Inzinerine Ekonomika-Engineering Economics, 2025, 36(3), 303–316

Specific Risk Modelling Approach Under Permacrisis Conditions: Some Empirical Evidence

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https://doi.org/10.5755/j01.ee.36.3.34487

The subject of the research is testing, analyzing, and considering the possibility of applying different risk modeling approaches to optimize the effects of investment activities. In order to have a realistic research basis, concrete data from certain markets were used to cover the studied phenomena as efficiently as possible. The aim is to obtain reliable, timely information about the accomplishment of the specific risk modeling approach under permacrisis conditions. Specific results and their significance for science and practice underscore the focus on distinct crisis periods. The findings confirm the practical relevance and advantages of applying EVT and CEVT-based Value-at-Risk models. This is achieved using different confidence levels (90% and 99%) and a 250-day moving window. The novelty of the research lies in the comparative assessment of investment risk in both developed and developing markets under permacrisis conditions, with the strengths and weaknesses of the tested models clearly identified. The study thereby contributes to creating an optimal market environment that supports informed investment decisions regarding expected returns. The limitations of the research reflect the distinct characteristics of developed and developing markets, with a particular challenge being the identification of systemic risk under the prevailing conditions.

Keywords: *Risk Modelling, Value at Risk, GARCH, Investment Activities, Permacrisis.*

Introduction

As a social phenomenon, the market necessarily presupposes supply and demand. Namely, it is impossible to imagine any market form without supply and demand in it. Regardless how banal and simple it sounds occasionally, this profoundly important fact is nevertheless a key premise of any market form. Altered supply and demand result in direct modifications of market conditions and opportunities, which are ultimately manifested through changes in market prices. From the very beginning of market relations, one of the key issues has been how to successfully anticipate changes in supply and demand, i.e. how to efficiently predict market trends and prices, and make optimal buying and/or selling decisions. It has remained so to this day. However, the structure, type, scope, and dynamics of changes in supply and demand have been constantly changing. Numerous factors participate in the process. Policy creators are focused to perceive and describe those factors to be able to know the market well, predict its changes and trends, and thus operate in it efficiently.

The modern age has challenged market participants to assess market conditions and opportunities. The circumstances from the recent past led to a complete redefinition of market behaviour and evaluation of the effects of market activities.

These tendencies are particularly evident in the case of financial markets, which are significantly more dynamic, volatile, and sensitive than other market forms, which is a direct consequence of the specific market trading materials. The beginning of the COVID-19 pandemic was also the beginning of significant turbulence in all, especially financial markets because all the above-mentioned parameters of supply and demand began to change in an unprecedented way. For instance, the return function behaved differently compared to the period before the pandemic, market participants changed their market preferences and deviated from the postulate that they usually used to be rational in their investment decision-making and the like. Such undeniably tectonic changes modified both market opportunities and market participants fundamentally, and to a significant extent, market instruments as well.

As is often the case, extreme circumstances did not subside with the slight abatement of the pandemic but only intensified, as an armed conflict began on European soil, leading to significant changes in the supply and demand of energy and food. Once again, this confirmed that the market is fundamentally a simple space where supply and demand for various market goods meet. Under such prevailing market circumstances, characterized by permacrisis conditions, questions arise about how to succeed in investment activities, how to optimally manage the associated risks, and whether previously established methods for assessing and evaluating investment risks remain effective.

Hoga and Demetrescu (2023) and Taylor (2022) argue that traditional Value-at-Risk (VaR) models often produce inadequate risk forecasts and fail to provide information about potential exceedances beyond the chosen quantile. This underscores the necessity of continuous monitoring and timely detection of forecast failures. Papadakis et al. (2025) analyze the emergence of a permacrisis-specific framework, defined as a persistent state of crisis marked by increasing frequency, transmission, and intensity of shocks. According to Bradford et al. (2024), this framework perpetuates a sequence of unprecedented events. Special attention is paid to conditions in developed and emerging markets. The key differences between them are reflected in investors' risk perception, which in turn influences the investment decision-making process (Brosig *et al.,* 2025).

To address these critical questions, the authors have undertaken research to confirm or challenge the effectiveness of key models for assessing and evaluating the impact of investment activities during extreme crisis periods. The study focuses on testing, analyzing, and evaluating various risk modeling approaches to optimize investment outcomes in specific permacrisis market conditions. Using data from both developing and developed countries provides a broader perspective and aims for a more accurate answer to this pressing question.

Furthermore, the authors aim to offer valuable insights into the applicability of specific models for investment risk assessment in today's distinct market conditions, which differ significantly from previous contexts, justifying this important line of inquiry. This research seeks to deliver reliable, timely information on the success of specific risk modeling approaches under permacrisis conditions. With an original and comprehensive approach, the study examines conditions and opportunities across both developing and developed markets (a novelty in comparable research) to evaluate the effectiveness of assessment models and investment risk anticipation in modern contexts—an analysis not previously undertaken.

The paper is structured as follows. The introductory part provides an overview of the subject and objectives of the research, along with an extensive review of the relevant theoretical foundations. The following section presents the methodology used, accompanied by explanations, and is followed by the presentation and discussion of the research results. The final section offers the conclusion, followed by a comprehensive list of references.

Research Objectives and Contribution

This research clarifies and identifies several gaps in knowledge regarding current models and approaches to investment risk prediction, particularly under permacrisis conditions. These gaps include inadequate handling of the dynamic nature of observed stock markets; failure to account for the frequent occurrence of extreme events and significant market fluctuations, which can lead to overestimation or underestimation of risk; limited input data consideration that can severely diminish the practical applicability of tested risk assessment methods; and a lack of comprehensive frameworks capable of integrating various risk modeling approaches.

This study responds to identified gaps in the literature by developing a specific risk modeling approach tailored to periods of permacrisis - notably, the COVID-19 pandemic and the onset of the war in Ukraine - where intense economic and geopolitical uncertainty prevails. Unlike prior studies that primarily compare recent crises with the 2008 global economic crisis, this research focuses on narrowly defined periods where crisis effects are at their peak, providing a more precise examination of market volatility under these unique conditions.

To enhance methodological robustness, we perform parallel analyses using multiple techniques, including GARCH modeling, Delta Normal VaR (DVaR), Conditional Delta Normal VaR (CDVaR), Extreme Value Theory (EVT), and Conditional Extreme Value Theory (CEVT). This approach allows for a comparative evaluation of standard versus conditional risk assessment methods, as the literature suggests that conditional models may yield more accurate insights into risk behavior during extended instability. By combining emerging and stable markets in the analysis, we aim to capture a broad spectrum of market responses, providing a richer context for assessing resilience and volatility across different economic settings.

In summary, this study addresses critical gaps by applying advanced methodologies to examine the effects of investment activity in permacrisis conditions, establishing a framework that supports more informed decision-making in periods of prolonged uncertainty.

