (2009).

The purpose of systemic risk modeling in this paper is primarily to scrutinize the main crises since 2019 through the perspective of high frequency data and to develop an indicator that can identify as quickly as possible the occurrence of a shock that has the potential to transmit and cause turbulence throughout financial networks and the economy, therefore developing a model that is able to react promptly to receiving information and to discern between volatility shocks and factors that influence prices without impacting their conditional volatility. High frequency data recording techniques are continuously improving and thus errors are becoming fewer and data series are becoming more consistent.

2. Literature review

The majority of research on volatility modeling and forecasting has relied on empirical analyses of financial markets, primarily using equity and foreign exchange data. Numerous studies have employed stock market series to assess the predictive performance of various volatility models. In parallel, another strand of literature has focused on exchange rate dynamics. These studies collectively provide insights into the behavior and predictability of market volatility. Together, they form the empirical foundation for understanding volatility across different asset classes.

Poon and Granger (2003) provide a comprehensive review of the literature on volatility forecasting, noting the lack of consensus on a single superior model. Despite this, there is a general, though often implicit, agreement that ARCH-type models, especially those in the GARCH family, outperform simpler methods such as moving averages, exponential smoothing, and linear regression. Harris and Sollis (2003) further evaluate these models, offering a systematic assessment of the relative performance of alternative ARCH and GARCH specifications. Collectively, these reviews underscore the empirical strength of GARCH-based approaches in capturing volatility dynamics. The findings highlight the continued relevance of model-based frameworks in volatility prediction.

Much of the empirical research on volatility forecasting has traditionally relied on low-frequency data, such as daily or weekly returns. With the rise of high-frequency intraday data, nonparametric methods have been developed to detect jumps in asset prices. Barndorff-Nielsen and Shephard (2006a, 2006b) and Jiang and Oomen (2008) introduced techniques to identify such discontinuities. Jiang *et al*. (2011) applied these methods to U.S. Treasury securities, showing that macroeconomic news often coincides with increased volatility and liquidity reductions. Their results highlight the importance of both news announcements and liquidity shocks in driving intraday price jumps.

These studies have advanced volatility modeling in commodity markets, particularly for energy prices, which are highly volatile and prone to sudden movements around information releases. Bjursell *et al*. (2015) applied a nonparametric approach using realized variance and bipower variation from intraday data to detect jumps in daily futures prices of crude oil, heating oil, and natural gas. Their analysis shows that natural gas futures exhibit the greatest realized volatility among the studied contracts. Moreover, periods of elevated volatility are often linked to significant jump components. These findings underscore the importance of intraday data in capturing abrupt price changes in energy markets.

Financial market volatility is unobservable, making its measurement and forecasting challenging and reliant on indirect estimation methods. Traditionally, parametric approaches such as ARCH and GARCH models (Engle, 1982; Bollerslev, 1986) have been employed. Stochastic volatility models provide an alternative framework (Melino and Turnbull, 1990; Harvey *et al*., 1994). More recently, nonparametric realized volatility measures from high-frequency data have emerged as accurate proxies for latent volatility. These measures are widely applied in areas including option pricing and risk management.

Realized volatility, introduced by Andersen and Bollerslev (1998), is widely used in empirical finance for its intuitive interpretation and ease of computation. It estimates latent volatility by summing squared intraday returns, providing an unbiased measure of variability. Andersen *et al*. (2001) show that it effectively approximates integrated volatility over a given period. As a nonparametric, model-free estimator, it overcomes limitations of traditional parametric approaches. High-frequency data allow volatility to be treated as observable, with intraday measures validated as consistent estimators of daily market volatility.

Realized volatility, while useful, has several important limitations. Its accuracy depends on the properties and dynamics of the return series, and market microstructure effects like bid-ask spreads and non-synchronous trading can distort estimates (Campbell *et al*., 1998). In markets without continuous trading, including overnight returns may reduce precision. Additionally, a trade-off exists between improving latent volatility estimates through high-frequency sampling and increasing exposure to microstructure noise. These factors must be carefully considered when applying realized volatility measures.

Hansen *et al*. (2012) proposed the Realized GARCH model that we will also use in this paper, model which integrates asset returns with realized volatility measures. The model extends conventional GARCH by including a measurement equation linking realized volatility to conditional return variance, and incorporates a leverage term to capture asymmetries. It addresses limitations of realized volatility caused by microstructure effects and non-trading periods. The framework allows simultaneous estimation of all parameters via maximum likelihood, offering computational efficiency. Compared to standard stochastic volatility models, it provides a more practical and effective approach for modeling return-volatility dynamics.

Using higher-frequency data introduces certain limitations in volatility measurement. While increased sampling can improve the accuracy of latent volatility estimates, it also magnifies distortions from market microstructure effects, including bid-ask bounce, non-synchronous trading, price discreteness, and infrequent transactions. This creates a trade-off between precision and noise in high-frequency volatility estimation. The issue has been examined in depth by Madhavan (2000), Biais *et al*. (2005), and Hansen and Lunde (2005). These studies highlight the challenges of balancing sampling frequency with measurement reliability.

3. The parametric model and methodology

The parametric model we will use is that of Hansen *et al*. (2012) which proposes three equations that model the returns (through the return equation), the conditional volatility (through the GARCH equation) and the natural relationship between the realized (observed) measure and the conditional volatility (through the measurement equation). It is a parsimonious model, through which the realized volatility is no longer exogenous, but is explained by the link with the return r_t, its estimator becoming a consistent estimator of the integrated variance, which is important from an empirical point of view. This dependence is modeled by the presence of $z_t$in the measurement equation, which proved important in the authors' empirical analysis. The measurement equation thus completes the model, and empirically it was proven that the Realized GARCH model outperformed other high frequency models with similar characteristics.

The general model of Realilzed GARCH(p,q) of Hansen *et al*. (2012), is given by the set of equations:

$$r_t = \sqrt{h_t} z_t$$

$$h_t = v(h_{t-1}, h_{t-2}, \dots, h_{t-p}, x_{t-1}, x_{t-2}, \dots, x_{t-p})$$

$$x_t = m(h_t, z_t, u_t)$$

where $z_t \sim iid(0,1)$ and $u_t \sim iid(0, \sigma_u^2)$, z_t and u_t being mutually independent. The third equation (of x_t) can be interpreted as the measure of h_t (the actual measurement of h_t, not its estimation). The simplest example of the measurement equation is $x_t = h_t + u_t$.

The basic model we propose to use for systemic risk indicators is Realized GARCH(1,1) (Hansen *et al*., 2012):

$$r_t = \sqrt{h_t} z_t$$

$$h_t = \omega + \beta h_{t-1} + \gamma x_{t-1}$$

$$x_t = \xi + \varphi h_t + \tau z_t + u_t$$

in which $z_t \sim iid(0,1)$ and $u_t \sim iid(0, \sigma_u^2)$ and $h_t = var(r_t | F_{t-1})$, with $F_{t-1} = \sigma(r_t, x_t, r_{t-1}, x_{t-1})$. The measurement equation is natural when x_t is an estimator of the integrated variance, because the integrated variance can be expressed as the sum of the conditional volatility and a random innovation. This innovation can be absorbed by $\tau z_t + u_t$.

It can be easily demonstrated that h_t is a process AR(1), $h_t = \mu + \pi h_{t-1} + w_{t-1}$, where $\mu = \omega + \gamma\varepsilon$, $\pi = \beta + \varphi\gamma$ and $w_t = \gamma\tau(z_t) + \gamma u_t$.

The Realized GARCH model with log-linear specification, given that we are working with financial variables, is more appropriate in this context (Hansen *et al.* 2012):

$$logh_t = \omega + \sum_{i=1}^{p} \beta_i \, logh_{t-i} + \sum_{j=1}^{q} \gamma_j \, logx_{t-j}$$

$$logx_t = \xi + \varphi logh_t + \tau z_t + u_t$$

where $z_t = r_t/\sqrt{h_t} \sim iid(0,1)$, $u_t \sim iid(0, \sigma_u^2)$ and $\tau(z)$ is called the leverage function. This function $\tau(z)$ is closely related to the news impact curve which describes how negative and positive price shocks influence future volatility. This news impact curve can be defined by the equation $\nu(z) = E(logh_{t+1}|z_t = z) - E(logh_{t+1})$, such that $100\nu(z)$ measures the percentage impact on volatility as a function of a standardized return. It follows that $\nu(z) = \gamma_1\tau(z)$.

