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The impact of economic sentiment on European stock markets

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ABSTRACT

Objective: This article aims to analyse the impact of sentiment indicators reflecting the condition of major economies on the returns and volatility of European developed, emerging, and frontier stock markets.

Research Design & Methods: We employed survey-based economic sentiment indicators, classified into forward-looking measures reflecting economic expectations and measures of current economic sentiment. We used survey-based economic sentiment indicators, namely the ZEW Economic Sentiment Index for Germany, the ZEW Economic Sentiment Index for the Eurozone, the ZEW Current Condition Index for the Eurozone and the Michigan Consumer Sentiment Index from the US. We modelled the daily stock returns for 27 markets over the period 2008-2022 using a GJR-GARCH model and a time-varying transition probability Markov switching model (TVPMS), where transition probabilities depend on lagged economic sentiment indicators.

Findings: The results from the GJR-GARCH model show that economic sentiment generally affects returns and their volatility. We observed the causal relationship between sentiment and returns for different types of markets. These results confirm that sentiment indicators in major economies have a global impact, affecting not only developed markets but also emerging and frontier markets. In addition to the GJR-GARCH methodology, the use of the TVPMS approach confirms the results and provides new insights. We found two market states: high and low volatility, and documented the impact of sentiment on market returns as a function of these states. The Michigan consumer sentiment index had the most substantial and persistent effect on European markets, with significant effects on volatility in both high- and low-volatility states; the ZEW economic sentiment indices affect volatility in high-volatility states, while the ZEW current situation index has a significant effect on volatility only in low-volatility states.

Implications & Recommendations: These findings provide investors and financial managers with valuable insights into the influence of different sentiment indicators on decision-making in various market conditions. During periods of high volatility, sentiment based on economic expectations can help to mitigate market fluctuations. In contrast, during stable periods, sentiment reflecting the current economic state is more informative. The U.S. Michigan Consumer Sentiment Index (MCSI) is particularly relevant in this regard, offering meaningful guidance about investment decisions in both stable and volatile environments. The influence of the same sentiment indicators on various European stock markets highlights the region's strong interconnections and suggests the presence of sentiment contagion.

Contribution & Value Added: This study makes an original contribution by combining two well-established models in a novel way. The GJR-GARCH model enables us to analyse the impact of economic sentiment on expected returns and conditional volatility, while the TVP-MS model identifies periods when sentiment exerts its greatest influence. Our research demonstrates that market behaviour responds differently to sentiment indicators, depending on their nature and the volatility regime.

Article type: research article

Keywords: stock markets; TVPMS model; AR(1)-GJR-Garch(1,1); ZEW; MCSI

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INTRODUCTION

Predicting financial market volatility is critical for investors and decision makers, and has therefore been the focus of extensive research aimed at identifying factors that reliably predict market behaviour. Many studies have examined the role of macroeconomic indicators in predicting market volatility (*e.g.*, Rapach *et al.,* 2005; Chen, 2009; Pilinkus, 2010; Larsson & Haq, 2016). However, it is also valuable to explore how economic sentiment influences markets, as sentiment-driven factors may play a significant role in market movements.

In recent years, the financial literature has widely discussed investor sentiment. Many proposed indicators of investor sentiment focus on the stock market and include measures such as market liquidity, turnover ratio, and VIX (*e.g.*, De Long *et al*., 1990; Baker & Stein, 2004; Wang *et al*., 2022; Bossman *et al.,* 2023) or survey-based measures, such as the Sentix index (Schmeling, 2007). According to classical financial theory, arbitrage should diminish the influence of investor sentiment on asset prices. In reality, arbitrage is limited and investors often interpret identical information differently, allowing sentiment to have a significant impact on the stock market (Baker & Wurgler, 2007). For example, Lee *et al*. (2002) show that stock returns adjust to changes in investor sentiment, while others find that periods of high sentiment lead to more aggressive investment by sentiment-driven investors (Karlsson *et al.*, 2009; Yu & Yuan, 2011).

The literature also includes studies on survey-based indicators of consumer confidence, such as the University of Michigan Consumer Sentiment Index (MCSI) (Lemmon & Portniaguina, 2006). In Europe, there is a survey-based index produced by the ZEW Institute that monitors sentiment in Germany or the euro area (see *e.g.*, Homolka & Pavelková, 2018). Both MCSI and ZEW are economic sentiment indices that measure the general mood of consumers (MCSI) and experts (ZEW) regarding the broader economic outcomes. Unlike investor sentiment, which is more focused on short-term market movements and investor behaviour, economic sentiment reflects the public's perceptions and expectations about the economy, which can significantly influence both market trends and consumer behaviour.

In our analysis, we considered the MCSI index, which reflects the state of the US economy, two indicators of sentiment in the euro area (the ZEW index of expected and current conditions), and the ZEW sentiment index for Germany as the largest European economy. We took all sentiment indicators from the Bloomberg database. We examined their impact on returns in 27 European equity markets, divided into developed, emerging and frontier markets. We took the data from the Morgan Stanley Capital International (MSCI).

The empirical study used two modelling approaches: the GJR-GARCH model with AR component and the time-varying transition probability Markov switching model (TVPMS). These models provide complementary insights into the dynamics of returns: the AR-GJR-GARCH model directly measures how sentiment affects returns and conditional volatility, while the TVPMS model captures shifts between high- and low-volatility regimes influenced by sentiment. By using both models, we could more fully assess the impact of sentiment indicators on stock market returns. The choice of the regime shift model was driven by research showing that investor behaviour changes with market conditions (Gervais & Odean, 2001; Nofsinger, 2005; Li & Luo, 2017).

For the TVPMS model, we employed Filardo's (1994) framework for regime shift analysis. This approach assumes two market states of high and low volatility, with transitions governed by a time-varying transition probability matrix. By allowing the transition probabilities to depend on lagged economic sentiment indicators, we could identify when the effect of sentiment on market volatility is the most pronounced. We measured volatility using the standard deviation, which is a parameter of the state-dependent conditional distribution constructed for daily returns.

The primary objectives of this study were:

1. To evaluate whether sentiment in major economies influences returns and volatility across European stock markets, including emerging, frontier, and developed markets.
2. To analyse how the type of economic sentiment measure – reflecting either economic expectations or current economic conditions – affects the strength of this influence.

3. To investigate the impact of economic sentiment on local markets – developed, emerging, and frontier – and determine whether this effect is more pronounced under low- or high-volatility conditions.

Our study confirmed the conjecture that economic sentiment in major economies affects European stock market returns and volatility. Regardless of the type of economic sentiment measure, increases in sentiment reduce return volatility not only in developed markets but also in emerging and frontier markets. These results highlight the global nature of economic sentiment. The TVPMS model provides additional insights, indicating that the impact of the sentiment indicator depends on market conditions. For example, the impact of the Michigan Consumer Sentiment Index is significant in both high- and low-volatility states, the two ZEW indices based on economic expectations are significant in high-volatility regimes, while the ZEW current conditions index is significant only in low-volatility states.

This study contributes to the literature in the following ways. First, it shows that economic sentiment affects stock market returns and volatility not only in countries where economic sentiment is measured, but also in countries with less developed stock markets. Second, we applied a dual-model framework (AR-GJR-GARCH and TVPMS) to assess not only the average effects of sentiment but also how these effects may vary across different volatility regimes. The use of time-varying transition probabilities driven by lagged sentiment indicators adds a dynamic and regime-sensitive perspective that complements traditional volatility models. Thirdly, we focused specifically on economic sentiment – both forward-looking (expectations-based) and current – rather than sentiment derived directly from financial markets. This distinction allowed us to explore whether broad economic perceptions, as opposed to market-specific moods, have predictive power for returns and volatility. To the best of our knowledge, this approach has received limited attention in the literature. Our study fills an important gap by extending the analysis to a wider range of countries, capturing differences in market development and regional sensitivity to sentiment, and by applying the TVPMS model to understand sentiment's impact in different market regimes. It extends and enriches research by providing new insights into the interaction between types of economic sentiment and market conditions.