The paper presents significant novelty and originality, particularly in its approach to analyzing specific risk modeling techniques and their practical applications under permacrisis conditions. Key aspects highlighting its contributions and potential value for target groups include:

- an innovative methodology that applies a specific risk modeling approach focused on assessing the most volatile periods, covering recent crises such as the COVID-19 pandemic and the Ukraine crisis;
- validation of chosen techniques within the specific risk approach through adequate tests and statistical analyses;
- practical value for policymakers and the professional community; and
- a contribution to academic discourse, offering insights valuable for researchers and academics interested in building on these findings and further exploring the subject area.

Literature Review

Many studies have focused on questions of the frequent crisis situations due to the COVID-19 pandemic. Additionally, in the given conditions, a special challenge was the possibility to predict and evaluate the effects of investment activities in the context of adequate risk management (Halbleib *et al.,* 2012; Ali *et al.,* 2012; Kinateder *et al.,* 2014; Ergen 2015; Huang *et al.,* 2021; Kumaran, 2022).

Abuzayed et al. (2021) studied risk spillovers through globally connected markets that had been most affected by the negative effects of the COVID-19 global pandemic. Applying the GARCH model, they identified a high degree of transmission of marginal extreme risk during the COVID-19 period in the observed markets. Consequently, the particular emphasis was on the importance of adequately determined systemic risk when making investment decisions in conditions of uncertainty induced by the COVID-19 pandemic.

Mathieu et al. (2021) explored the global database related to COVID-19 vaccination activities, particularly emphasizing the volume and pace of given activities. In this way, it was possible to create an adequate predictive framework to perceive the end of the active phase of the pandemic as well as global perspectives.

Castillo et al. (2021) focused their research on the impact of the COVID-19 pandemic on returns from investment activities. By testing the most important stock market and sector indices through the EGARCH model, the authors provided an extensive view of COVID-19 with its impact on the Value-at-Risk (VaR) measure of risk. The research is significant because it identifies a sudden change in the distribution of returns in the context of adopting reliable measures in investment risk management, i.e. the VaR prediction.

Using Conditional Extreme Value Theory (CEVT), Omar et al. (2020) predicted the Value-at-Risk (VaR) of financial markets under the conditions of the COVID-19 global pandemic. In particular, they pointed out the high risk of unprecedented conditions of uncertainty, causing significant losses in investment processes. Extreme tail behaviour requires testing and analysing of a special methodological framework for VaR prediction, particularly CEVT. The selection of a diversified investment portfolio together with the necessity of modeling extreme events are essential in crisis conditions.

Das et al. (2020) analysed the impact of the COVID-19 pandemic on market risk, in the context of the successful application of the Value-at-Risk (VaR) model. The significance of the research is reflected in the fact that the negative effects of the crisis induced by the Coronavirus are comparatively analysed with the global financial crisis 2007-2008. They simultaneously investigated both positive and negative fluctuations, as well as investors' reactions to information during the crisis period. Based on the results of the research, the authors emphasised the importance of the correct perception of the short-term dynamics in the observed market and the predictive usability of such information in investment processes.

Using the extreme value theory (EVT), i.e. the selected methodological approach, Nair (2021) analysed the periods before and after the COVID-19 pandemic, and the market reaction to the accomplished expected return rate from investment activities. The extreme market behaviour explained the observed market volatility, while the application of technical indicators and EVT significantly improved the predictive success of the tested models. The author’s conclusion was that the COVID-19 crisis significantly affected the efficiency of the market, which was crucial both for the investment public and policymakers in the subject area.

Khan et al. (2021) applied the generalised Pareto distribution (GPD) under the conditions of the COVID-19 pandemic. The comparative advantage of this research is reflected in the use of high-frequency return data in the pandemic period. The results of the research imply that the GPD provides a realistic picture of the uncertainty caused by the pandemic to facilitate minimal risks and negative effects from investment activities, with the continuous monitoring of the application of the tested risk management model.

The empirical study by Ahadiat et al. (2021) analysed the success of risk assessment and market share prices in the conditions of the COVID-19 global pandemic on the example of a highly volatile financial sector. The given sector was particularly affected by the intensified crisis with accompanying health and economic effects. The study focused on determining the maximum possible loss from investment activities and its minimisation using different VaR models, with a special emphasis on Autoregressive AR (1)-GARCH (1). Based on the results of the study, it can be concluded that investors need to reconsider and justify investing in the financial sector.

Considering the reliability of the application of different VaR models, extreme value theory (EVT) should be applied with simpler VaR models, such as historical VaR (HS VaR) and delta normal VaR (D VaR) (Djakovic *et al.*, 2021).

Many authors (Angabini et al. (2011); Orhan et al. (2012); Yang et al. (2013); Lean et al. (2014); Oberholzer et al. (2015); Sekmen (2015); Totic (2015); Roni et al. (2017); Ahsanuddin et al. (2019); Tabasi et al. (2019); Sharma et al. (2020); Hung (2021); Muzindutsi et al. (2020); Adenomon et al. (2022)) also dealt with the application of GARCH and EGARCH models in volatile business conditions with special reference to opportunities and limitations when quantifying the effects of investment activities.

Cevik et al. (2024) has focused on the global stock markets with special attention to the movement of stock market indices and the existence of downside risk. While performing a critical analysis of the conducted research the following limitations and strengths are pointed out. The limitations observed comprises: sample size and scope thus not enabling more comprehensive analyses; data limitations regarding the use of GDP as a proxy for stock market weights because not acquiring market capitalization data for some stock markets which directly affects the analyses of market dynamic itself; methodological constraints understand the exclusive usage of the Component Expected Shortfall (CES) method for investigating systemic risk which affects robustness of the research; entire research is focused on the stock markets, disregarding systemic risks from other sectors of the financial markets; static analyses of the research is disregarding the dynamic nature of financial markets. The strengths observed comprise: significant time period of analyzed data (1995-2021); the application of the Component Expected Shortfall (CES) method for identifying systemically important markets and quantile spillover analysis that is significant for the identification of risk spread in the volatile market conditions; adequate temporal and regional analyses that especially stress the shift to China and India and pointing to the systemic risk origine; the research is significant for the policy makers and broader investment community which is aimed to limit risk spillovers with adequate risk assessment tools.

Zhang and Dufour (2024) examine managing portfolio risk during crisis times using the Dynamic Conditional Correlation (DCC) model. The limitations observed comprise: robustness of the research results and concluding remarks are questionable while using intraday correlations, that is, data frequency used with limited focus; contagion phenomenon that stresses the importance of heterogeneous shocks instead of contagion effects, which generalize the obtained results rather than enabling its application to different crises conditions; the Dynamic Conditional Correlation (DCC) model assumes that correlations are time-varying, that is, it is difficult to adequately incorporate extreme events in crisis conditions; The strengths observed comprise: detailed analyses understand not only correlation analyses but also Value at Risk (VaR) forecasting in portfolio management; the research is significant while focusing the European government bonds and its fluctuation rates and its market nature, providing valuable insights to the policy makers and the professionals in the subject field.