The model becomes like this:

$$r_t = \sqrt{h_t} z_t$$

$$h_t = \exp(\omega + \beta h_{t-1} + \gamma x_{t-1})$$

$$x_t = \xi + \varphi h_t + \tau z_t + u_t$$

h_t it is the first systemic risk indicator that we will use.

4. Data

We used 5-minute sampled data, for the period January 2, 2019 - February 11, 2025, of eleven stock market indices (BET of Romania, BUX of Hungary, FTSE of UK, IMOEX of Russia, OMXS30 of Sweden, OSEBX of Norway, PX of Czech Republic, SOFIX of Bulgaria, SSMI of Switzerland, WIG of Poland, XU100 of Turkey), sourced from DataScope of LSEG. We also used French CAC, US NASDAQ - CCMP, S&P 500 - SPX and Dow Jones Industrial Average - INDU, German DAX, Italian FTSE MIB - FTSEMIB, Spanish IBEX, Japanese Nikkei - NKY, Chinese Shanghai Stock Exchange - SHCOMP, and the British FTSE 100 - UKX from Bloomberg for a more focused analysis of COVID-19 period (January 28, 2019 - July 9, 2020) (we shortened to only the period with the highest market volatility).

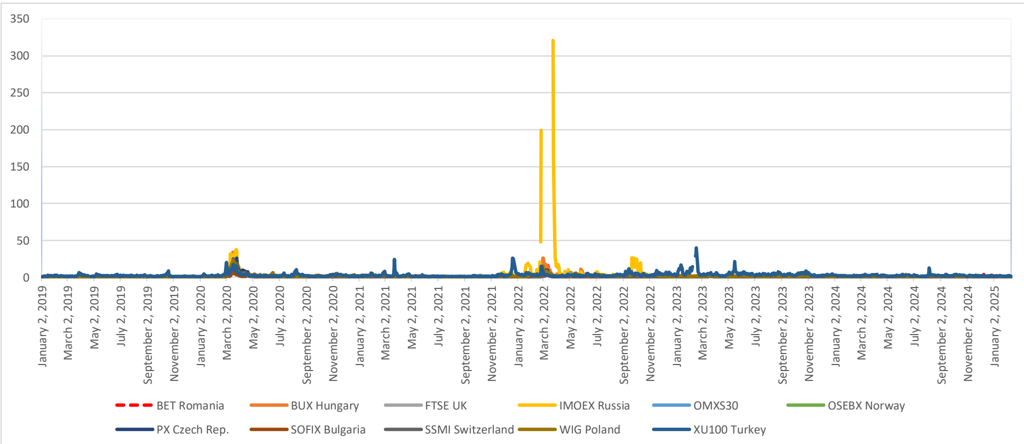
We clean the data by removing the weekends and the low trading days, such as those around the Christmas and the Easter. Therefore, the data underwent a complex cleaning and preparation process, given that the 5-minute sampled series contained numerous erroneous or incomplete records. Days characterized by a substantial proportion of missing observations were also excluded from the dataset, and where data were sufficient, blanks were filled in with previous values. Five-minute and daily price returns were calculated, as well as the realized variance as a measure of intraday volatility. We used GMT data. In all other cases, when no transaction occurred within a five-minute interval, a return value of zero was assigned. Overall, the full sample comprises approximately 1,528 trading days and more than 152,893 individual observations for each data series. Conditional volatility and volatility shocks were estimated.

5. Results

5.1 Development of crises

In what follows we describe the development of the largest crises between 2019-2025 that emerge from the volatility graphs, two of them being known as COVID-19 crisis and Russia-Ukraine war crisis. While the crisis of the Russian-Ukrainian war can be identified as starting exactly on February 24, 2022, the date of Russia's invasion of Ukraine, the COVID-19 crisis does not have an exact start date, but can be placed as starting in January 2020 and having an apex around March 20, when markets began to realize that an economic crisis was underway, emerging from a medical crisis, and that the economic consequences at the level of production output, supply chains, unemployment and liquidity were about to occur. From Fig. 1 it can be seen that the volatility of the Russian index generated by the start of the war was so high that the volatility of the other indices, over the entire length of the interval, seems almost perfectly flat due to the extreme dynamics encountered by the Russian index as a result of the start of the war.

Fig. 1. Conditional volatility, 2019-2025



Source: Author's own research

Another detail that stands out in addition to the extremely high volatility around the time of the invasion, is that the data on the Moscow Exchange index (IMOEX) are missing on February 23, 2022 and between February 28, 2022 and March 23, 2022, given that trading on the Russian stock market was suspended for a prolonged period as a result of exceptional market turbulence following the outbreak of the war in Ukraine. On February 24, 2022, coinciding with the launch of Russia's full-scale military operation (Russia invasion in Ukraine), the IMOEX shut down all trading activity after prices collapsed and volatility surged amid extreme uncertainty. The closure lasted several days, including the following Monday and Tuesday, representing one of the most significant stock market shutdowns since the 1998 financial crisis. Trading only resumed gradually in late March 2022, and even then in a limited form: only certain securities were traded, primarily by domestic investors, while foreign participants were subject to strict selling prohibitions and other constraints.

This suspension was not merely the result of automatic volatility control mechanisms, such as circuit breakers commonly used in Western markets, but rather reflected severe geopolitical and financial pressures. These included widespread selloffs driven by uncertainty surrounding the conflict, international sanctions, and disruptions to capital flows; a sharp depreciation of the ruble accompanied by intervention efforts from Russian authorities; and sanctions that impaired settlement systems and limited investor participation, effectively freezing market activity. When trading eventually resumed, it did so under tight regulatory oversight. Measures such as bans on short selling and continued restrictions on foreign investors remained in place. Although the market continued to experience heightened volatility influenced by geopolitical developments and sanctions, authorities managed these pressures through regulatory controls rather than by imposing further prolonged trading halts.

Excluding Russia from the chart, the movement of the other indices from the perspective of estimated volatility becomes more nuanced, being able to identify three major stress periods (Fig. 2): 1. February 14, 2020 - April 26, 2020, known as the coronavirus (COVID-19) crisis, 2. February 15, 2022 - March 30, 2022 known as the Russia-Ukraine war crisis, preceded by persistent inflation in energy, food, and goods that compounded investor uncertainty during late 2021 into 2022, to which central banks (notably the U.S. Federal Reserve and European Central Bank) responded by raising interest rates and tightening policy after a long period of ultra-low rates. Notable here to mention is also Evergrande liquidity crisis and China property sector stress that echoed into markets in late 2021. Finally, 3. April 5, 2022 - June 15 2022 known as the energy crisis - a combination of Russia - Ukraine war effects and energy price spikes, dominated by inflation concerns and central bank tightening, and swift market corrections. The spike was mostly global, driven by the Russia -Ukraine war's impact on energy and commodities, high inflation and aggressive rate hike expectations, and recession fears - not a single energy crisis, but the combination of geopolitical and macroeconomic shocks. We disregard for the moment large spikes in the Turkish index that occurred during 2021-2024, resulting mainly due to local events (Fig. 2).