This article is structured as follows. The next section presents a literature review. The literature review is followed by a description of the data and methodology used in the empirical analysis. The Results and Discussion section presents the main findings, and the Conclusions section briefly summarises the results.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Numerous studies have examined the factors influencing financial markets, including political events, economic conditions, and investor expectations (Pilinkus, 2010; Larsson & Haq, 2016). Rapach *et al*. (2005) demonstrated that one can predict stock returns using macroeconomic variables, while Chen (2009) found that these variables can even signal recessions in stock markets. Mahmood and Dinniah (2009) discussed relationships between stock prices and economic indicators, while Humpe and Macmillan (2009), Kim *et al*. (2008), and Chang (2009) utilised the Hidden Markov Model (HMM) to assess the effects of macroeconomic variables on stock market volatility.

Investor sentiment has garnered significant attention for its influence on stock markets, and the literature provides several methods for its measurement. Baker and Wurgler (2006) proposed sentiment proxies such as retail transactions, closed-end fund discounts and IPO yields. Bossman *et al.* (2023) used the VIX volatility index as a sentiment proxy to study EU sector stocks amid geopolitical turmoil. Wang *et al*. (2022) found that the turnover ratio, used as a sentiment proxy, affects returns differently in bull and bear markets, with higher sentiment being associated with higher returns in bull markets but lower returns in bear markets. Lee *et al*. (2002) analysed the impact of the Investor Intelligence Index on the U.S. market and found that the direction of stock returns aligns with changes in investor sentiment. Optimism correlates with higher future returns and reduced conditional volatility, while pessimism aligns with lower returns and increased volatility. Using the measure of investor sentiment proposed by Baker and Wurgler (2006), Chung *et al*. (2012) found that investor sentiment predicts stock returns during economic expansions but not recessions, highlighting sentiment-driven asymmetric pricing behaviour.

Many studies measure sentiment based on media or survey data. For example, Shi *et al*. (2019) developed a sentiment measure from investor forum posts, Siganos *et al*. (2014) from Facebook, while Petit *et al*. (2019) used web search data to create sentiment indicators for investment portfolios. Ballinari *et al*. (2022) examined the effect of a firm's social media attention on return volatility. García (2013) demonstrated that sentiment derived from financial news columns significantly impacts U.S. stock markets, with negative news exerting a stronger influence on stock performance during recessions. Similarly, Lischka (2015) found that negative sentiment in German media intensifies stock market declines. Schmeling (2007) found that institutional sentiment is a stronger predictor of returns for major indices in the US, Europe, and Japan compared to individual sentiment.

Global events such as the 2008 financial crisis and recent geopolitical tensions highlight the interconnectedness of economies and the spillover of sentiment across markets. These events demonstrate how investor sentiment extends beyond local markets, influencing multiple economies through mechanisms like risk aversion, foreign direct investment (FDI), and global trade adjustments. Research by Baker *et al*. (2012) highlights the importance of a global sentiment. They showed that the investors across major economies share a common sentiment, and it influenced the markets more than the local fluctuations in the mood of investors. Corredor *et al*. (2015) further confirmed the impact of global sentiment on Central and Eastern European markets, highlighting how sentiment in major economies affects regions with close trade and investment links.

While scholars often study sentiment in the context of forecasting economic metrics, its relationship with financial markets remains less explored. Research on economic sentiment, measured primarily through surveys, often focuses on forecasting economic metrics such as GDP (Hansson *et al*., 2005) or industrial production (Schröder & Hüfner, 2002). Studies linking economic sentiment to financial markets remain relatively limited. On the other hand, Lemmon and Portniaguina (2006) established a relationship between investor sentiment and MCSI. Cieślik and Ghodsi (2021) show that the European Economic Sentiment Indicator affects FDI flows within the EU. Homolka and Pavelková (2018) documented that the German ZEW Economic Sentiment Index predicted the 2008 crisis in the German market three months in advance, a result confirmed by Rakovská (2021).

Based on the literature and prior findings, we proposed the following hypotheses:

H1: Economic sentiment in major economies influences returns and volatility across European markets, including developed, emerging, and frontier markets, due to economic linkages and market contagion.

H2: The type of economic sentiment measure – whether reflecting economic expectations or current economic conditions – modifies the strength of its impact on stock market returns and volatility.

H3: The impact of economic sentiment on European stock markets varies under different market conditions, with the effect being more significant during high-volatility (crisis) periods compared to low-volatility (prosperous) periods.

While we focused on the predictive role of economic sentiment indicators, the observed effects may also reflect cross-market sentiment spillovers. Given increasing economic and financial integration, sentiment in one region, such as the US or Eurozone, can influence investor expectations and market behaviour elsewhere. This highlights the potential role of underlying macroeconomic linkages in transmitting sentiment internationally.

RESEARCH METHODOLOGY

Sentiment Indices

Sentiment indicators are meant to capture subjective assessments of the current or expected state of the economy or financial markets. They are increasingly used in financial and economic research to explain or predict market behaviour, especially stock returns and volatility. These indices reflect the psychological and behavioural components of decision-making, often preceding real economic activity or market adjustments.

In the literature, scholars commonly distinguish two broad categories of sentiment indicators (Wang *et al*., 2022). The first includes investor sentiment indices, such as the VIX index or measures based on trading volume and market flows. These capture emotions and moods within financial markets themselves. The second category, *i.e.*, economic sentiment indicators, which are the focus of this study, reflect broader perceptions and expectations regarding the economy, as reported by either financial analysts or consumers.

These indicators differ across several key dimensions:

– Perspective – whether they are forward-looking, capturing economic expectations, or focused on current conditions.
– Respondents – ranging from financial experts to general consumers.
– Geographic scope – from specific countries to broader regions such as Germany, the Eurozone, or the United States.
– Construction methodology – based on net balances of optimistic and pessimistic responses or standardised composite scores.

In this study, we employed four sentiment indices to capture economic perceptions in three major economies: the United States, the Eurozone, and Germany. As the strongest European economy and the largest source of foreign direct investment in Europe (Davies, 2022), Germany is represented by a separate indicator. The selected indices were the ZEW Economic Sentiment Index for the Eurozone (ZEW-ES) and Germany (GER-ES), the ZEW Current Condition Index (ZEW-CS), and the Michigan Consumer Sentiment Index (MCSI).

ZEW Economic Sentiment Index (ZEW-ES and GER-ES) are forward-looking indicators based on monthly surveys conducted by the ZEW Institute (Leibniz Centre for European Economic Research). They reflect the economic outlook of up to 350 financial analysts and economists for the next six months. Respondents assess whether the economy will improve, remain unchanged, or deteriorate. The index is calculated as the net balance of positive and negative responses, producing values from –100 (total pessimism) to +100 (total optimism), with 0 indicating a neutral stance. While the ZEW-ES covers the Eurozone as a whole, the GER-ES specifically targets expectations about the German economy. This distinction allows for comparisons between regional and national sentiment and their respective impacts on European markets.

ZEW Current Condition Index (ZEW-CS), derived from the same ZEW survey, differs by focusing on the present state of the economy rather than future expectations. Analysts assess whether current conditions are good, neutral, or poor. This distinction is important, as sentiment about present conditions may influence markets differently than forward-looking expectations, especially in varying economic environments.

The Michigan Consumer Sentiment Index (MCSI) is a widely respected indicator published monthly by the University of Michigan. Based on telephone interviews with at least 500 US households, it captures consumer views on personal finances and both short- and long-term prospects for the US economy. The index is standardised to a base value of 100 (set in Q1 1966) and is considered one of the most influential sentiment indicators globally. Its significance stems from the size and global reach of the US economy and the fact that US consumer spending accounts for a large share of global demand. As financial markets become more globally integrated, sentiment in the US can affect investor expectations far beyond domestic borders, including in Europe.