Harjoto and Rossi (2023) recently publicated the research which handled market reaction to the COVID-19 pandemic with focus on the emerging markets. The limitations observed comprise: timings of the wide variety of countries to the COVID-19 pandemic occurrence; the identification of the COVID-19 pandemic effect on the specific industry sectors, because there is not a single outbreak impact date on each emerging market observed; the lack of government measures and fiscal and monetary policies of the Central Banks analyses that directly affects the tested emerging markets; the analyses of emerging markets integration and co-movements to the research results and recommendations. The strengths observed comprise: comparative analyses of emerging and developed markets reactions to the extreme business conditions characterized by global shocks; coverage a wide variety of eleven different sectors with identifications of each sector opportunities and threats; innovative methodology that relies to the event study methodology, particularly Carhart and GARCH(1,1) models used for an event study, thus enabling pointing out to different market reactions with various time windows; historical perspective is enabled by the comparative analyses of two major crises, the global economic crisis (2008) and COVID-19 pandemic, especially regarding negative effects and recovery pace; the conducted research offers substantial empirical evidence that emerging markets are more negatively impacted by global shocks compared to developed markets; the research results point to the resilience of both emerging and developed stock markets regarding COVID-19 pandemic as is the case with the global economic crisis (2008).

Shackleton et al. (2024) presented the research covering two substantial crisis: COVID-19 and the global financial crisis (2008). The limitations observed comprise: the research utilized a single predictor, the daily newspaper-based infectious disease index, for the functional regression analysis, thus disregarding the impact of other significant variables to the stock market volatility; sample size and scope, especially the use of data span only for specific markets observed and from 2000 to 2021 time period, which affects the research findings utilization; methodological constraints understand that machine learning and/or artificial intelligence could be used for the prediction of extreme events occurrence, beside used functional regression analyses; external factors like government policies and global economic conditions affected the research analyses but are not comprised in the tested market volatility. The strengths observed comprise: the application of Functional Data Analysis (FDA) techniques enables flexibility to a greater extent in terms of volatility dynamics; enables optimal investment decision making in the extreme market volatility conditions induced by crisis occurrence; quantitative and qualitative implications for the adequate future risk assessment in conditions characterized by frequent occurrence of extreme shocks that affects market volatility; identification that the realized volatility of tested stock markets returned to pre-COVID level faster than during the 2008 financial crisis; broader historical analyses and timeframe comprising the negative effects of the global financial crisis give further insight of market behavior and dynamics.

Melina et al. (2023) tested the use of the Extreme Value Theory (EVT) with machine learning in function of the investment risk prediction. The limitations observed comprise: the use of static models that are used for investment risk prediction, based on daily stock returns, limits their usage in multivariate scenarios; data sets are directly affecting the applied model output in the function of improving model accuracy and reliability; publication bias while performing a selection of the appropriate methodology for the investment-return prediction. The strengths observed comprise: dynamic predictive model that comprises extreme events occurrence in the stock market thus enabling up to date model in real time; special attention on extreme events helps to minimize prediction errors and provides a more realistic framework for an explanation of market risks; innovative and advance methodology provides integration of extreme value theory (EVT) with machine learning and offers various useful practical implications by using such predictive model.

Methodology

In this paper, the following six stock exchange indices were subjected to the empirical risk analysis: BELEX15 (Serbia), BUX (Hungary), CROBEX (Croatia), SBITOP (Slovenia), DAX (Frankfurt, Germany), and DJIA (New York, USA). The sample contains indices from four markets from financially emerging countries, as well as two indices from developed financial markets. Such sample choice was made in order to provide best-practice insight regarding enabling the adequate benchmark for the analyses of the investment decision processes. Hence, DAX and DJIA represent the blue-chip stock market indices, comprised of top companies in their industries. The selected period covers the COVID-19 pandemic and the onset of the war in Ukraine, characterized as a phase of permacrisis due to prolonged uncertainty and overlapping crises. This approach not only enhances the methodological correctness by facilitating a comparative analysis but also allows for the assessment of market volatility in emerging markets against the resilience of more stable, developed markets. Thus, the study seeks to explore how both types of markets respond under sustained economic and geopolitical stress.

For the six afore-mentioned indices, relative daily stock returns were calculated. The calculations were made for the period starting from March 1, 2018 to March 31, 2022, therefore for each of six variables the observed sample comprised of over one thousand observed values: from n=1028 for BELEX15, to n=1075 for DAX (the differences in sample sizes are due to the different number of working days for investigated markets in the observed period).

In order to target the most volatile periods we focused solely on the monthly periods, more precisely the Values-at-risk are calculated for the March, because both critical situations (COVID-19 pandemic and the Ukraine crisis) emerged in that month. Of course, all other values were indirectly included in the analysis because the chosen time frame was set to 250, corresponding roughly to a number of working days per year.

The empirical analysis consisted of three stages. Firstly, we validated our chosen technique by means of basic descriptive analysis, where we compared overall measures with the ones applied only to data subset observed on the months of March (2019 – 2022). The purpose of this introductory stage was to provide empirical evidence for our assumption that the volatility of the daily returns was extreme in the chosen month. Also, as a preparation for GARCH modelling: the stationarity of data series was confirmed by Augmented Dickey-Fuller stationary test; Kolmogorov-Smirnov normality test was performed and the normality of data was rejected; and the presence of ARCH-effect, ie. the autocorrelation of square values of time series, was established. The obtained results suggested that our data is suitable for the next phase, which is GARCH modelling.

Secondly, our goal was to test the assumption that conditional VaR methods are better suited for challenges of extreme volatility. This hypothesis, widely supported in the literature (see the literature review in the previous section), assumes that the residuals obtained by GARCH modeling are subjected to Value-at-Risk estimation instead of original values of daily returns.

The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is a widely used statistical framework for modeling and forecasting volatility, developed to capture the phenomenon of volatility clustering. It extends the traditional autoregressive moving average (ARMA) model by incorporating a conditional variance component that captures the time-varying volatility. It assumes that the variance of the error term in a financial time series is a function of both past error terms and past conditional variances. This allows the model to capture the persistence and clustering of volatility, which is a common characteristic of financial data.

The GARCH model has several variations, the most commonly used is GARCH(1,1), which considers the first lag of both the error term and the conditional variance in capturing volatility dynamics. In recent years, the GARCH model has been further extended and refined to incorporate additional features, such as asymmetric effects (Exponential GARCH – EGARCH and Threshold GARCH – TGARCH), and long memory (Fractionally Integrated GARCH). For more details about the topic, we refer a reader to Tsay (2010).