Across the above three crisis periods, surges in volatility in Europe's largest stock markets were driven by distinct but interrelated shocks that sharply increased uncertainty and risk premia. During the first mentioned high stress period, that we called the COVID-19 crisis (February 14, 2020 - April 26, 2020), volatility spiked as the rapid global spread of the coronavirus led to unprecedented lockdowns, abrupt halts in economic activity, disruptions to global supply chains, and fears of a deep recession, compounded by uncertainty over public-health outcomes and the scale and effectiveness of fiscal and monetary policy responses. During the second major stress period, that we named as Russia-Ukraine war crisis (February 15, 2022 (including here the short period before invasion) till March 30, 2022), volatility was fueled by the sudden outbreak of a major geopolitical conflict in Europe, triggering sharp increases in risk aversion, heavy sell-offs in equities, and large swings in energy, agricultural, and financial markets as investors reassessed growth prospects, sanctions risks, and exposure to Eastern Europe. We also note that the stock market in Russia reacted short before the invasion date. Finally, during the third major stress period, that we called energy crisis (April 5, 2022 - June 15, 2022), volatility remained elevated as soaring natural gas and electricity prices - driven by reduced Russian energy supplies, supply constraints, and fears of shortages - intensified inflationary pressures, weakened corporate earnings outlooks, and heightened expectations of aggressive monetary tightening by the European Central Bank, further unsettling equity valuations across European markets.

To those, a remarkable high volatility may be added with respect to the Turkish stock market index (Fig. 2), which had five more peaks in volatility (additional to the three of the other indices) related to domestic events:

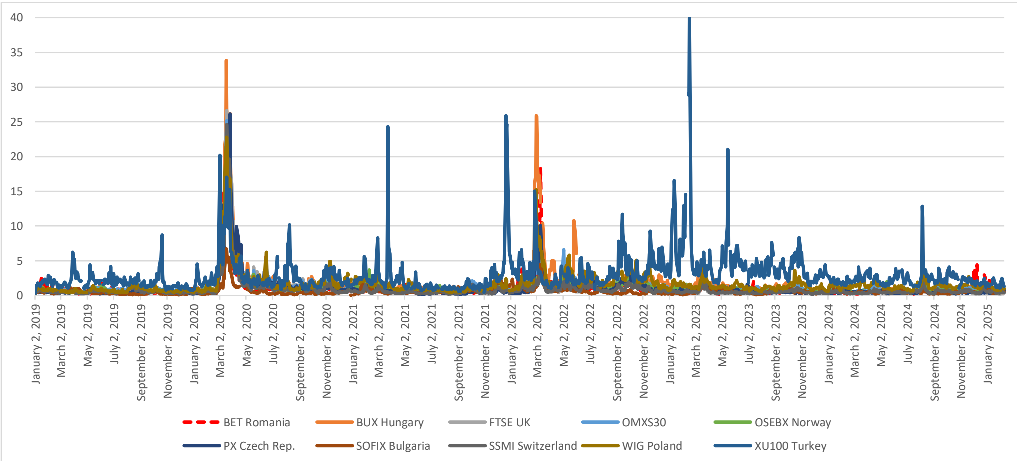
1. January - May 2021 related to post-pandemic recovery and easing expectations, domestic monetary policy and weakness of lira.
2. December 2021 - January 2022, period in which the Turkish lira has crashed to record lows and the central bank of Turkey has cut monetary policy rates repeatedly and

consistently, even in the context of high inflation, as annual inflation rose from 21% in November 2021 to over 36% in December 2021.

3. August 2022 - February 2023 during which Turkey's inflation soared, and the central bank cut policy rates aggressively even as inflation exceeded 80%. This negative real interest rate environment fuelled equities, with Turkish stocks being among the best-performing emerging market indices due to the "inflation trade". As well, a devastating earthquake occurring on February 6, 2023 significantly impacted economic activity and markets.
4. April - May 2023 overlapped with presidential and parliamentary elections, markets reacting strongly to electoral uncertainty. As a result, Turkish lira weakened sharply, sovereign bonds and equities fell and implied volatility measures for the lira jumped.
5. August 2024. The increased volatility in Turkey since August 2024 was the combined result of a sharp loss on the Istanbul Stock Exchange, still very high inflation, the withdrawal of the carry trade strategy due to global risks, uncertainty related to domestic monetary policy, and the impact of adverse global developments.

We may also notice a spike on the Romanian BET at the end of the sample period, that overlaps with the cancellation of presidential elections at the beginning of December 2024 (6th of the month).

Fig. 2. Conditional volatility (without Russia), 2019-2025



Source: Author's own research

Given the very different patterns in the Turkish and Russian indices, we will list in what follows (Table 1) the major international and national developments which mark the peaks in their volatility.

Unlike the volatility variable, the volatility shocks show (Fig. 3) somewhat equal amplitudes across stock indices, suggesting that the impact of the events that generated them is approximately equivalent for all stock markets. At the same time, we note that positive shocks (associated with events with a negative impact) are overwhelmingly more numerous than negative shocks (associated with events with a positive impact).

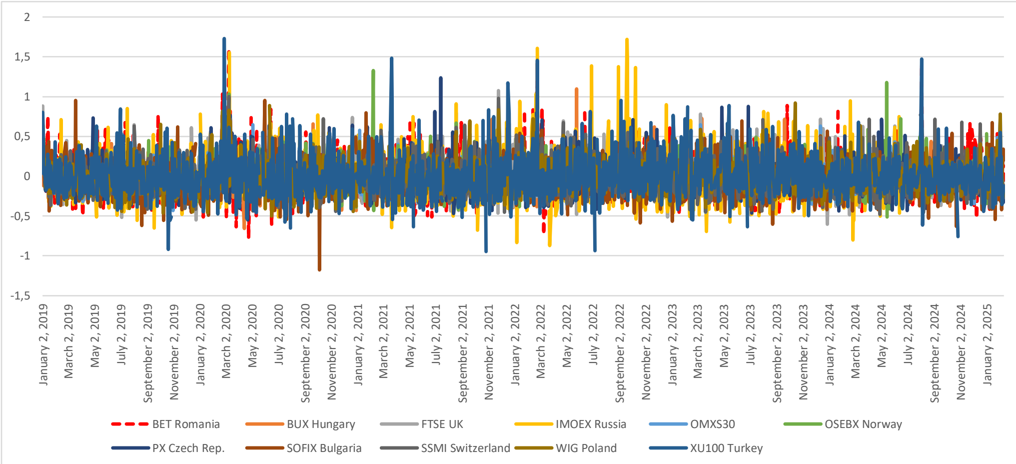
Table 1. Major events that cause surges in volatility, 2019-2025

IMOEX Russia	
2019	No globally-recognised singular shock with a clear stock market impact in 2019, but structural FX interventions and ongoing geopolitics shaped sentiment throughout the year (continuing from prior years).
2020	Early March 2020: COVID-19 market crash affects global equities, including Russia's MOEX, which saw sharp sell-offs alongside global risk-off sentiment (consistent with global markets). (implicit global event)
2021	Throughout 2021: IMOEX reached record levels, in part driven by high energy prices and global equities rebound after pandemic lows - IMOEX made highs around Oct 2021.
Feb 24, 2022	Russia launches full-scale invasion of Ukraine causing IMOEX and RTS plunge sharply; major Western sanctions begin, isolating Russian markets and restricting foreign participation.
Sep 2, 202	G7 agrees oil price-cap sanctions on Russian crude to restrict revenue funding for the war - major influence on energy earnings and Russian equities.
Throughout 2023	Continuous sanctions iterations and war progress kept Russian equities volatile with repeated sell-offs/ rallies tied to geopolitical news flow.
Jun 12 - 13, 2024	U.S./UK sanctions specifically target the Moscow Exchange, forcing the halt of dollar/euro trading on IMOEX - a major market structure shock.
Aug 7, 2025	IMOEX rallied on news of a potential U.S. - Russia meeting (optimism on possible breakthrough in peace negotiations), resulting in a notable spike.
Oct 8, 2025	IMOEX suffers its sharpest single-day drop in 3 years linked to diplomatic statements suggesting stalled progress on Ukraine peace talks.
Oct 23, 2025	U.S. sanctions on Rosneft and Lukoil trigger sharp falls in Russian energy majors and broader IMOEX declines (approx. 3.6%).
Nov 21, 2025	IMOEX rose approx. 2.4% on optimism about a U.S.-brokered peace plan scenario despite broad sanctions pressure.