These indices vary in their time horizons, respondent types, and geographic coverage, all of which may influence their predictive power regarding stock market behaviour. Economic optimism or pessimism can lead to changes in asset prices, investment flows, and risk assessments. Expectations-based sentiment may reduce uncertainty, lowering volatility and contributing to market stability during turbulent times. In contrast, current-condition sentiment, if negative during economic upswings, can act as an early warning signal of future downturns, thus potentially increasing perceived risk and market volatility.

By incorporating different types of sentiment indicators, we aimed to capture how both forward-looking economic optimism/pessimism and present-day assessments of economic health influence European stock markets under both normal conditions and during periods of financial stress.

Models

Market returns are calculated as $r_t = ln\ (P_t/P_{t-1})$, where P_t represents the closing price of the index at time t and P_{t-1} is a closing price of the previous day. We used two approaches in empirical analysis: the GARCH model, which is the most popular in sentiment research (Wang *et al*. 2022), and the less popular TVPMS model (Aloy *et al*., 2014). This study is the first to jointly apply the AR-GJR-GARCH and TVPMS models to examine the impact of economic sentiment on returns and volatility across different types of European stock markets (developed, emerging, and frontier). While scholars have widely used the GARCH-type models to capture volatility dynamics, and applied TVPMS models in regime-switching analyses, their combined use in the context of sentiment analysis remains novel. This approach allowed us to examine both the average and regime-dependent effects of sentiment, and thus offer a more comprehensive understanding of how economic sentiment influences markets under varying conditions.

The GARCH Model Specification

As the first step in our analysis, we employed sentiment-augmented GARCH-family models to study the effect of sentiment indices on daily returns. Specifically, we used the GJR-GARCH model with an AR(1) component, augmented with external sentiment indicators. This model effectively captures asymmetries in volatility responses to shocks, aligning with the study's objectives. In these models, one treats the sentiment indices as external variables. We specifically considered sentiment values from the previous month as external sentiment indicators. The indices analysed included ZEW-ES, GER-ES, ZEW-CS, and MSCI, which serve as the external sentiment variables influencing daily stock returns.

The mean equation follows:

$$r_t = \mu + \beta_{mean} x_{t-1} + \phi \mathrm{r}_{t-1} + \epsilon_t \tag{1}$$

in which:

μ - is the constant;

β_{mean} - represents the external regressor term for sentiment x at time $t-1$;

$\phi \mathrm{r}_{t-1}$ - is the autoregressive term capturing the influence of the previous return;

$\epsilon_t = \sigma_t z_t$ - is the error term, with z_t as i.i.d. standard normal and σ_t is the conditional volatility of stock returns at time t.

For the variance equation, we assumed that:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma \mathrm{I}_{t-1}\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \beta_{var} x_{t-1} \tag{2}$$

in which:

ω - is the constant variance term;

α - represents the ARCH term for past squared shocks;

$\gamma \mathrm{I}_{t-1}\epsilon_{t-1}^2$ - captures the leverage effect, where I_{t-1} is an indicator function equal to 1 if $\epsilon_{t-1} < 0$ (indicating an asymmetric response to negative shocks);

β - represents the GARCH term for the prior period's conditional variance;

β_{var} - is the external regressor term, where x_{t-1} denotes the economic sentiment indicator, allowing sentiment to influence conditional volatility directly.

The parameter β_{mean} in the mean equation captures the effect of sentiment on returns whereas the parameter β_{var} in the variance equation captures the effect of sentiment on volatility.

While GARCH models are effective at capturing the dynamic behaviour of returns and variance, they fall short in addressing *when* sentiment affects market returns – during periods of stability or periods of high volatility. To fill this gap, we used a regime switching model with two distinct states. In this framework, the transition probabilities in the hidden Markov chain are explicitly linked to sentiment indicators. This approach allowed us to disentangle the timing of sentiment's influence on market dynamics. By identifying transitions between high-volatility and low-volatility states, we aimed to examine whether sentiment has a more significant impact during periods of market turmoil versus more stable market conditions. This approach helped us understand how market participants respond to economic sentiment in different market environments.

The HMM and TVPMS Models

The Hidden Markov Model (HMM) provides a basic framework for capturing transitions between market states in financial time series. Building on the Hidden Markov Model (HMM), the Time-Varying Probability Markov Switching Model (TVPMS) incorporates dynamic transition probabilities influenced by economic sentiment indicators. This approach provides a more nuanced understanding of how sentiment drives regime shifts between high- and low-volatility states.

We assumed two distinct market states: a high-volatility state and a low-volatility state, where the transition between regimes is governed by a time-varying probability matrix (Aloy *et al*., 2014; Hamilton, 1994). We assumed that the returns r_t, $(t = 1,2, \dots)$ were described as follows:

$$r_t = a_{s_t} + b_{s_{t-1}} (r_{t-1} - a_{s_{t-1}}) + \sigma^2_{s_t} \varepsilon_t \tag{3}$$

in which:

$s_t \in \{1,2\}$ and $\varepsilon_t \sim i.i.d.N(0,1)$.

Parameters a_{s_t} and b_{s_t} are regime-specific intercepts and slopes, $\sigma^2_{s_t}$ is the regime-specific variance, where higher values indicate a high-volatility state and lower values indicate a low-volatility state.

The model identified four distinct cases based on current and previous states, which allowed us to capture how returns evolve based on state transitions. We discussed the following four cases:

$$r_t = a_1 + b_1 (r_{t-1} - a_1) + \sigma_1^2 \varepsilon_t \tag{3a}$$

$$r_t = a_2 + b_1 (r_{t-1} - a_1) + \sigma_2^2 \varepsilon_t \tag{3b}$$

$$r_t = a_1 + b_2 (r_{t-1} - a_2) + \sigma_1^2 \varepsilon_t \tag{3c}$$

$$r_t = a_2 + b_2 (r_{t-1} - a_2) + \sigma_2^2 \varepsilon_t \tag{3d}$$

Parameters a_1, b_1, σ_1^2 characterise the high-volatility regime, while a_2, b_2, σ_2^2 describe the low-volatility state. Since (3) formula, we could find that the Hidden Markov Model (HMM) follows a four-state Markov chain with transition matrix:

$$\boldsymbol{P}^* = \begin{bmatrix} p_{11} & p_{12} & 0 & 0 \\ 0 & 0 & p_{21} & p_{22} \\ p_{11} & p_{12} & 0 & 0 \\ 0 & 0 & p_{21} & p_{22} \end{bmatrix} \tag{4}$$

in which:

p_{ij} denotes $P\{s_t = i | s_{t-1} = j\}$;

$p_{12} = 1 - p_{11}$ and $p_{21} = 1 - p_{22}$.

The density function of returns is defined as:

$$f(r_t | s_t = i, s_{t-1} = j, \Omega_t; \Theta) = 1/(2\pi\sigma_i^2) exp\left(-\left(r_t - a_i - b_j(r_{t-1} - a_j)\right)^2 / 2\sigma_i^2\right) \tag{5}$$

in which:

Ω_t - denotes historical information up to time t;

Θ - is the vector of model parameters.

In TVPMS, the probabilities are governed by lagged economic sentiment indicators. Specifically, for an economic sentiment indicator x_t, we assumed that:

$$p_{11}(t) = \frac{\exp(\alpha_1 + \beta_1 x_{t-1})}{1 + \exp(\alpha_1 + \beta_1 x_{t-1})} \tag{6a}$$

$$p_{22}(t) = \frac{\exp(\alpha_2 + \beta_2 x_{t-1})}{1 + exp(\alpha_2 + \beta_2 x_{t-1})} \tag{6b}$$

We estimated the model's parameters using maximum likelihood (ML) optimisation, following the method used in Aloy *et al*. (2014). To assess the significance of sentiment effects, we performed significance tests on the β parameters. The sign and significance of β_1 and β_2 indicate how sentiment affects transitions, with β_1 affecting high-volatility states and β_2 affecting low-volatility states. In addition, we tested whether the TVPMS model significantly outperforms the HMM using the Vuong (1989) likelihood ratio test:

$$LM = 2\big(L(r_t;\Theta) - L_F(r_t;\Theta)\big) \tag{7}$$

in which $L(r_t;\Theta_1)$) and $L_F(r_t;\Theta_{\mathrm{F}})$) are the log-likelihoods of the TVPMS and HMM models, respectively. Under the null hypothesis, the statistic follows a chi-squared distribution with degrees of freedom based on the parameter count difference (Czapkiewicz, 2018). The comparison test between two models, *i.e.*, the HMM and the TVPMS model, using this restriction test, allowed us to assess whether the economic sentiment indicator really affects returns.