EGARCH model was proposed by Nelson (1991), as a new approach to handle asymmetric effects between positive and negative returns. The general version of EGARCH(p,q) model is defined as follows:

$$x_t = \mu + a_t, \quad a_t = \sigma_t \times \epsilon_t, \;\; \epsilon_t \sim Pd(0,1),$$

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left(|e_{t-i}| + \gamma_i \epsilon_{t-i}\right) + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2$$

Where:

- x_t is the time series value at time t;
- μ is the mean of the GARCH model;
- a_t is the model's residual at time t;
- ϵ_t is the standardized residual at time t;
- $Pd(0,1)$ is the probability distribution;
- σ_t is the conditional standard deviation (i.e. volatility) at time t;
- p and q are orders of the ARCH (GARCH) components of the model, respectively;
- α_i, γ_i, and β_j are the parameters of the ARCH (GARCH) components of the model, respectively.

In this research, we chose EGARCH (1,1) model with normally distributed standardized residuals, usually referred to as innovations. This choice was made after several attempts, according to the criteria of minimal AIC, maximal LLF and residual analysis. Akaike Information Criterion (AIC) is a statistical measure designed to balance the goodness of fit of a model with its complexity, therefore it is commonly used in the context of selecting the optimal order of autoregressive class of models, such as GARCH. The AIC penalizes models with a larger number of parameters to avoid overfitting. When comparing different models using the AIC, the log-likelihood function (LLF) is used to calculate the likelihood values required for the AIC formula and to estimate the parameters of a model by maximizing the likelihood of the observed data.

The numerical calibration of model parameters is performed by using GRG nonlinear solving method with forward derivatives and convergence criterion 0,0001. Generalized Reduced Gradient (GRG) nonlinear solver is a numerical optimization algorithm used to solve nonlinear programming problems, designed as a combination of gradient-based and heuristic search techniques.

In total 24 GARCH models were produced, one for each of six indices and for each of four years included in the time frame of the research. Calculations were performed using MS Excel with add-ins NumXL and Solver. Series of standardized residuals were calculated from each model, and subjected to the final, third part of the analysis. The correlation matrix between original values and residuals was also computed, in order to demonstrate strong positive correlation between the data series.

Third part consisted of quantitative risk estimation by means of Value-at-risk. To conduct quantitative risk modeling, four Value at Risk (VaR) methods were simultaneously utilized:

- Delta Normal VaR (DVaR),
- Conditional Delta Normal VaR (CDVaR),
- Extreme Value Theory (EVT), and
- Conditional Extreme Value Theory (CEVT).

DVaR and EVT were performed on the original data values, whereas their conditional counterparts, namely CDVaR and CEVT, were executed on the residuals obtained by EGARCH modeling. The objective of these methods was to estimate the level of risk based on past daily returns over a specified period of time. Specifically, the aim was to determine a threshold value that would not be exceeded by the relative loss on a given day, with a predetermined level of confidence. The analysis focused on a confidence levels of 90% and 99%, and rolling window was set to the value of 250 days, meaning that for each day of March (years 2019 to 2022) calculated VaR was made based on the previous 250 values.

The realized daily returns and the model-generated values were then compared for each day. If the realized value was higher (indicating a lesser relative loss) than the estimated value, it was deemed a successful day. Conversely, if the loss exceeded the estimated value, it was considered a VaR break. The total number of VaR breaks per month was summarized and tabulated for each method, stock exchange index, and two confidence intervals.

Delta normal VaR is a well-known and easy to compute parametric model used for risk calculation, assuming that the empirical distribution of daily returns follows a normal distribution N(m, σ). The parameters of the normal distribution are estimated using point estimates obtained through the method of moments from the realized sample of the previous k days. Specifically, the mean (m) is estimated using the sample mean, and the standard deviation (σ) is estimated using the sample's standard deviation. To compute DVaR for day k + 1 at a given confidence level (c), the inverse value of the distribution function for argument 1-c is calculated. Although original values of daily returns are shown to be non-normally distributed and thus not suitable for this method, standardized residuals are by definition close to normal distribution so conditional counterpart of DVaR is justified. Both methods are performed in parallel for comparative purposes.

Extreme Value Theory (EVT) is a modeling approach that focuses on fitting the tail of the distribution, unlike the DVaR model that considers the entire distribution of daily returns. Empirical evidence supports the superiority of EVT over classical VaR models. Two classic approaches within EVT are the Block Maxima approach, using the General Extreme Value (GEV) distribution, and the Peaks Over a Threshold approach (POT), employing the Generalized Pareto (GP) distribution, introduced by Picklands (1975).

$$G(x) = \begin{cases} 1 - \left(1 + \dfrac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}, & \xi \neq 0 \\ 1 - \exp\left(-\dfrac{x-\mu}{\sigma}\right), & \xi = 0 \end{cases}$$

The GP distribution depends on shape (ξ), location (μ), and scale (σ) parameters, with μ representing the threshold or starting point of the right tail. The excess distribution function is defined in terms of conditional probability. Threshold selection is crucial to balance the availability of data for precise parameter estimation and the inclusion of relevant data points in the right tail. Various methods exist for threshold selection, including graphical methods and goodness-of-fit-based methods. Once the threshold is determined, the estimation of shape (ξ) and scale (σ) parameters follows. Numerous estimation methods are available, including the commonly used Maximum Likelihood Estimator (MLE). In this research, due to the large number of calculations, a robust approach based on quantiles of the empirical distribution was chosen. The threshold selection was influenced by the 90th quantile of the innovation distribution obtained by historical simulation, while the MLE was utilized for parameter estimation. Calculations were performed using the POT package (Ribatet and Dutang, 2019) of the programming language R (R Core Team, 2020). The same methodology was applied for both EVT and CEVT, with exception of the input data series.

Results and Discussion

The first step in the analysis was to provide an empirical justification for the chosen time frame of observations. We calculated basic descriptives of absolute values of relative return distributions for the total observed period (January 1st, 2018 – March 31st, 2022), and separately for the four emphasized monthly periods: March 2019, March 2022, March 2021 and March 2022. The results are presented in Table 1 and illustrated by Figure 1.