XU100 Turkey	
2019 - 2020	FX & policy turmoil: Continued selling of FX reserves by the Turkish central bank triggered lira declines and affected market confidence (especially 2019-2020).
Mar 2020	Global COVID-19 crash hit The reference index sharply along with most global indices.
2021	Turkish markets broadly rose as global stimulus boosted emerging markets; however, persistent inflation and monetary policy uncertainty kept volatility elevated (annual context).
Feb 6-20, 2023	Earthquake: The magnitude 7.8 Kahramanmaraş earthquakes in early 2023 caused significant economic damage and increased BIST volatility, especially in construction, banking, and insurance sectors.
Jul 18, 2024	The reference index reached a new historic peak (about 11,252 points), reflecting periods of strong foreign inflows, easing inflation expectations, and monetary policy moves.
Mar 19, 2025	Arrest of Istanbul Mayor Ekrem İmamoğlu, a major political rival, spiked political uncertainty: The reference index plunged and the lira hit record lows amid sell-offs.
Mar 24, 2025	Borsa Istanbul rebounded approx. 3% after regulatory responses such as short-selling bans and eased share buybacks.
May 12, 2025	Turkish stocks jumped on news of PKK disbandment, boosting markets on improved stability outlook.
Sep 1, 2025	Short-selling ban lifted - positive market signal following the March crisis.
Sep 2, 2025	Court ousted Istanbul opposition leadership causing the reference index drop about 6% on heightened political risk.
Dec 31, 2025	The reference index ended the year up versus previous year but lagged inflation and FX-adjusted performance - a mixed performance indicator.

Source: Author's own research

Fig. 3. Volatility shocks, 2019-2025



Source: Author's own research

5.2 Cross-index comparison on volatility persistence and panic sensitivity

A rigorous cross-index comparison requires also evaluating standardized structural metrics from the high-frequency model used. To implement this, we introduce a comparison table along with an analysis of volatility persistence (β) and panic sensitivity (leverage coefficients - т). Specifically, we find that: volatility persistence (β), for indices such as SOFIX Bulgaria and OSEBX Norway, exhibit higher β parameters, demonstrating a prolonged memory of systemic shocks during the 2020 and 2022 crises compared to IMOEX Russia and XU100 Turkey. With respect to panic sensitivity (leverage effects - т), the measurement equation coefficients mapping high-frequency intraday movements to systemic risk, for SOFIX Bulgaria and WIG Poland, reveal significantly steeper asymmetric responses during crisis episodes than SSMI Switzerland and IMOEX Russia. т shows the highest sensitivity to sudden shifts in downside sentiment (Table 2):

Table 2. Volatility persistence (β) and panic sensitivity (leverage) (τ) coefficients for all indexes

	BET Romania	BUX Hungary	FTSE UK	IMOEX Russia	OMXS30 Sweden	OSEBX Norway	PX Czech Rep.	SOFIX Bulgaria	SSMI Switzerland	WIG Poland	XU100 Turkey
β	0,627	0,653	0,668	0,555	0,672	0,693	0,693	0,787	0,622	0,617	0,462
τ	- 0,109	- 0,070	-0,150	- 0,177	- 0,155	- 0,104	- 0,076	- 0,018	- 0,169	- 0,062	- 0,153

Source: Author's own research

Furthermore, by combining β and т, we can classify the international indices into three distinct behavioral categories:

Group A: High persistence / Low panic sensitivity (The "Slow Burners"): SOFIX (Bulgaria: β = 0.787, т = -0.018), OSEBX (Norway: β = 0.693, т = -0.104), PX (Czech Republic: β = 0.693, т = -0.076). We can interpret this as: when bad news hits, these markets don't experience a massive, immediate structural panic spike (т is low/close to zero). However, once volatility enters the system, they take the longest time to recover (β is high). The shock lingers in the system.

Group B: Low persistence / High panic sensitivity (The "Reacters"): IMOEX (Russia: β = 0.555, т = -0.177), XU100 (Turkey: β = 0.462, т = -0.153). We may interpret them as: these markets are highly sensitive to sudden sentiment shifts. Bad news triggers an immediate, aggressive surge in volatility and systemic risk (highly negative τ). However, these shocks are strictly episodic; the panic clears out of the system rapidly, showing a very short volatility memory (lowest β values).

Group C: Developed and deep markets (The "Balanced Profiles"): SSMI (Switzerland: $\beta = 0.622$, $\tau = -0.169$), FTSE (UK: $\beta = 0.668$, $\tau = -0.150$), OMXS30 (Sweden: $\beta = 0.672$, $\tau = -0.155$). We will interpret this as: these highly liquid, developed European indices show standard, robust financial characteristics. They have an immediate, pronounced leverage effect to bad news (τ from -0.15 to -0.17), balanced by moderate volatility persistence (β between 0.62 to 0.67), meaning they process and clear systemic shocks efficiently but transparently.

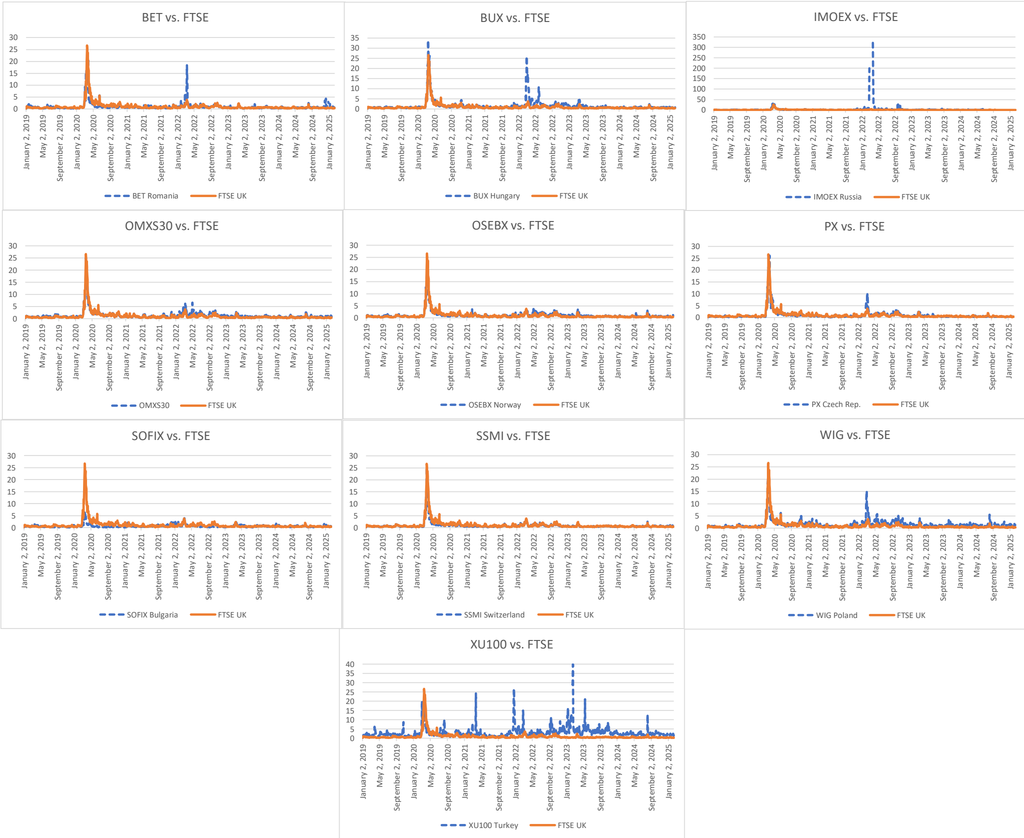
Emerging or highly geopolitically exposed markets over the 2019-2025 period (like Russia and Turkey) exhibit a pattern of "high intensity, short duration" systemic risk signals. Meanwhile, smaller frontier European markets show a "low intensity, long duration" footprint, indicating structurally illiquid environments where risks take a long time to be absorbed and cleared by market participants.

5.3 Micro-shocks vs. systemic threats

An additional conclusion is that index volatility is a matter that has more to do with international events than with domestic ones. For example, taking the FTSE as a benchmark index for international developments, in two-by-two comparisons (Fig. 4), we observe that the developments of the indices of the other countries have mostly similar patterns with that of the benchmark index. The only exceptions are the Turkish XU100 index and Russia IMOEX index which, marked by domestic political and economic developments, exceeded international influences. Another observation is that the stock markets of countries located proxy to Russia reacted much more to the start of the war than other countries, showing that geography and physical distance to the source of the conflict plays a role in the volatility spikes when major shocks (such those that involve military conflicts) occur.