Data

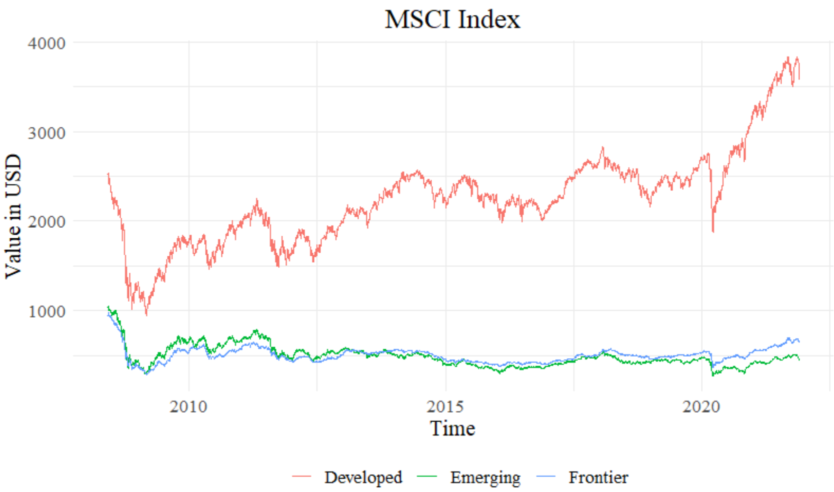
We investigated the influence of economic sentiment in major economies on stock market behaviour in Europe. The analysis spanned from January 2008, to January 2022, with a separate examination of the pre-COVID-19 period to ensure robustness. We sourced the data on sentiment indicators from the Bloomberg database and the European market data from the MSCI database.

European markets are divided into three groups: developed, emerging, and frontier. The 15 developed markets are Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. The six emerging markets are the Czech Republic, Greece, Hungary, Poland, Turkey and Russia, while the seven frontier markets are Croatia, Estonia, Lithuania, Kazakhstan, Romania, Serbia, and Slovenia. To represent these groups, we used three aggregate indices from the MSCI database, *i.e.*, the MSCI Europe Developed Markets Index (Developed), the MSCI Europe Emerging Markets Index (Emerging), and the MSCI Europe Frontier Markets Index (Frontier). These indices are calculated based on local stock market indices and are weighted by market capitalisation, with adjustments for free float. They reflect the performance of representative equity markets within each group. The MSCI indices are denominated in USD. Stock market data are observed at a daily frequency, while sentiment indices are available on a monthly basis. To address the lower frequency of sentiment indices (monthly) compared to daily stock market returns, we followed a common approach in the literature by assigning the same monthly sentiment value to all trading days within that month. This method allowed us to align the sentiment data with the daily frequency of stock market returns while preserving the temporal consistency of the sentiment indicators.

Figure 1 presents the data used in the analysis, *i.e.*, the top panel displays the daily prices of the selected MSCI indices, while the bottom panel shows the corresponding economic sentiment indicators over the study period. During major crises, such as the 2008 financial crisis, the Eurozone crisis, and the COVID-19 pandemic, the ZEW-ES and GER-ES indices dropped sharply, reflecting a significant decline in economic optimism. These indices typically rebounded strongly following each crisis. In contrast, the ZEW-CS index often exhibits low or negative values even during periods of optimism in the ZEW-ES and GER-ES, highlighting its focus on current economic conditions rather than future expectations. The MCSI values are consistently positive due to the index's construction. However, in this study, the MCSI has been detrended to capture deviations from a linear trend. We interpreted positive deviations as optimism and negative deviations as growing pessimism.

Table 1 (upper panel) presents basic descriptive statistics for stock market returns across developed, emerging, and frontier European markets. The data revealed that all return series exhibited high kurtosis and negative skewness, indicating fat tails and a tendency toward negative outliers. Emerging markets display the highest standard deviation and maximum return, highlighting their greater volatility and potential for larger gains (or losses). In contrast, frontier markets show the lowest standard deviation and maximum return, reflecting their relatively lower risk and reward. Developed markets exhibit the highest median and average returns, suggesting more consistent performance over time.

The lower panel of Table 1 presents descriptive statistics for the sentiment indices. The ZEW-ES and GER-ES indices, which reflect economic expectations, both show negative skewness and moderate kurtosis, with values ranging from strong pessimism to strong optimism. The ZEW-CS index, focused on current conditions, has the most negative mean and exhibits positive skewness, indicating more frequent mildly positive assessments but occasional severe downturns. The MCSI, reflecting U.S. consumer sentiment, shows low kurtosis and slightly negative skewness, with values always positive due to its construction. Its relatively low standard deviation suggests more stable consumer perceptions over time.



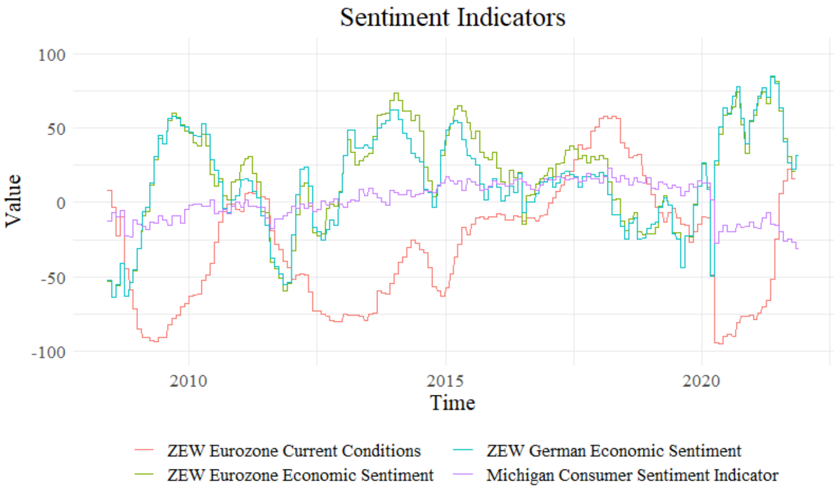


Figure 1. Daily prices of aggregate indices (top panel) and economic sentiment indicators (bottom panel) from June 2008 to January 2022
Source: own elaboration.

Table 1. Descriptive statistics of market returns and economic sentiment indices

Markets	Median	Mean	SD	Skewness	Kurtosis	Minimum	Maximum
MSCI indexes							
Developed	0.0005	0.0000	0.0141	-0.4342	13.5277	-0.1406	0.1070
Emerging	0.0003	-0.0003	0.0189	-0.4923	16.7588	-0.1993	0.1860
Frontier	0.0003	-0.0001	0.0116	-0.9644	13.9058	-0.1005	0.0794
Sentiment Indexes							
ZEW-ES	21.250	16.607	35.038	-0.400	2.423	-63.700	84.00
GER-ES	13.800	13.281	33.900	-0.205	2.415	-63.900	84.400
ZEW-CS	-23.300	-27.875	40.697	0.148	2.072	-95.000	57.700
MCSI	81.850	82.002	12.544	-0.208	1.966	55.300	101.400

Note: Descriptive statistics of daily indices' returns and economic sentiment indices from June 2008 to January 2022.
Source: own study.

Correlations between sentiment indicators states revealed other characteristics. The ZEW-ES and GER-ES indices were highly correlated (0.95), reflecting similar expectations for the euro area and Germany. However, the ZEW-ES showed a weak positive correlation with the MCSI (0.205) and a negative correlation with the ZEW-CS (-0.223 for the euro area and -0.347 for Germany). On the other hand, the

ZEW-CS and MCSI indices showed a moderate positive correlation (0.474), suggesting some convergence between current sentiment in Europe and consumer confidence in the US.