Table 1

Mean and Standard Deviation of Absolute Values of Relative Daily Returns

index	N	total		March 2019		March 2020		March 2021		March 2022	
		mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
BELEX15	1028	0.45%	0.57%	0.39%	0.33%	1.74%	1.54%	0.43%	0.56%	0.48%	0.49%
BUX	1055	0.96%	1.04%	0.67%	0.47%	3.48%	2.88%	0.94%	0.64%	2.54%	2.40%
CROBEX	1058	0.47%	0.72%	0.29%	0.37%	2.82%	2.86%	0.36%	0.31%	0.81%	0.73%
SBITOP	1058	0.58%	0.73%	0.42%	0.34%	2.46%	2.20%	0.42%	0.25%	1.52%	1.09%
DAX	1075	0.89%	1.03%	0.55%	0.46%	3.27%	3.29%	0.66%	0.73%	1.80%	1.86%
DJIA	1072	0.84%	1.10%	0.50%	0.41%	5.33%	3.24%	0.72%	0.53%	0.99%	0.67%

Source: the authors

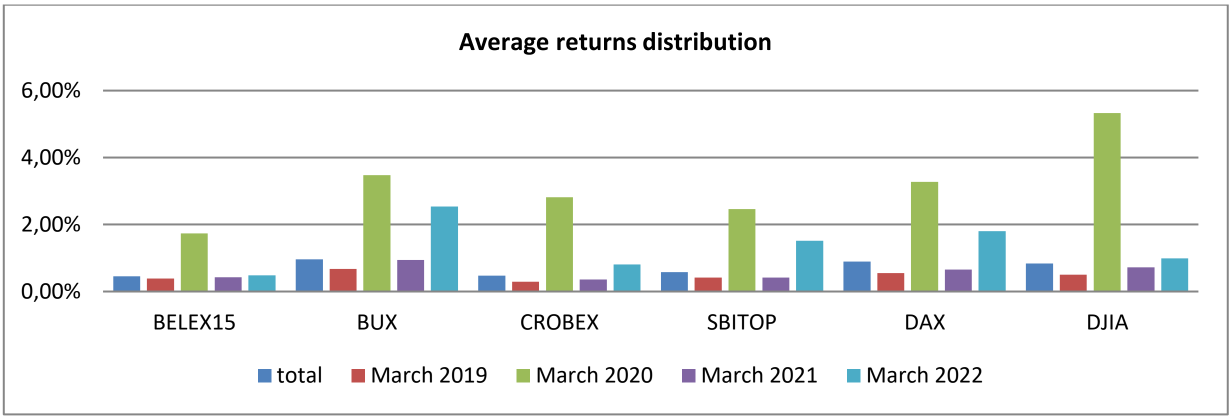

Figure 1. Distribution of Average Absolute Values of Relative Daily Returns

Source: the authors

From Table 1 and Figure 1, we see that for all six indices, March 2020 is by far the most volatile period, exceeding multiple times the total average. The total averages of relative daily returns vary from 0.45±0.57%, in case of BELEX15, up to 0.96±1.04%, in case of BUX. Meanwhile, March 2020 averages range from 1.74±1.54% to 5.33±3.24%. The highest average is observed for DJIA and the smallest one for BELEX15. March 2022 is the second most volatile time frame for all indices, ranging from 0.48±0.49% (BELEX15) to 2.54±2.40% (BUX). However, the differences among the indices are highly significant – while BELEX15 shows only slight increase, BUX is in that period more than 2.5 times more volatile comparing to total observed period. As expected, March 2019, representing period before global crises is the most stable period, followed by also quite stable March 2021. The average relative returns for the former period vary from 0.29±0.37% (CROBEX) to 0.67±0.47% (BUX), whilst for the latter period they range from 0.36±0.31% (CROBEX) to 0.94±0.64% (BUX). The presented analysis reveals extreme volatility for some of emphasized periods, as well as significant differences among different observed monthly periods, thus providing justification for the particular sample choice.

The next analysis step consisted of building and evaluating of the number of EGARCH models (for six indices and four observed annual periods), in order to obtain their standardized residuals for conditional VaR models. Table 2 contains the summary of 24 constructed EGARCH models, presenting the models' parameters, model evaluation statistics and descriptive measures of the obtained residuals.

Table 2

EGARCH Models Construction and Evaluation Summary

period	index	EGARCH(1,1) model parameters					model evaluation		residual analysis			
		μ	α_0	α_1	γ_1	β_1	LLF	AIC	mean	SD	skewness	kurtosis
1/3/2018 - 28/2/2019	BELEX15	0.00	-0.45	0.29	0.59	0.98	933.41	-1856.82	-0.04	1.02	0.16	0.93
	BUX	0.00	-0.76	0.16	0.00	0.93	758.61	-1507.22	-0.01	0.99	-0.04	0.00
	CROBEX	0.00	-8.13	0.06	2.28	0.26	997.72	-1985.45	0.01	1.00	-0.11	0.56
	SBITOP	0.00	-9.97	0.11	0.34	0.04	912.73	-1815.45	0.00	1.00	0.85	4.77
	DAX	0.00	-3.70	0.04	-8.37	0.61	815.57	-1621.15	-0.01	1.01	-0.16	0.43
	DJIA	0.00	-0.46	0.08	-2.83	0.96	825.41	-1640.81	-0.03	1.00	-0.58	1.66
1/3/2019 - 28/2/2020	BELEX15	0.00	-17.06	0.37	0.07	-0.61	950.11	-1890.22	-0.02	1.00	0.41	5.43
	BUX	0.00	-1.14	0.25	-0.24	0.90	815.50	-1620.99	-0.06	1.00	-0.64	1.61
	CROBEX	0.00	-3.17	0.10	-0.45	0.70	924.75	-1839.50	0.03	1.00	-2.89	27.46
	SBITOP	0.00	-3.75	0.33	-0.48	0.66	933.51	-1857.02	-0.01	1.00	-1.29	10.36
	DAX	0.00	-1.10	0.00	-113.4	0.88	839.96	-1669.92	-0.02	1.00	-0.67	1.19
	DJIA	0.00	-0.81	0.02	-16.60	0.92	898.32	-1786.64	-0.03	1.00	-0.55	0.83
1/3/2020 - 28/2/2021	BELEX15	0.00	-0.49	0.18	-1.01	0.96	899.55	-1789.11	0.01	0.99	0.27	2.27
	BUX	0.00	-0.26	0.25	-0.40	0.99	695.87	-1381.75	0.04	0.95	-0.14	0.78
	CROBEX	0.00	-2.04	0.82	0.00	0.85	825.27	-1640.54	0.05	1.00	0.11	4.46
	SBITOP	0.00	-0.22	0.24	-0.35	1.00	816.02	-1622.03	0.02	0.95	-0.26	1.59
	DAX*	0.00	-7.41	-0.19	-0.03	0.22	-2.7E+85	5.3E+85	8.5E+33	4.6E+41	0.95	6.84
	DJIA	0.00	-0.87	0.49	-0.09	0.94	709.75	-1409.50	-0.04	1.01	-0.39	1.41
1/3/2021 - 28/2/2022	BELEX15	0.00	-7.68	0.01	0.00	0.25	933.58	-1857.17	0.00	1.00	1.21	10.94
	BUX	0.00	-1.18	0.19	-1.14	0.88	775.25	-1540.49	0.01	1.01	-0.46	2.19
	CROBEX	0.00	-1.71	0.56	0.11	0.87	933.50	-1857.00	-0.03	1.00	-1.43	9.01
	SBITOP	0.00	-4.27	0.54	-0.57	0.61	886.74	-1763.47	0.00	1.00	-0.69	2.26
	DAX	0.00	-1.51	0.03	-12.28	0.84	840.94	-1671.88	0.04	1.00	-0.60	1.37
	DJIA	0.00	-1.04	0.10	-2.58	0.90	879.94	-1749.87	0.04	1.01	-0.39	0.21