To document whether our high-frequency indicator signals an isolated micro-shock or a broader collapse of global diversification, we evaluate the joint behavior of high-frequency volatility spikes and cross-index dynamic conditional correlations. Empirically, the 2019-2025 timeline reveals a sharp divergence between international shocks and localized events. When a systemic threat originates or fully materializes in major liquid hubs - such as during the March 2020 COVID-19 crisis - the high-frequency volatility spikes across the core European indices (FTSE UK, SSMI Switzerland, OMXS30 Sweden) are accompanied by an instantaneous, uniform upward shift in dynamic correlations. During these episodes, the global financial system demonstrates a total loss of diversification capacity. In contrast, during localized shocks (such as idiosyncratic political or currency events impacting the Turkish XU100, Russian IMOEX, or isolated spikes in the Hungarian BUX), our indicator registers a severe local volatility surge, yet the conditional cross-correlations between these indices and the FTSE remain decoupled and low. This empirical pattern demonstrates 'systemic absorption,' where international capital successfully diversifies away from the localized risk, confirming that our indicator can effectively separate localized micro-shocks from systemic contagions.

Fig. 4. Conditional volatility of various indices vs. FTSE, 2019-2025



Source: Author's own research

To evaluate whether the proposed high-frequency indicator suggests an isolated, localized shock or a broader collapse of global diversification capacity, we analyze the joint high-frequency volatility dynamics of individual international indices relative to a major developed market benchmark (FTSE) (Fig. 4). Empirically, the 2019-2025 period across the eleven equity markets reveals a sharp structural divergence between global systemic crises and decoupled, localized shocks:

a) Global systemic threats (diversification failure): The March 2020 COVID-19 liquidity crash serves as the expression of a synchronized global shock. As shown across almost all panels (most notably SSMI Switzerland, OMXS30 Sweden, OSEBX Norway, and PX Czech Republic), the immense high-frequency volatility spike in the global benchmark (FTSE) is matched instantaneously and symmetrically by local market volatilities. During this window, cross-index decoupling disappears entirely, signaling a total collapse of global diversification capacity.

b) Idiosyncratic and regional shocks (systemic absorption): In contrast, several prominent country-specific shocks register as massive local volatility surges while the global benchmark remains entirely unperturbed. This is most clearly demonstrated by:

b.1) IMOEX (Russia): It experiences an unprecedented, isolated volatility surge in early 2022 due to severe geopolitical conflict, yet the FTSE baseline remains flat, confirming the shock was structurally contained.

b.2) XU100 (Turkey): Exhibits frequent, highly intense, episodic volatility spikes throughout 2021, 2023, and 2024 that are completely absent from the FTSE baseline, highlighting its decoupled, sentiment-driven nature.

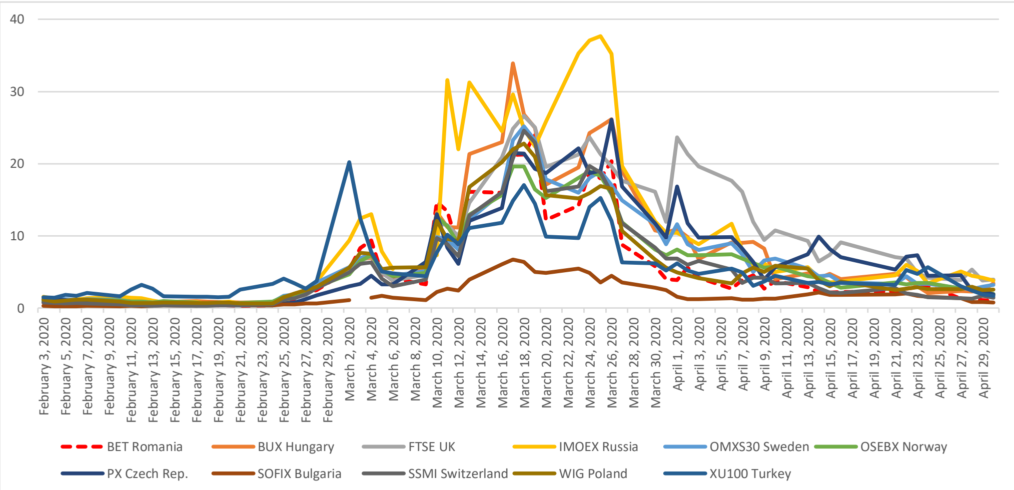
b.3) CEE clusters (BET Romania, BUX Hungary, WIG Poland): Show a secondary, regional volatility escalation in early 2022 - reflecting localized geographic proximity to geopolitical risks - which the broader international system (FTSE) successfully absorbs with minimal spillover.

This confirms that our high-frequency indicator differentiates between localized asset-specific micro-shocks (where the international system safely dampens the threat via ass*et al*location) and true global market contagions.

5.4 Systemic risk indicator

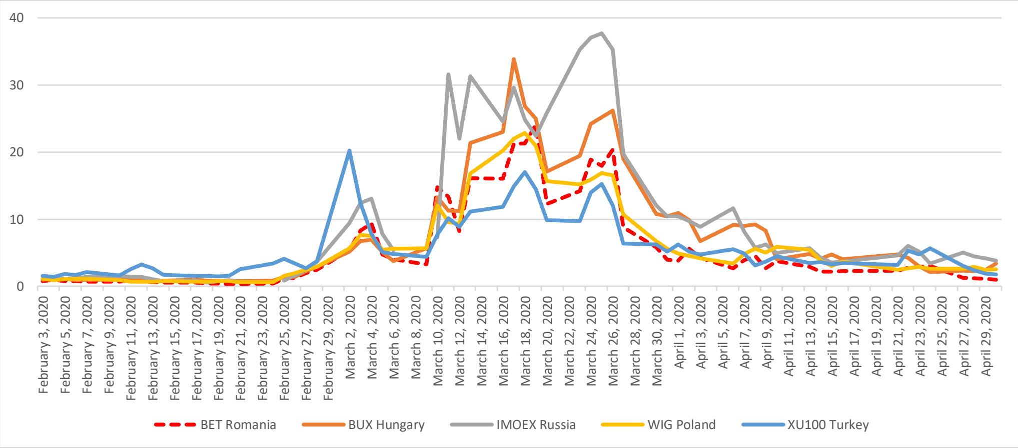
Regarding the identification of a systemic risk indicator, we note that some volatility estimators consistently behave in a timing and with an amplitude that can serve as predictors of the beginning of periods of turbulence and possibly of financial crises. In particular, for the beginning of the COVID-19 crisis (Fig. 5), it is observed that the XU100 and IMOEX indices had the largest and fastest increase in volatility, which can serve as a predictor for the other indices. In particular for BET, these indices can serve as predictors of the increase in volatility in BET (Fig. 5, 6).