RESULTS AND DISCUSSION

GJR-GARCH Model Results

Firstly, we used the AR(1)-GJR-GARCH augmented with external sentiment indicators to model daily returns. We designed the empirical study for all stock returns, but we restrict the discussion to aggregated indices such as developed, emerging, and frontier. To assess the impact of economic sentiment on stock market return dynamics, we discuss each sentiment index separately. Table 2 summarises the results of the AR(1)-GJR-GARCH model, which shows the estimated values of the model parameters and the p-values. We are particularly interested in the significance and sign of the coefficients corresponding to each sentiment index for developed, emerging, and frontier market aggregates.

Table 2. Estimation results for AR(1)-GJR-GARCH model

CATEGORY?		μ	ϕ	β_{mean}	ω	α	β	γ	β_{var}
Panel A: Developed									
MCSI	Estimate	0.0002	-0.0073	**-0.0002****	2.11E-06	0.0132*	0.9003***	0.1465***	3.97E-13
	p-value	0.367	0.687	**0.009**	0.061	0.024	0.000	0.000	0.999
ZEW-ES	Estimate	0.0001	-0.0075	-0.0003	2.03E-06*	0.0167*	0.9001***	0.1427***	**1.08E-08*****
	p-value	0.541	0.662	0.256	0.048	0.028	0.000	0.000	**0.000**
ZEW-CS	Estimate	-0.0002	-0.0086	**-0.0009****	2.12E-06	0.0117***	0.9002***	0.1492***	6.67E-13
	p-value	0.302	0.637	**0.005**	0.069	0.000	0.000	0.000	0.998
GER-ES	Estimate	0.0003	-0.0076	-0.0006	2.52E-06	0.0216***	0.8882***	0.1414***	4.18E-13
	p-value	0.120	0.708	0.112	0.346	0.000	0.000	0.000	0.999
Panel B: Emerging									
MCSI	Estimate	0.0000	0.0557**	-0.0002	2.53E-06*	0.0150***	0.9296***	0.0900***	4.52E-12
	p-value	0.982	0.002	0.275	0.019	0.000	0.000	0.000	0.987
ZEW-ES	Estimate	0.0000	0.0544**	**-0.0004*****	2.42E-06*	0.0154*	0.9297***	0.0901***	**1.27E-07*****
	p-value	0.906	0.002	**0.000**	0.029	0.047	0.000	0.000	**0.000**
ZEW-CS	Estimate	-0.0001	0.0560**	-0.0001	2.5E-06**	0.0157***	0.9294***	0.0895***	3.03E-11
	p-value	0.686	0.002	0.794	0.010	0.000	0.000	0.000	0.949
GER-ES	Estimate	0.0000	0.0543**	-0.0001	2.76E-06	0.0058***	0.9364***	0.0842***	**2.17E-08*****
	p-value	0.965	0.005	0.793	0.101	0.000	0.000	0.000	**0.000**
Panel C: Frontier									
MCSI	Estimate	0.0003*	0.0502**	**-0.0003****	2.99E-06	0.0353***	0.8942***	0.0762***	7.91E-13
	Estimate	0.044	0.006	**0.018**	0.000	0.000	0.000	0.000	0.999
ZEW-ES	Estimate	0.0001	0.0506***	0.0005	2.87E-06	0.0380***	0.8951***	0.0727***	**7.11E-08*****
	p-value	0.562	0.000	0.231	0.006	0.000	0.000	0.000	**0.000**
ZEW-CS	Estimate	0.0001	0.0509***	**-0.0006***	2.94E-06	0.0367***	0.8948***	0.0742***	6.82E-14
	p-value	0.594	0.000	**0.045**	0.000	0.000	0.000	0.000	0.999
GER-ES	Estimate	0.0005**	0.0500**	**-0.0008****	3.3E-06	0.0108***	0.9014***	0.0799***	**5.4E-07*****
	p-value	0.006	0.011	**0.009**	0.000	0.000	0.000	0.000	**0.000**

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Source: own study.

According to the results, the sentiment indicators significantly influence market returns by impacting the mean, the conditional variance of returns, or both. Specifically, we observed a positive, significant coefficient for sentiment in the variance equation (β_{var}) and a negative, significant coefficient in the mean equation (β_{mean}). The positive coefficient for β_{var} suggests that improved sentiment is associated with increased volatility, while the negative coefficient for β_{mean} suggests that positive sentiment could reduce returns. We may explain this seemingly counterintuitive finding by the inherent comovement between realised returns, variances, and sentiment indicators. Sentiment reflects aspects of past market behaviour.

Furthermore, the results suggest that during periods of positive sentiment, large jumps in returns are corrected the following day, resulting in relatively low daily return variance. Conversely, during periods of negative sentiment, returns tend to be more volatile, leading to higher daily return variance. Moreover, β_{var} represents relative change, compared to the previous day. Thus, even for negative β_{var} expected conditional variance is higher when sentiment is worse (see Equation (2))

The Michigan Consumer Sentiment Index and the ZEW Current Situation Index, both of which gauge perceptions of the current economic situation, significantly affect returns. However, their impact is minimal in emerging markets. The distinct roles of sentiment regarding current and future economic conditions are also evident. The Michigan Consumer Sentiment Index and ZEW Current Situation Index primarily influence returns, while the ZEW Indicator of Economic Sentiment (ZEW-ES) and the German ZEW Indicator, which measure future economic expectations, primarily affect variance. This suggests that current sentiment influences immediate market performance, whereas forward-looking sentiment plays a critical role in shaping future volatility. Notably, the impact of ZEW-ES is evident across all market types*, i.e.*, developed, emerging, and frontier.

The extent of these sentiment effects varies across markets. In developed markets, sentiment effects are primarily driven by major economies, as reflected in the Michigan index and the two ZEW indices from the euro area. In emerging markets, sentiment about the future economy strongly impacts both the mean and volatility of returns (ZEW-ES) and volatility alone (German ZEW Indicator). In frontier markets, which are less integrated with global economic trends, sentiment indicators tied to both major and local economies (such as Germany) significantly influence returns. Among these, the German ZEW Indicator (GER-ES) is particularly impactful, affecting both the mean and volatility of market returns.

The results seem to support our hypotheses. Most sentiment indicators from the major economies affect emerging and frontier markets, as presumed in Hypothesis 1, and the effect is even more pronounced than for the developed markets. According to Hypothesis 3, we notice the significant impact of the US sentiment indicator among developed and frontier markets, although it does not affect the volatility directly. Meanwhile, we tested Hypothesis 2, stating that the impact of sentiment indicators differs by regimes using the TVPMS model in the next section.

Regime-switching Model Results

The AR(1)-GJR-GARCH model provides us with information on the importance of economic sentiment for expected returns and their conditional variances. However, it does not determine whether the variance during periods of strong market turbulence is indeed significantly different from the variance of returns during periods of weak turbulence, nor does it answer the question of when sentiment has the greatest impact on returns. To address these issues, we used a methodology based on switching models. Firstly, we used an HMM to identify two distinct states in which the variance of returns is significantly different. We then applied a regime switching model, where the transition matrix depends on economic sentiment indicators, to determine when sentiment affects the markets – in a high- or low-volatility state.

Hidden Markov Model

We use a fixed probability Hidden Markov Model (HMM) to test for the existence of two distinct states. Table 3 shows the parameter estimates of the HMM model, which we obtained by maximising the likelihood function using the Hamilton filter (Hamilton, 1994). Therefore, the last column of Table 3 (ML) shows the maximum likelihood value. This table also includes the expected market duration in each state: ED_1 for the high volatility state and ED_2 for the low volatility state. We calculated these expected durations as follows:

$$ED_1 = 1/(1-p_{11}) \text{ and } ED_2 = 1/(1-p_{22}) \quad (8)$$

Furthermore, we perform a restriction test according to (7) to confirm our conjecture that the states in the HMM model differ mainly in the variances of the return distribution (p-value < 0.001 for all cases). State I is characterised by high variance and negative mean return, while state II is associated with lower variance and positive mean return. The results in the last two columns indicate that the duration in the high volatility state was relatively short compared to the duration in the low volatility state. The pattern of volatility across markets was similar to that shown in Table 1. In both cases, emerging markets had the highest volatility, while frontier markets had the lowest. On the other hand, emerging markets had the shortest expected duration in the high volatility state, while frontier markets had the longest expected duration in the low volatility state.