Source: the authors

From 24 constructed models, 23 was evaluated as successful, all except the model for DAX index for March 2021. This model was therefore replaced by GARCH(1,1) model with Student distribution of innovations, whose evaluation statistics were significantly better (LLF=657.7, AIC=-1307.4). Standardized residuals for such model, with mean 0.00, standard deviation 0.99, skewness -0.59 and kurtosis 8.97, were included into further conditional VaR modelling. The relation between original relative daily returns and standardized EGARCH residuals was also investigated and the results are presented in Table 3. It shows that all 24 Pearson correlation coefficients, ranging from 0.635, for BELEX15 in March 2020, to 0.999, for SBITOP in March 2019 and BELEX15 in March 2022, are positive and statistically highly significant ($p<0.01$). The observed strong linear correlations imply that it is adequate to replace original returns by their residual counterparts in conditional VaR analyses.

Table 3

Pearson Correlation between Original Returns and EGARCH Residuals for 6 Indices and Four Time-Frames (* Denotes Statistical Significance at Level 0.01)

Pearson r	Mar-19	Mar-20	Mar-21	Mar-22
BELEX15	0.983*	0.635*	0.958*	0.999*
BUX	0.998*	0.971*	0.995*	0.880*
CROBEX	0.998*	0.962*	0.972*	0.963*
SBITOP	0.999*	0.967*	0.996*	0.892*
DAX	0.980*	0.803*	0.998*	0.896*
DJIA	0.993*	0.897*	0.977*	0.957*

Source: the authors

The final step of the data exploration comprises of Value-at-Risk analyses. Four VaR models were implemented – two dealing with original daily returns (namely DVaR and EVT) and two conditional, dealing with the residuals obtained by EGARCH modelling (namely CDVaR and CEVT). For each of the applied VaR models, two levels of confidence were considered, namely 90% and 99%. Rolling window was set to the value of 250, corresponding to approximate number of observations per year. The results are organized in chronological order, and presented in Tables 4 – 7.

Table 4

VaR Analyses for March 2019

Mar-19		**RW = 250, CL=90%**			**RW = 250, CL=99%**		
	Index	succ. days (No)	tot. days (No)	% of succ. days	succ. days (No)	tot. days (No)	% of succ. days
DVaR	BELEX15	21	21	100.00%	21	21	100.00%
	BUX	20	20	100.00%	20	20	100.00%
	CROBEX	20	21	95.24%	20	21	95.24%
	SBITOP	20	21	95.24%	21	21	100.00%
	DAX	19	21	90.48%	21	21	100.00%
	DJIA	20	21	95.24%	21	21	100.00%
CDVaR	BELEX15	21	21	100.00%	21	21	100.00%
	BUX	20	20	100.00%	20	20	100.00%
	CROBEX	20	21	95.24%	20	21	95.24%
	SBITOP	20	21	95.24%	21	21	100.00%
	DAX	19	21	90.48%	21	21	100.00%
	DJIA	19	21	90.48%	20	21	95.24%
EVT	BELEX15	21	21	100.00%	21	21	100.00%
	BUX	20	20	100.00%	20	20	100.00%
	CROBEX	20	21	95.24%	20	21	95.24%
	SBITOP	21	21	100.00%	21	21	100.00%
	DAX	21	21	100.00%	21	21	100.00%
	DJIA	20	21	95.24%	21	21	100.00%
CEVT	BELEX15	21	21	100.00%	21	21	100.00%
	BUX	20	20	100.00%	20	20	100.00%
	CROBEX	20	21	95.24%	20	21	95.24%
	SBITOP	21	21	100.00%	21	21	100.00%
	DAX	21	21	100.00%	21	21	100.00%
	DJIA	21	21	100.00%	21	21	100.00%

Source: the authors

For the relatively stable period such as March 2019, all four VaR models provided successful estimations. The percentage of successful days for 90% confidence level ranged from 90.48% to 100% (corresponding to 0-2 VaR breaks per month), while the percentage of successful days for 99% confidence level ranged from 95.24% to 100% (which corresponds to 0-1 VaR breaks per month). Noting that there are only minor differences among the models, one could observe that the most prominent were CEVT and EVT, followed by DVaR, while the least successful was CDVaR. The ranking is consistent for both applied confidence level.

Table 5

VaR Analyses for March 2020

Mar-20	RW = 250, CL=90%				RW = 250, CL=99%		
	Index	succ. days (No)	tot. days (No)	% of succ. days	succ. days (No)	tot. days (No)	% of succ. days
DVaR	BELEX15	11	22	50.00%	14	22	63.64%
	BUX	13	22	59.09%	16	22	72.73%
	CROBEX	15	22	68.18%	15	22	68.18%
	SBITOP	12	22	54.55%	14	22	63.64%
	DAX	14	22	63.64%	17	22	77.27%
	DJIA	12	22	54.55%	14	22	63.64%
CDVaR	BELEX15	12	22	54.55%	15	22	68.18%
	BUX	15	22	68.18%	20	22	90.91%
	CROBEX	15	22	68.18%	16	22	72.73%
	SBITOP	16	22	72.73%	18	22	81.82%
	DAX	17	22	77.27%	19	22	86.36%
	DJIA	15	22	68.18%	18	22	81.82%
EVT	BELEX15	15	22	68.18%	17	22	77.27%
	BUX	15	22	68.18%	16	22	72.73%
	CROBEX	17	22	77.27%	19	22	86.36%
	SBITOP	17	22	77.27%	20	22	90.91%
	DAX	20	22	90.91%	21	22	95.45%
	DJIA	17	22	77.27%	21	22	95.45%
CEVT	BELEX15	16	22	72.73%	18	22	81.82%
	BUX	15	22	68.18%	16	22	72.73%
	CROBEX	17	22	77.27%	19	22	86.36%
	SBITOP	18	22	81.82%	21	22	95.45%
	DAX	20	22	90.91%	21	22	95.45%
	DJIA	17	22	77.27%	21	22	95.45%

Source: the authors

Due to the extreme volatility of the observed period, the results for March 2020 are, as expected, the most interesting. All four models failed to estimate risk to the desired extent given by prescribed confidence levels. However, there are highly significant differences among the percentages of the successful estimations. The least successful method was DVaR. The percentage of successful days ranged from 50.00% to 68.18% for 90% confidence level, and from 63.64% to 77.27% for 99% confidence level. The next method in the ascending order is CDVaR, with 54.55 - 77.27% successful risk estimations for the 90% confidence level, and 68.18 - 90.91% successful risk estimations for the 99% confidence level. In comparison with DVaR, CDVaR provided better estimations in 11/12 cases. Both models based on extreme value theory were superior in comparison to models based on normal distribution. The percentages vary from 68.18% to 90.91% for 90% confidence level, and from 72.73% to 95.45% for 99% confidence level. A slight advantage is given to CEVT, that provided higher percentage of successful estimations in 4/12 of the total number of observed cases: two cases for 90% confidence level and two more fore 99% confidence level.