Fig. 5. Conditional volatility during COVID-19 crisis, 2020



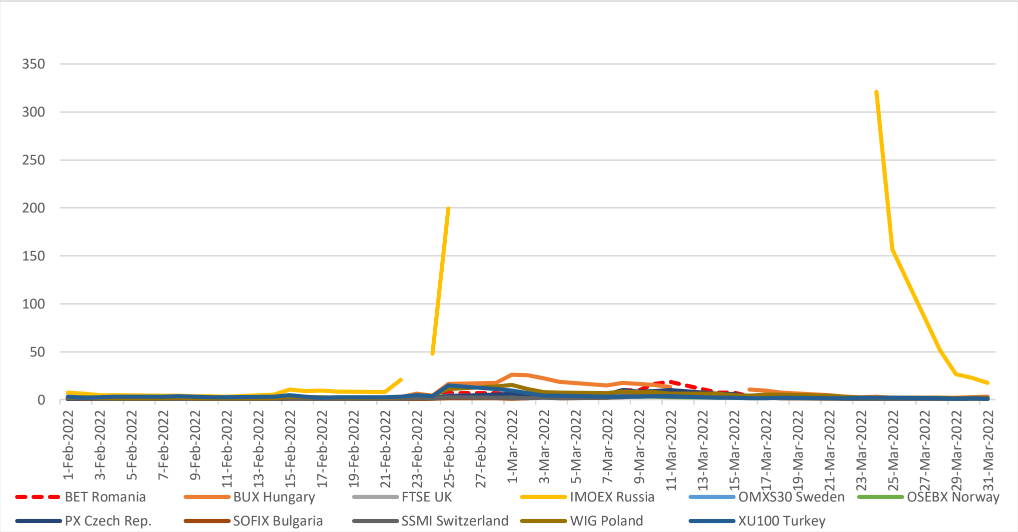
Source: Author's own research

Fig. 6. Regional index conditional volatility during COVID-19 crisis, 2020



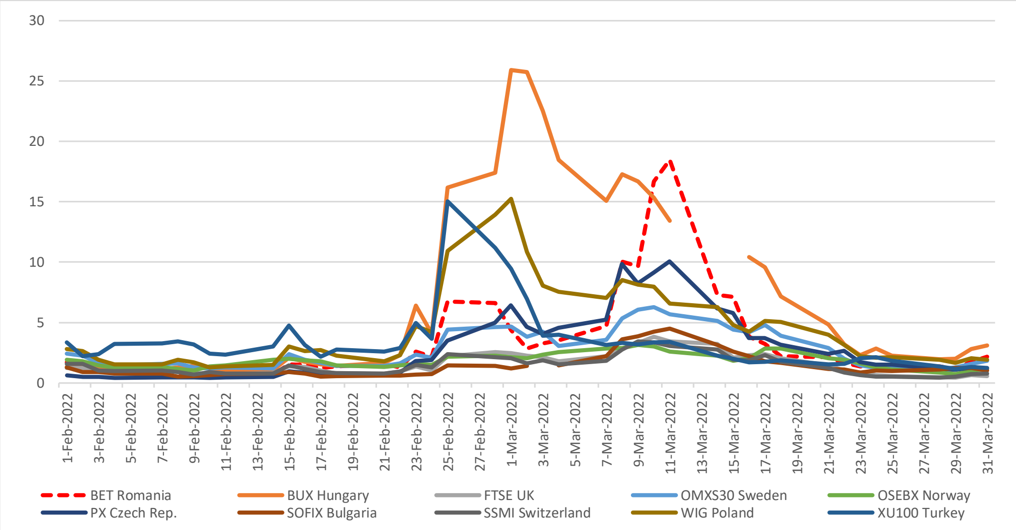
Source: Author's own research

Fig.7. Conditional volatility during Russia invasion, 2022



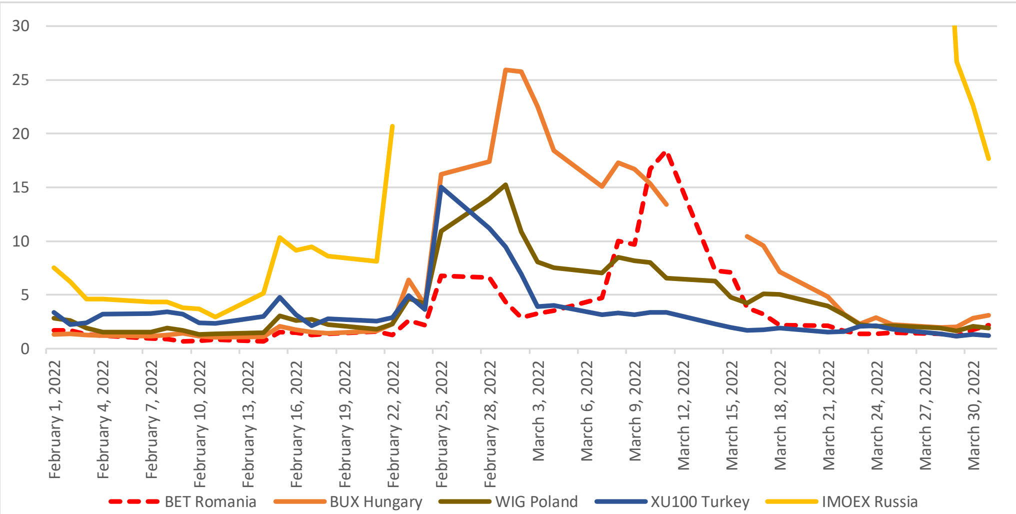
Source: Author's own research

Fig. 8. Conditional volatility during Russia invasion (excluding Russia), 2022



Source: Author's own research

Fig. 9. Regional index conditional volatility during Russia invasion, 2022

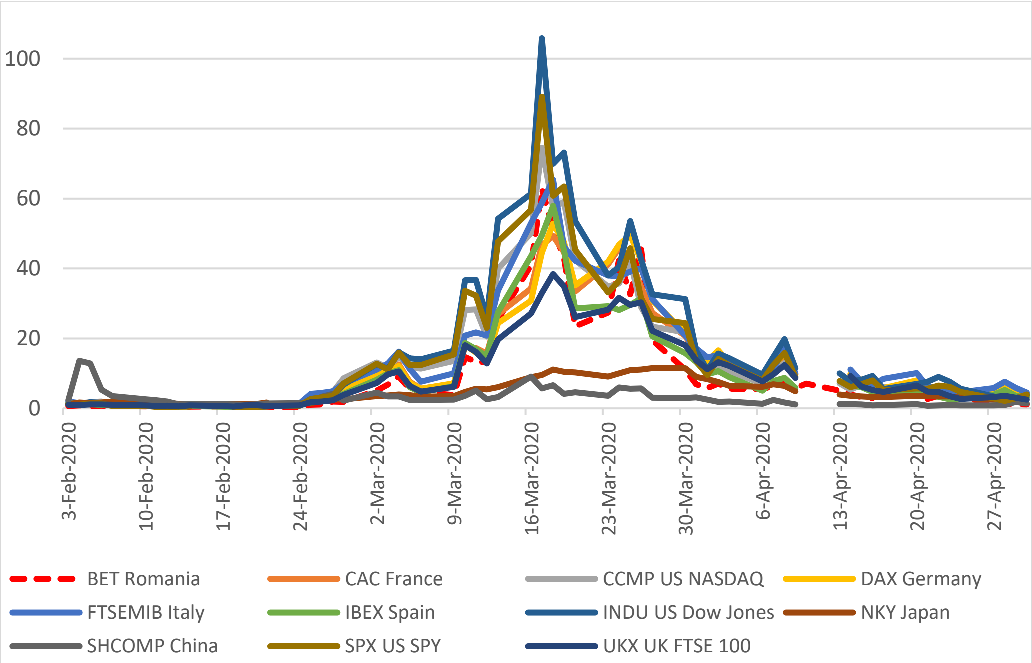


Source: Author's own research

Regarding the crisis generated by Russia's invasion of Ukraine, these two indices (IMOEX and XU100) bear the same characteristics as in the previous crisis (the COVID-19) (Fig. 7). IMOEX rises sharply on February 21, 2022, which the BET achieves only a few days later, on February 25, 2022. XU100 also rises on February 22, 2022, three days before BET. Looking carefully at the beginning of the crisis and abstracting from what happens to IMOEX, since the amplitude of this index sets the conditions for creating a scale that makes other indicators irrelevant, we observe that the BUX, WIG and PX indices can also serve as predictors (Fig. 8, 9). All these depict that regional volatility (volatility of countries that are in the closer neighborhood to Romania) can be as relevant in forecasting stress periods of volatility as major stock markets.