Table 3. Estimates of HMM model parameters and expected market duration in high and low volatility states

a_1	b_1	σ_1	a_2	b_2	σ_2	p_{11}	p_{22}	ED_1	ED_2	ML
Developed										
-0.001*	0.030	0.022***	0.001*	-0.035	0.008***	0.956	0.983	23	60	10634.917
(0.040)	(0.290)	(0.000)	(0.016)	(0.139)	(0.000)	–	–	–	–	–
Emerging										
-0.002	0.075*	0.036***	0.000	0.054**	0.011***	0.942	0.986	17	69	9745.576
(0.153)	(0.046)	(0.000)	(0.257)	(0.008)	(0.000)	–	–	–	–	–
Frontier										
-0.002*	0.095***	0.022***	0.001**	0.037.	0.007***	0.954	0.988	22	84	11333.586
(0.027)	(0.000)	(0.000)	(0.003)	(0.063)	(0.000)	–	–	–	–	–

Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1.
Parameters a_1, b_1 (I state) and a_1, b_1 (II state) are from formula (1).
Source: own study.

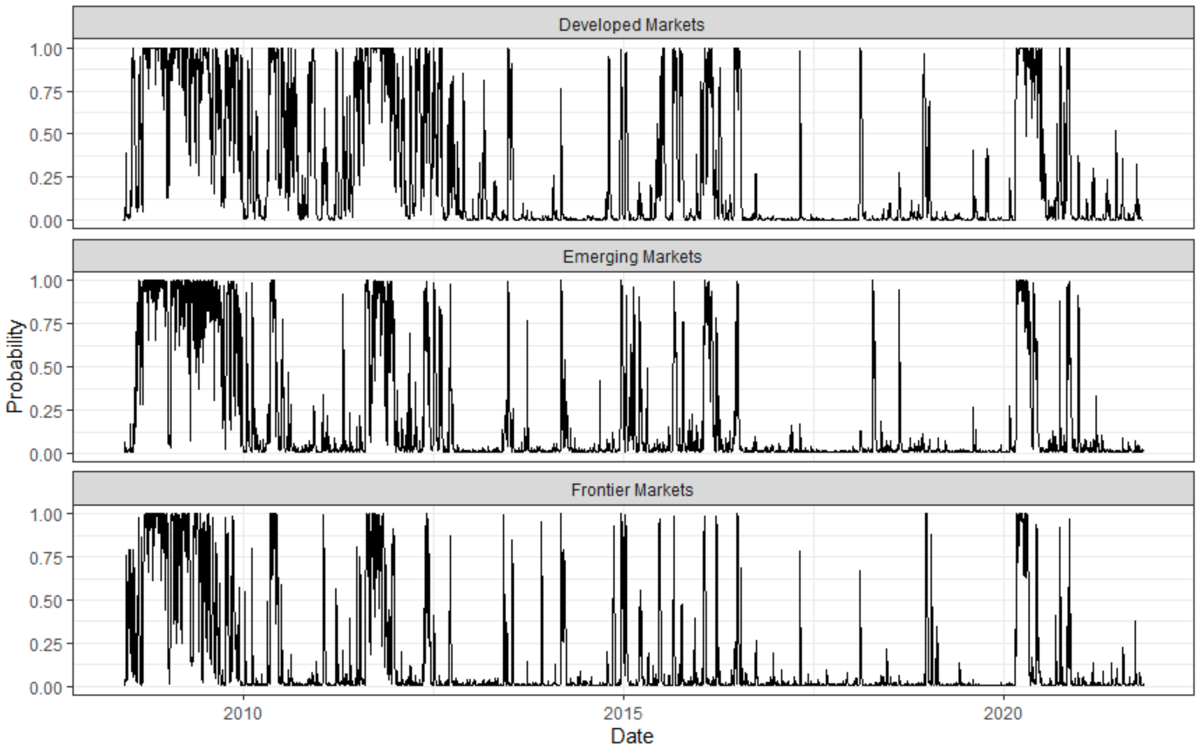


Figure 2. onditional probabilities of remaining in the high volatility regime for developed, emerging, and frontier markets from June 2008 to January 2022
Source: own elaboration.

The significance of the parameters a_1, b_1 (I state) and a_2, b_2 (II state) confirms the conclusions drawn from the analysis using the GARCH family model approach. However, the HMM illustrates the component of AR(1) relationships in two different states. We found that the lagged return parameters in both states were insignificant for developed markets and significant for emerging and frontier markets. This is similar to the results from the GARCH models, where the autoregressive parameters were also significant for emerging and frontier markets, but not for developed markets.

Figure 2 shows the conditional probabilities of being in the high volatility regime. The top panel shows that developed markets are in this regime mainly during periods of index declines. We may observe similar patterns in the middle and lower panels for emerging and frontier markets, respectively. Markets are predominantly in the high volatility regime during the financial crisis of 2007-2008. The probability of this state is also high in the mid-2010s (European debt crisis) and in 2020 (COVID-19 pandemic).

TVPMS Model

In the next step of the analysis, we assumed that the transition matrix in the regime switching model depends on lagged economic sentiment indicators, denoted as x_{t-1}. Since we considered daily market returns together with monthly survey-based sentiment indicators, we had a transition matrix with monthly dynamics. Table 4 shows the parameter estimates for the TVPMS model, with p-values in brackets. Panel A presents the results for developed markets, panel B for emerging markets and panel C for frontier markets. The last column presents the maximum log-likelihood (ML) for the TVPMS model. Comparing the ML values presented in Table 3 and Table 4, we found that the TVPMS model outperformed the HMM model. Furthermore, the TVPMS model was statistically superior to the HMM model according to the LM test performed for all cases (the p-values are less than 0.05). These results can document the fact that economic sentiment impacts market returns.

We noticed that for all market types (developed, emerging, and frontier) there was a negative beta parameter in the high volatility state (State I) and a positive beta parameter in the low volatility state (State II). As sentiment indicators rise, the probability of remaining in a high volatility state decreases, while the probability of remaining in a low volatility state increases. This interpretation is consistent with the findings of the GARCH model, but presented in a different framework, allowing us to directly confirm the Hypothesis 2.

Comparing the ML values in Table 4, we found that US economic sentiment generally has the strongest impact on European markets, in line with Hypothesis 3. The beta parameters in both states (β_1 and β_2) related to the MCSI were significant for all markets. However, sentiment seems to be more influential in the high-volatility regime, where the p-value is close to zero, compared to the low-volatility regime, where the p-values were 0.086 (developed markets), 0.098 (emerging markets), and 0.055 (frontier markets). This result highlights the advantage of the state-dependent framework of the TVPMS model. This distinction was not apparent in the GARCH-based approach, highlighting the value of the regime switching approach for a comprehensive analysis of the impact of sentiment.

The significance of the beta values in relation to the ZEW-ES shows that sentiment about economic expectations for the euro area is important for all markets, but mainly in the high-volatility regime. High economic sentiment reduces return variance not only in developed markets, but also in emerging and frontier markets, confirming Hypothesis 1. The insignificant beta parameters in the low volatility regime suggest that the ZEW-ES has a small impact on markets in stable periods. We obtained the same results for the GER-ES index, but this sentiment had a weaker predictive power compared to the ZEW-ES (lower ML). The beta parameter associated with the GER-ES in the high volatility regime was significant for emerging and frontier markets, but insignificant for developed markets. Similar to the results from the GARCH family model, the impact of German economic sentiment on developed markets is not confirmed.

The ZEW Current Situation Index (ZEW-CS) impacted the returns only in the low-volatility state. The β_2 parameters were significant at the 10% level for all types of markets. Moreover, we confirmed the impact of the ZEW-CS in emerging markets, which the GJR-GARCH approach did not confirm.