Table 6

VaR Analyses for March 2021

Mar-21	RW = 250, CL=90%				RW = 250, CL=99%		
	Index	succ. days (No)	tot. days (No)	% of succ. days	succ. days (No)	tot. days (No)	% of succ. days
DVaR	BELEX15	22	23	95.65%	22	23	95.65%
	BUX	22	22	100.00%	22	22	100.00%
	CROBEX	23	23	100.00%	23	23	100.00%
	SBITOP	23	23	100.00%	23	23	100.00%
	DAX	23	23	100.00%	23	23	100.00%
	DJIA	23	23	100.00%	23	23	100.00%
CDVaR	BELEX15	22	23	95.65%	23	23	100.00%
	BUX	20	22	90.91%	22	22	100.00%
	CROBEX	22	23	95.65%	23	23	100.00%
	SBITOP	20	23	86.96%	23	23	100.00%
	DAX	23	23	100.00%	23	23	100.00%
	DJIA	23	23	100.00%	23	23	100.00%
EVT	BELEX15	22	23	95.65%	23	23	100.00%
	BUX	22	22	100.00%	22	22	100.00%
	CROBEX	23	23	100.00%	23	23	100.00%
	SBITOP	23	23	100.00%	23	23	100.00%
	DAX	23	23	100.00%	23	23	100.00%

Mar-21		**RW = 250, CL=90%**			**RW = 250, CL=99%**		
	Index	succ. days (No)	tot. days (No)	% of succ. days	succ. days (No)	tot. days (No)	% of succ. days
	DJIA	23	23	100.00%	23	23	100.00%
CEVT	BELEX15	22	23	95.65%	23	23	100.00%
	BUX	22	22	100.00%	22	22	100.00%
	CROBEX	23	23	100.00%	23	23	100.00%
	SBITOP	23	23	100.00%	23	23	100.00%
	DAX	23	23	100.00%	23	23	100.00%
	DJIA	23	23	100.00%	23	23	100.00%

Source: the authors

After the extremely turbulent year 2020, it was expected that all VaR models overachieve for March 2021, and the results presented in Table 6 confirm such expectations. EVT and CEVT behave in the identical way in this period, scoring perfect 100% of successful estimations for 99% confidence level; 95.65% for BELEX15 and 100% for remaining five indices for confidence level of 90%. DVaR is almost equipotent with only one point of difference (BELEX15 for CL=99%), whilst CDVaR is the least successful, yet very good risk estimation method. It made perfect 100% of successful estimations for 99% confidence level, but it also made the only underachieving estimation for this period: in case of SBITOP index and 90% confidence level it made 86.96% of successful estimations.

Table 7

VaR analyses for March 2022

Mar-22		**RW = 250, CL=90%**			**RW = 250, CL=99%**		
	Index	succ. days (No)	tot. days (No)	% of succ. days	succ. days (No)	tot. days (No)	% of succ. days
DVaR	BELEX15	20	23	86.96%	22	23	95.65%
	BUX	17	21	80.95%	20	21	95.24%
	CROBEX	20	23	86.96%	21	23	91.30%
	SBITOP	19	23	82.61%	21	23	91.30%
	DAX	18	23	78.26%	20	23	86.96%
	DJIA	19	23	82.61%	22	23	95.65%
CDVaR	BELEX15	20	23	86.96%	22	23	95.65%
	BUX	17	21	80.95%	20	21	95.24%
	CROBEX	21	23	91.30%	23	23	100.00%
	SBITOP	21	23	91.30%	21	23	91.30%
	DAX	18	23	78.26%	20	23	86.96%
	DJIA	19	23	82.61%	22	23	95.65%
EVT	BELEX15	22	23	95.65%	23	23	100.00%
	BUX	19	21	90.48%	20	21	95.24%
	CROBEX	23	23	100.00%	23	23	100.00%
	SBITOP	22	23	95.65%	23	23	100.00%
	DAX	22	23	95.65%	23	23	100.00%
	DJIA	23	23	100.00%	23	23	100.00%
CEVT	BELEX15	21	23	91.30%	23	23	100.00%
	BUX	19	21	90.48%	20	21	95.24%
	CROBEX	23	23	100.00%	23	23	100.00%
	SBITOP	22	23	95.65%	23	23	100.00%
	DAX	22	23	95.65%	23	23	100.00%
	DJIA	23	23	100.00%	23	23	100.00%

Source: the authors

Finally, Table 7 contains results of the risk estimations for March 2022, the second most volatile period of four observed ones. This level of volatility enabled clear distinction between two pairs of models: CEVT & EVT on one side, and CDVaR & DVaR on the other. The former pair provided successful estimations for the accounted levels of confidence for all analyzed cases. Percentage of success ranges from 90.48% to 100.00% when confidence level is set to 90%, and from 95.24% to 100.00% for CL=99%. There is only one point of difference – the 90% risk of BELEX15 was slightly better estimated by EVT than by its conditional counterpart. The latter pair of models was significantly less well-behaved. DVaR did not achieve any sufficiently high percentage for CL=90%, with percentages ranging from 78.26% to 86.96%; and 3/6 sufficiently high percentages for CL=99%, with percentages ranging from 86.96% to 95.65%, thus making it the least successful method. CDVaR was better, but still less successful than the other pair – its percentages varied from 78.26% to 91.30% for CL = 90% (2/6 sufficiently high ones), while for CL = 99% the percentages varied from 86.96% to 100.00%, 5/6 being considered as high enough. Bearing in mind the above-mentioned results, the authors' decision to focus the research on 2020, 2021, and 2022 has been justified, especially in March, when the volatile conditions in the observed markets were evident. The situation indicated presumable uncertainty in investment processes, in cases when the risks were unpredictable and unmanageable.

Effective and efficient risk management implies the selection of an adequate methodology and especially the selection of models that enable making optimal investment decisions, in addition to continuous assessment of the investment effects. In this sense, the wide range of choices of VaR models applied in the research is based on the conceptual-methodological foundations and the fitting of the given models, i.e. the adjustment of the calculation parameters of the same to maximise the effects of investing activities with a special emphasis on the prediction of the maximum possible investment loss.