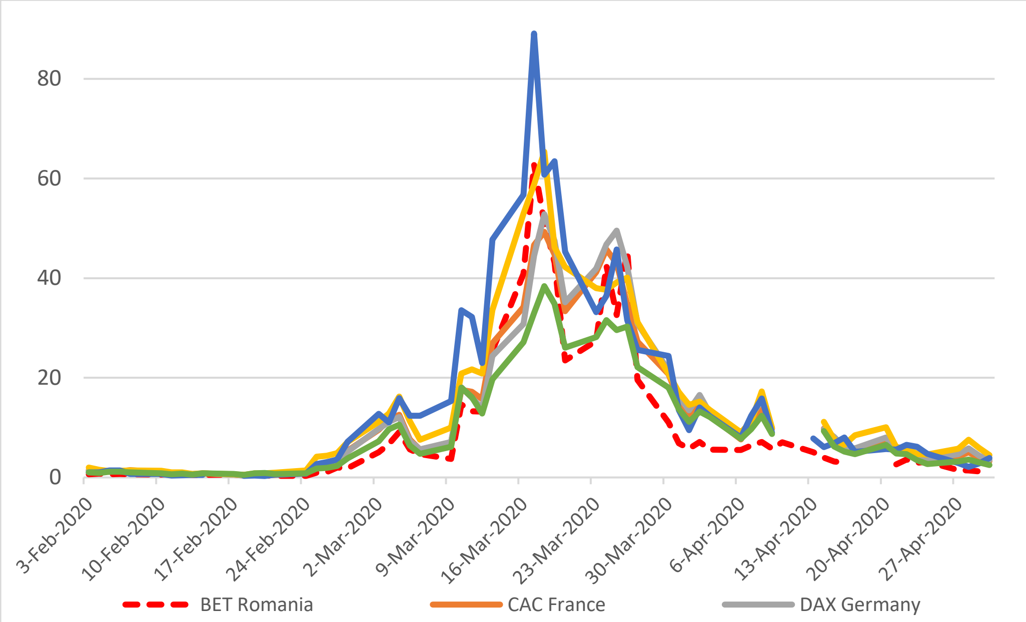
To strengthen the conclusions regarding the ability of alternative indices to forecast announced changes in volatility relative to the BET index, we conduct in what follows a more detailed examination of the COVID-19 period from the perspective of some other major, global, benchmark indices. These include the French CAC, the U.S. NASDAQ Composite (CCMP), S&P 500 (SPX), and Dow Jones Industrial Average (INDU), the German DAX, the Italian FTSE MIB (FTSEMIB), the Spanish IBEX, the Japanese Nikkei (NKY), the Chinese Shanghai Stock Exchange Composite (SHCOMP), and the British FTSE 100 (UKX).

Fig. 10. Conditional volatility, global indices, COVID-19 February -April 2020



Source: Author's own research

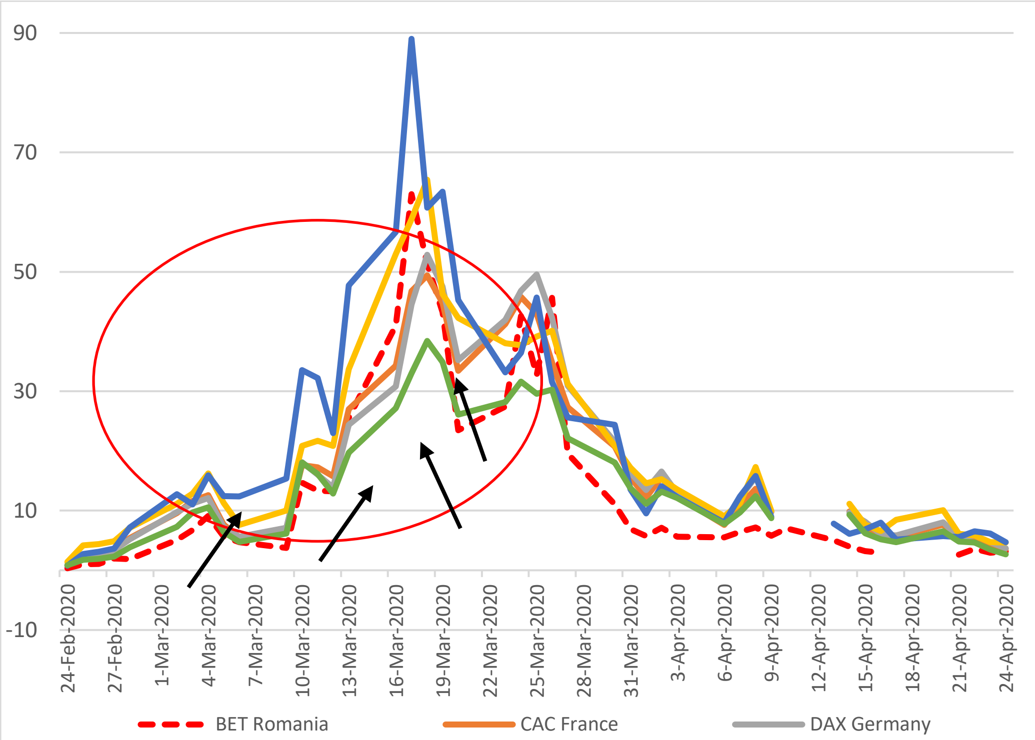
Fig. 11. Conditional volatility, relevant indices for BET, COVID-19 February -April 2020



Source: Author's own research

An inspection of Figures 10 and 11 indicates that the Chinese and Japanese stock market indices are the only ones that do not co-move with the remaining indices. Also in this case, BET index of the Romanian stock market closely mirrors the dynamics of the other indices-excluding NKY and SHCOMP. This pattern can be attributed to the absence of external interventions aimed at constraining the movements of the stock market index (as compared to what usually happens in the currency markets). Such dynamics more clearly underscore the relevance of an indicator in signaling periods of market stress: when the conditional volatility estimated from intraday data rises for major stock market benchmarks - namely those of the U.S. capital market (SPX, CCMP, and INDU), as well as the French (CAC), German (DAX), British (UKX), Italian (FTSEMIB), and Spanish (IBEX) markets - this increase reflects a systemic intensification of market stress and, implicitly, of systemic risk. This signal can therefore be used to anticipate similar developments in the Romanian capital market. As we explained above, the short-term anticipations are equally reflected by the stock market indicies of the neighbouring countries as those of the major stock markets. Evidence that the behavior of the BET index can be anticipated during stress episodes based on the conditional volatility of other reference indices is provided in Figure 12, which illustrates the evolution of conditional volatility around the COVID-19 crisis:

Fig. 12. Conditional volatility for BET, CAC, DAX, FTSEMIB, SPX and UKX, during the COVID-19 crisis (February - March 2020)



Source: Author's own research

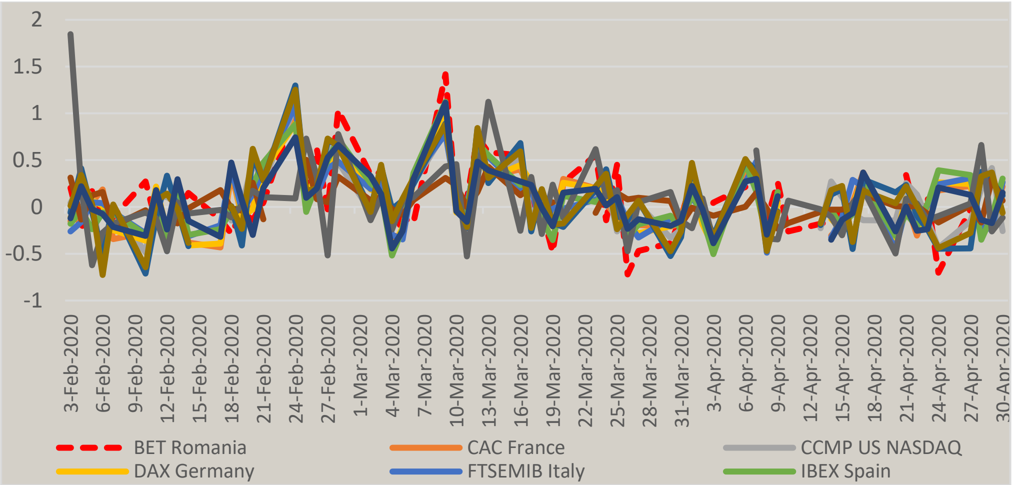
Accordingly, beginning on 24 February 2020, a marked increase in volatility can be identified across all analyzed indices (BET, CAC, DAX, FTSEMIB, SPX, and UKX). However, the BET index exhibits a slower response, adjusting only after movements observed in the benchmark indices. Put differently, the conditional volatility estimated from high-frequency data behaves as a lagging indicator for BET, while it acts as a leading indicator for the reference markets. During the initial phase of the crisis, BET volatility trails that of all other indices by one period, suggesting that fluctuations in the benchmark indices may be interpreted as early warning signals of heightened risk. Moreover, the synchronized rise in volatility across these international indices highlights the systemic character of the observed stress.