To explore the impact of sentiment in more detail, we computed the models for each country separately. The Appendix presents these results. Table A1 presents estimates for developed markets, and Table A2 for emerging and frontier markets. These results confirm our hypotheses, that: H1) major economies' sentiment impacts developing and frontier markets, H2) sentiment's impact differs by state (and the pattern is the same as in the aggregated analysis), and H3) the US sentiment index has a strong influence on European markets (especially developed markets and frontiers).

Table 4. Estimation results of TVPMS model

Sentiment	State	a_i	b_i	σ_i^2	α_i	β_i	ML
Panel A: Developed markets							
MCSI	**I**	-0.001 (0.104)	0.029 (0.326)	0.023*** (0.000)	3.080*** (0.000)	**-5.633**** (0.006)	**10658.740**
	II	0.001** (0.001)	-0.067** (0.002)	0.008*** (0.000)	3.997*** (0.000)	**2.851 .** (0.086)	–
ZEW-ES	**I**	-0.001 . (0.092)	0.031 (0.300)	0.023*** (0.000)	3.408*** (0.000)	**-1.497 .** (0.082)	10655.162
	II	0.001** (0.001)	-0.067** (0.003)	0.008*** (0.000)	4.094*** (0.000)	0.017 (0.986)	–
GER-ES	**I**	-0.001 (0.066) .	0.038 (0.195)	0.022*** (0.000)	3.454*** (0.000)	-1.116 (0.178)	10653.878
	II	0.001** (0.003)	-0.068** (0.002)	0.008*** (0.000)	4.158*** (0.000)	0.316 (0.744)	–
ZEW-CS	**I**	-0.001 . (0.090)	0.031 (0.303)	0.023*** (0.000)	2.997*** (0.000)	-0.437 (0.539)	10652.390
	II	0.001) ** (0.001)	-0.061** (0.006)	0.008*** (0.000)	4.282*** (0.000)	**1.008 .** (0.076)	–
Panel B: Emerging markets							
MCSI	**I**	-0.002 (0.168)	0.070 . (0.061)	0.036*** (0.000)	5.815*** (0.000)	**-3.877**** (0.001)	**9758.750**
	II	0.001 (0.351)	0.060** (0.003)	0.011*** (0.000)	1.287 (0.451)	**2.933 .** (0.087)	–
ZEW-ES	**I**	-0.002 (0.151)	0.055 (0.098)	0.036*** (0.000)	3.110*** (0.000)	**-1.685*** (0.016)	9755.232
	II	0.001 (0.399)	0.056** (0.005)	0.011*** (0.000)	4.399*** (0.000)	0.031 (0.969)	–
GER-ES	**I**	-0.002 (0.132)	0.080* (0.035)	0.036*** (0.000)	3.301*** (0.000)	**--1.423 .** (0.062)	9754.612
	II	0.001 (0.283)	0.057** (0.005)	0.0011*** (0.000)	4.656*** (0.000)	0.055 (0.955)	–
ZEW-CS	**I**	-0.002 (0.124)	0.074* (0.049)	0.036*** (0.000)	2.883*** (0.000)	-0.076 (0.915)	9754.004
	II	0.001 (0.249)	0.054** (0.008)	0.011*** (0.000)	4.896*** (0.000)	**1.451*** (0.021)	–
Panel C: Frontier markets							
MCSI	**I**	-0.003* (0.035)	0.160** (0.001)	0.026*** (0.000)	4.848*** (0.000)	**-4.619**** (0.002)	**11372.944**
	II	0.001 (0.673)	0.047* (0.022)	0.008*** (0.000)	1.530*** (0.344)	3.520 (0.055)	–
ZEW-ES	**I**	-0.003** (0.028)	0.072 . (0.061)	0.024*** (0.000)	2.199*** (0.000)	**-1.500*** (0.036)	11369.855
	II	0.001 (0.538)	0.040* (0.050)	0.007*** (0.000)	3.743*** (0.000)	0.972 (0.225)	–
GER-ES	**I**	-0.003** (0.042)	0.073 . (0.062)	0.025*** (0.000)	2.207*** (0.000)	**-1.735*** (0.026)	11368.361
	II	0.001 (0.465)	0.037 . (0.052)	0.007*** (0.000)	3.987*** (0.000)	0.306 (0.762)	–
ZEW-CS	**I**	-0.004** (0.020)	0.084* (0.041)	0.024*** (0.000)	2.328*** (0.000)	-0.299 (0.915)	11365.970
	II	0.001 (0.673)	0.040* (0.038)	0.007*** (0.000)	4.899*** (0.000)	**1.657 .** (0.077)	–

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Note: α_i and β_i are the parameter from the transition probability matrix, given in the equation (2).
Source: own study.

Consistent Patterns Across Models

The combined results of the AR(1)-GJR-GARCH and TVPMS models show that economic sentiment has a significant impact on European market returns, with different effects depending on market type and sentiment indicator. While the TVPMS model effectively captures the probability of transition between states with different distributions, in particular different volatilities as measured by return variances, the GJR-GARCH model complements these findings by providing nuanced details on daily returns and conditional volatility adjustments of sentiment indices.

This comparative analysis highlights the complementary nature of the two modelling approaches. While the GJR-GARCH model provides insights into the immediate effects of sentiment on returns and volatility, the TVPMS model offers a more nuanced view of how sentiment influences market dynamics across regimes. Together, these models enrich our understanding of the role of sentiment in shaping market behaviour.

Robustness

Figure 1 shows significant fluctuations in returns and economic sentiment indicators around 2020, mainly due to the COVID-19 pandemic. For robustness, we re-estimated both models using only data up to 31 December 2020. Table 5 shows the results for TVPMS model (results for AR(1)-GJR-GARCH are presented in Appendix, Table A3), confirm the initial findings and highlight the persistent impact of economic sentiment on market returns and volatility across market types.

The Michigan consumer sentiment index continues to have a significant effect, especially in the high volatility regime. This is consistent with our hypothesis that the Michigan index has a stronger impact on volatility when markets are more volatile. Similarly, the ZEW Economic Sentiment Index (ZEW-ES) also shows a significant impact, especially in periods of high volatility. This pattern confirms that US and European sentiment about future economic conditions has a stronger impact during periods of market instability.

Furthermore, the comparison of the maximum likelihood values for the ZEW-ES and the GER-ES indices shows that the GER-ES has a weaker impact on market returns compared to the ZEW-ES, in line with our previous findings. In particular, the GER-ES had no significant impact on the frontier markets. The ZEW Current Condition Index (ZEW-CS) retained its significance in the low-volatility state for emerging and frontier markets. For developed markets, the beta parameter associated with the ZEW-CS remained positive, but its significance was marginal (p-value = 0.134).

The results of this robustness check underlined the stability of the results even when excluding the period most affected by the COVID-19 pandemic. This strengthens the argument that economic sentiment indices are important determinants of European stock market returns and volatility.

Discussion

Our results are consistent with the existing literature and extend it in several important ways. Firstly, we confirmed the significant impact of economic sentiment on returns and volatility, supporting the role of sentiment as a predictor in financial markets. They can influence investor decisions across European markets, regardless of the level of market development. Baker *et al*. (2012) and Corredor *et al*. (2015) also observed this 'global' nature of sentiment. The positive influence of survey-based sentiment indicators on markets is consistent with the findings of Homolka and Pavelková (2018) and Rakovská (2021), as well as the impact documented for institutional investor sentiment (Schmeling, 2007). In particular, the influence of the Michigan Consumer Sentiment Index (MCSI) on European markets is consistent with its established role in the US, analysed by Ung *et al*. (2023) for the S&P 500. This relationship highlights the role of US sentiment in shaping expectations and behaviour in European markets, reflecting a broader, interconnected financial environment.