In particular, it has been observed that the more volatility growth, the more distinct superiority of EVT-based models in relation to normal distribution models. Namely, the modeling of the thick tails of the empirical return distribution implies an adequate evaluation of the parameters of the applied VaR models, bearing in mind that the standard models, based on the normal distribution, largely underestimate the risk and cause inadequate capital allocation and risk coverage in the observation period. This statement justifies the application of EVT-based VaR models, especially in the observed cases.

Based on the research results, it can be additionally concluded that the volatility growth leads to better performance of models using residuals, compared to methods using original returns in the observed markets. The difference is more noticeable when comparing CDVaR and DVaR than when doing the same with CEVT and EVT, which is actually expected because the latter pair gives less maneuver space, considering the overall better performance. It is the pronounced volatility in the observed periods that requires a special analytical approach when considering the success of the application of the tested VaR models, with special attention on the distribution of the research sample. The focal point on the residuals, instead of the original returns, proved to be justified, especially due to a strong linear correlation between them.

However, the standard VaR calculation models, e.g. DVaR, have an adequate place, role, and importance in determining the success of risk anticipation. Namely, it cannot be concluded that CDVaR is generally a better model than DVaR because in more stable periods DVaR is more successful in risk anticipation.

The success of applying different VaR models coincides with different periods, that is, conditions and opportunities, both in developed markets and markets in developing countries.

Conclusions

Characterized by the permanent frequent crisis situations and extremes, permacrisis conditions affect rational investors in terms of investment decisions, especially considering risk anticipation and its minimisation. Based on the research results while using a comprehensive research sample from either developed and/or developing markets, it can be concluded that the simultaneous application of different VaR models, both standard and specific, is justified.

Focused on distinct crisis periods and by using diverse confidence levels of 90% and 99% as well as a moving window of 250 days, the research gave a comprehensive overview of the success of the VaR model application. Specifically significant was the application of two VaR calculation models on original returns, DVaR and EVT, as well as the application of two VaR calculation models on residuals, CDVaR and CEVT. The performance of the tested VaR models was particularly interesting in March 2020 when there was no successful risk prediction due to high volatility. However, the superior models were those that basically had EVT. The results in March 2022 also confirmed the given superiority.

Specific risk modeling under permacrisis conditions implies empirical testing of the application of given models, whose performance is affected by periods of extreme volatility that were specifically explicit at the time of the COVID-19 pandemic, and continued and further conditioned by the Ukrainian crisis. The analysis of extreme volatility and the focus on monthly periods implied the particular attention of the VaR calculation to the months of March (2019 – 2022), which provides relevant performance results of VaR model application in crisis conditions.

Consequently, a significant contribution to the research realised in the paper is to enable investors and the wider investment public to adequately manage risks in the permacrisis conditions, when market postulates are fundamentally redefined in terms of supply/demand behaviour, as well as the behaviour of the investment returns. Hence, the special quality of the research is reflected in the fact that it tested specific models of investment risk assessment in actual market circumstances, i.e. it tested their success to anticipate expected returns. A comparative review of the conducted research in the area has not sufficiently explored the dilemmas and traps that the market circumstances in permacrisis conditions pose to the tested models. In this statement lies the originality of the conducted research, in the sense of "opening up" a new approach to the analysis of the market and the behaviour of market participants. Additionally, the research contribution is a scientifically verified and pragmatically tested basis for creating an adaptive risk management model, which will have adequate performance even in daily extreme conditions.

Policy implications include establishing a detailed list of activities necessary for implementation, as well as supporting decision-making in conditions characterized by a lack of quality information. The need for reliable and high-quality data on financial market conditions is growing day by day, especially in light of the extremely volatile environment. The research presented in this article provides policy makers with important tools for optimal information gathering and, consequently, improved market efficiency. It also offers clear guidelines for risk management and the investment decision-making process. In this way, investment decisions can be further optimized, particularly from the perspective of policy makers, and the findings of the research can significantly enhance their practical application. It is especially important to emphasize that better information about investment processes directly contributes to greater market efficiency, thereby fostering a more favorable investment climate.

The foregoing confirms the justified practical application and advantages of EVT and CEVT VaR model testing, with clear advantages and disadvantages identified in the tested period. The research limitations imply specificities of both developed and developing markets, with the challenge to determine a high-level immanence of systemic risk in given conditions.

The permacrisis determines the direction of further research, which implies the continuous monitoring of conditions and opportunities in the observed markets, special attention to the analysis of the characteristics of the data used, and the need for flexibility and adaptability of the applied VaR models with the aim to gain and maintain a competitive advantage generated by adequate risk prediction and capital allocation, as a distinctly lacking resource in the given permacrisis conditions.

The applied models in this study come with certain limitations. First, while conditional VaR methods, such as CDVaR and CEVT, are generally effective in modeling risk under permacrisis conditions, they may overestimate short-term risk during periods of extreme volatility, leading to more conservative risk estimates that could limit their utility in highly dynamic environments. The use of a 250-day rolling window approach for VaR modeling, though helpful for capturing volatility changes, can "smooth over" sudden shifts or short-lived shocks due to its retrospective nature. Furthermore, models like GARCH and EVT, which rely on historical data, can exhibit model bias and limited adaptability when confronted with unprecedented events, such as the COVID-19 pandemic or the war in Ukraine, where market conditions differ markedly from prior crises. The limited diversity in the dataset, spanning only the 2018-2022 period, risks overfitting the models to specific events, which may affect the generalizability of findings to future crises. Additionally, the restricted scope of analyzed markets, while useful for comparing emerging and stable economies, may limit the representativeness of results for the broader global market.

Future research could address these limitations by exploring alternative window lengths or adaptive models that dynamically respond to changes in volatility, potentially enhancing model responsiveness to sudden shifts in market conditions. Expanding the dataset to include additional crisis periods could further test model robustness across diverse economic circumstances. Hybrid models that combine standard and conditional approaches with advanced techniques, such as machine learning algorithms or convolutional neural networks, could mitigate the historical data bias and improve accuracy under severe volatility. Finally, including a wider range of markets—potentially incorporating sector-specific indices and varying levels of regulatory and liquidity characteristics—would support the generalizability of findings across different economic contexts.

Acknowledgment

This research has been supported by the Ministry of Science, Technological Development and Innovation (Contract No. 451-03-137/2025-03/200156) and the Faculty of Technical Sciences, University of Novi Sad through project "Scientific and Artistic Research Work of Researchers in Teaching and Associate Positions at the Faculty of Technical Sciences, University of Novi Sad 2025" (No. 01-50/295).

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The article has been reviewed.

Received in June 2023; accepted in June 2025.