It should also be emphasized that the BET index functions as a lagging variable only during the initial phase of the crisis. This characteristic is nonetheless sufficient for the objectives of the present analysis, which seeks to identify an early signal indicating the emergence of conditions conducive to crisis development, the accumulation of market stress, and the buildup of systemic risk with potential spillover effects to Romania. As market participants gradually internalize the unfolding crisis, and depending on specific market structures, the BET may exhibit heightened volatility relative to other indices, in which case its conditional volatility could assume a leading role with respect to certain markets. For the purposes of this study, however, the primary focus remains on the initial, signal-generating phase, during which increases in systemic risk affecting the BET are forecast through the dynamics of other reference indices.

The procedure for constructing and applying the systemic risk indicator, as developed in the context of capital market indices, can be summarized as follows:

1. Identify the benchmark indices that are expected to provide signals of systemic risk.
2. Compute intraday returns and the corresponding realized daily variance for these indices.
3. Estimate conditional volatility measures and associated volatility shocks.
4. Upon detecting statistically significant increases in realized returns and variance - at both five-minute and daily frequencies - the previously estimated conditional volatility is examined.

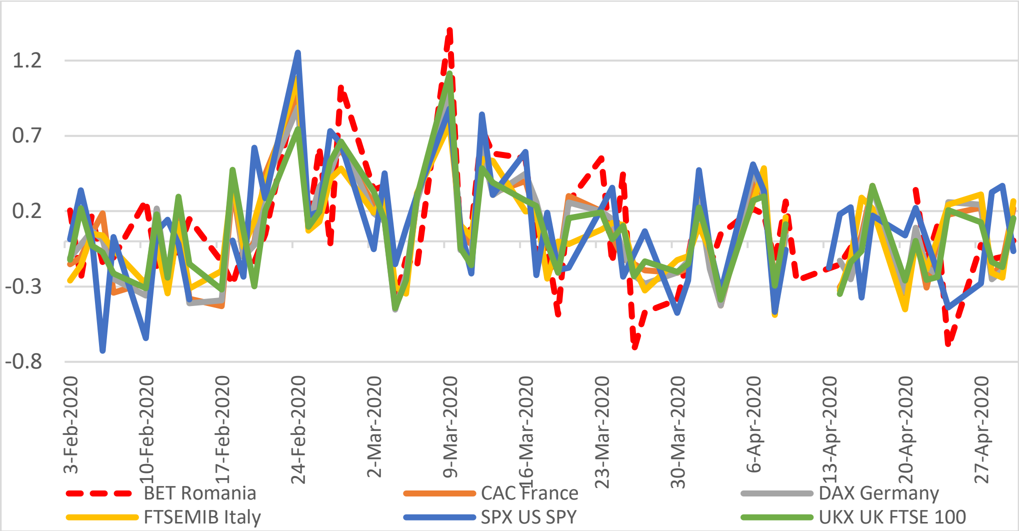
Fig. 13. Conditional volatility shocks, all indices



Source: Author's own research

When a pronounced and contemporaneous rise in conditional volatility is observed across the benchmark indices - formally, this can be assessed by defining threshold levels beyond which volatility becomes economically relevant, such as the median plus three or four standard deviations over a specified interval, following Eichengreen *et al.* (1996) - the origin of the stress-inducing announcements would be examined to determine whether they are domestic or international in nature. To this end, volatility shocks may be identified, as illustrated in Figures 13 and 14, by isolating days characterized by unusually large volatility increases. If volatility shocks in the BET index coincide with those recorded for other indices, given that such shocks reflect the arrival of news or unexpected announcements, the underlying events can be classified as international, as their significance generates simultaneous volatility responses across multiple markets. Accordingly, the temporal overlap of volatility shocks serves to distinguish between domestic and international announcements: when a BET shock in Figures 13 and 14 occurs concurrently with at least one shock in another index, the triggering event is deemed international, whereas shocks that do not coincide with movements in other markets are attributed to country-specific developments. Since domestically generated shocks do not propagate to international markets, they are not associated with systemic risk. Consequently, the analysis may focus exclusively on internationally driven shocks that affect the BET index alongside at least one other reference index.

Fig. 14. Conditional volatility shocks, relevant indices for BET



Source: Author's own research

When volatility shocks are observed concurrently in the BET index and in at least one other benchmark index, and when conditional volatility rises simultaneously across multiple indices, this constitutes an instance of systemic risk with a high likelihood of transmission to BET. The propagation of such risk can be monitored through the conditional volatility series, as illustrated in Figure 12. Specifically, the conditional volatility of BET may be expected to increase with a lag, and its trajectory can be anticipated by tracking the conditional volatility patterns of the other indices.

6. Conclusions

This paper set out to analyze the behavior of financial market volatility during major crisis episodes between 2019 and 2025 and to develop a practical, high-frequency-based indicator capable of signaling the emergence of systemic risk, with particular relevance for the Romanian and European capital markets. Using intraday data sampled at five-minute intervals and a Realized GARCH modeling framework, the analysis demonstrates that volatility and volatility shocks derived from high-frequency data contain rich information about the timing, intensity, and transmission of financial stress across markets.

Several key conclusions emerge from the empirical results. First, major crisis episodes - most notably the COVID-19 pandemic and the Russia - Ukraine war - are clearly reflected in sharp and persistent increases in conditional volatility across virtually all analyzed stock market indices. These volatility surges coincide closely with the onset of major economic, geopolitical, and policy-related shocks, confirming the suitability of high-frequency volatility measures for real-time stress monitoring. The extreme behavior of the Russian stock market during the invasion of Ukraine further illustrates how geopolitical events can generate unprecedented market disruptions, including prolonged trading suspensions that themselves become indicators of systemic distress.

Second, the analysis shows that stock market volatility is driven predominantly by international rather than domestic factors. For most countries in the sample, including Romania, volatility dynamics are closely synchronized with developments in major global markets, particularly during periods of heightened stress. Domestic events matter mainly in specific cases - such as Turkey and Russia - where idiosyncratic political, monetary, or institutional factors generate volatility patterns that diverge from global trends. For Romania, however, the evidence indicates that international shocks dominate, with domestic events playing a secondary role except in isolated episodes.

Third, and most importantly from a policy perspective, the results demonstrate that conditional volatility estimated for major global and regional indices acts as a leading indicator for the Romanian BET index during the early stages of crises. In both the COVID-19 and Russia - Ukraine war episodes, increases in volatility in benchmark markets and in neighboring countries systematically precede similar increases in BET volatility. This lagged response implies that monitoring a carefully selected set of external indices can provide early warning signals of rising systemic risk in Romania. While the BET index may eventually exhibit comparable or even higher volatility as crises unfold, it is the initial lead - lag relationship that is crucial for timely risk detection.

The proposed systemic risk indicator - based on conditional volatility and volatility shocks estimated within the Realized GARCH framework - offers a structured procedure for distinguishing between domestically generated disturbances and internationally driven systemic shocks. By focusing on contemporaneous volatility shocks across multiple markets and identifying threshold exceedances in conditional volatility, the indicator allows for the classification of stress episodes with a high likelihood of cross-market transmission. Such an approach is particularly valuable for small open economies, where external shocks are a primary source of financial instability.

Overall, the findings underscore the advantages of using high-frequency data and integrated volatility models for systemic risk monitoring. Compared to low-frequency approaches, the proposed methodology delivers faster, more informative signals that are better suited to real-time policy analysis and crisis management. Future research could extend this framework by incorporating additional asset classes, exploring nonlinear spillover mechanisms, or formally integrating the volatility-based indicator into macroprudential policy decision rules.

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