Table 5. Estimation results of TVPMS model (up to 2019)

Sentiment	State	a_i	b_i	σ_i^2	α_i	β_i	ML
Panel A: Developed markets							
MCSI	**I**	-0.001 (0.112)	0.028 (0.357)	0.021*** (0.000)	3.287*** (0.000)	**-8.494 .** (0.052)	**9203.765**
	II	0.001** (0.011)	-0.046 . (0.066)	0.008*** (0.000)	3.996*** (0.000)	4.302 (0.397)	–
ZEW-ES	**I**	-0.001 (0.185)	0.021 (0.485)	0.021*** (0.000)	3.618*** (0.000)	**-1.603**** (0.049)	9202.163
	II	0.001** (0.023)	-0.045 . (0.078)	0.008*** (0.000)	3.961*** (0.000)	0.504 (0.609)	–
GER-ES	**I**	-0.001 (0.204)	0.029 (0.326)	0.021*** (0.000)	3.548*** (0.000)	-0.815 . (0.327)	9201.228
	II	0.001** (0.045)	-0.034 (0.193)	0.008*** (0.000)	3.985*** (0.000)	0.329 (0.795)	–
ZEW-CS	**I**	-0.001 (0.117)	0.019 (0.536)	0.021*** (0.000)	3.075*** (0.000)	-0.667 (0.379)	9202.494
	II	0.001 (0.010)	-0.043 . (0.089)	0.008*** (0.000)	4.262*** (0.000)	0.977 (0.138)	–
Panel B: Emerging markets							
MCSI	**I**	-0.002 (0.149)	0.094** (0.020)	0.036*** (0.000)	2.901*** (0.000)	**-8.530 .** (0.068)	**845.947**
	II	0.001 (0.390)	0.073*** (0.001)	0.011*** (0.000)	4.538 (0.451)	6.979 (0.311)	–
ZEW-ES	**I**	-0.002 (0.179)	0.093** (0.021)	0.036*** (0.000)	3..195*** (0.000)	**-1.380**** (0.050)	845.751
	II	0.001 (0.366)	0.073*** (0.001)	0.011*** (0.000)	4.450*** (0.000)	0.016 (0.987)	–
GER-ES	**I**	-0.002 (0.307)	0.075** (0.065)	0.036*** (0.000)	2.904*** (0.000)	**--1.168 .** (0.073)	8404.093
	II	0.001 (0.672)	0.088*** (0.000)	0.011*** (0.000)	4.370*** (0.000)	0.082 (0.945)	–
ZEW-CS	**I**	-0.002 (0.149)	0.084** (0.035)	0.036*** (0.000)	2.629*** (0.000)	-0.619 (0.402)	8407.085
	II	0.001 (0.496)	0.072*** (0.001)	0.011*** (0.000)	4.800*** (0.000)	**1.597**** (0.025)	–
Panel C: Frontier markets							
MCSI	**I**	-0.002** (0.045)	0.094** (0.014)	0.022*** (0.000)	2.130*** (0.000)	**-9.768**** (0.047)	**9818.311**
	II	0.001 (0.264)	0.031** (0.014)	0.007*** (0.000)	3.911 (0.344)	6.163 (0.244)	–
ZEW-ES	**I**	-0.004** (0.019)	0.083** (0.027)	0.022*** (0.000)	2.292*** (0.000)	**-1.887** (0.026)**	9817.477
	II	0.001 (0.238)	0.022 (0.322)	0.007*** (0.000)	3.733*** (0.000)	0.083 (0.936)	–
GER-ES	**I**	-0.003** (0.032)	0.096** (0.012)	0.022*** (0.000)	2.732*** (0.000)	-1.109 (0.270)	9816.418
	II	0.001 (0.165)	0.046** (0.012)	0.007*** (0.000)	4.164*** (0.000)	0.277 (0.873)	–
ZEW-CS	**I**	-0.002** (0.034)	0.087** (0.027)	0.023*** (0.000)	2.044*** (0.000)	-0.205 (0.856)	9815.507
	II	0.001 (0.196)	0.032 (0.143)	0.007*** (0.000)	4.347*** (0.000)	**1.708.** (0.064)	–

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Note: : α_i and β_i are the parameter from the transition probability matrix, given in the equation (2).
Source: own study.

Our study further supports previous research (Gervais & Odean, 2001; Nofsinger, 2005; Li & Luo, 2017) by confirming that investor behaviour varies according to market conditions. Specifically, we found that sentiment on various economic issues can be relevant in different market states: The ZEW Economic Sentiment Indicator (ZEW-ES) and the German Economic Sentiment Indicator (GER-ES) have a significant impact on the markets in periods of high volatility, while the assessment of the current situation (ZEW-CS) has a stronger impact in periods of low volatility.

The added value of our work is the presentation of properties of regime switching models (with a dynamic transition matrix), which are rarely used in practice, compared to the GARCH model family. While the results of the GARCH approach confirm the influence of sentiment on market returns and volatility, the TVPMS approach is able to capture state-dependent transitions between high and low volatility regimes depending on market conditions.

CONCLUSIONS

We examined the impact of economic sentiment in major economies on the average returns and volatility of European stock markets. The analysis used several survey-based indicators of economic sentiment, the two ZEW Economic Sentiment Indices, the ZEW Current Situation Index and the Michigan Consumer Sentiment Index, to focus on sentiment related to the broader economy rather than just investor sentiment. We analysed how sentiment indicators influenced stock market behaviour in developed, emerging, and frontier markets. To examine the role of sentiment in market returns, we considered two models: GARCH-based approach with exogenous factors and a time-varying transition probability Markov switching model, where the probabilities depend on lagged economic sentiment indicators.

Our results show that market returns fluctuate between two states: high and low volatility, as measured by their one-month standard deviation. In the high volatility state, rising positive sentiment increases the probability of leaving that state, while during the low volatility state, rising sentiment increases the probability of staying in that state. The statistical significance of the impact of sentiment depends on the sentiment indicator and the state of the market. The GARCH-approach verified the robustness of the TVPMS results.

MCSI: The Michigan index showed a strong influence in both the GJR-GARCH and TVPMS models, especially for developed and frontier markets. In the GJR-GARCH model, the significant negative coefficients in the mean equation and positive coefficient in the variance equation indicated a stabilising effect on returns and volatility. This is consistent with the TVPMS model, where MCSI was significant in all markets, particularly in high volatility regimes. However, we observed no significant effect of MCSI for emerging markets in either model.

ZEW-ES: Both models confirmed that the ZEW-ES had a significant impact on market volatility, which is measured in different ways. The results of the TVPMS showed that the ZEW-ES had a stronger impact during periods of high volatility in the developed, emerging and frontier markets. This finding underlined the importance of forward-looking sentiment in turbulent times.

ZEW-CS: Both models confirmed that the ZEW-CS had a significant impact on market volatility, which was measured in different ways, but this sentiment had a stronger impact during periods of low volatility in the developed, emerging and frontier markets**.** Moreover, ZEW-CS showed a stronger influence in periods of low volatility for emerging and frontier markets, suggesting that sentiment about the current economic situation was stronger in stable conditions.

GER-ES: The German ZEW index had a weaker impact than the ZEW-ES in both models. In the TVPMS model, the GER-ES had a significant impact on emerging and frontier markets during periods of high volatility, while it had no significant impact on developed markets. These results are consistent with the GJR-GARCH results, which also indicate the insignificance of the GER-ES for developed markets. This discrepancy highlights the regional nature of the impact of German sentiment, which is more relevant for less developed markets.

Overall, our findings suggest that sentiment in major economies had a global reach, affecting not only developed markets but also emerging and frontier markets.

The findings have practical implications for investors and managers. Understanding economic sentiment indicators can help make informed investment decisions. Our results suggest that these indicators can help predict market performance over the next month in terms of returns and volatility. In low-volatility regimes, investors may benefit from focusing on current economic assessments, while in high-volatility regimes, attention should shift to forward-looking sentiment indicators. The US sentiment index (MCSI) is particularly valuable in both regimes, irrespective of the level of market development.

There are some limitations to this study. The frequency of the survey data is monthly, which limits the ability to capture the immediate impact of changes in sentiment. Future research could examine the impact of economic sentiment indicators derived from news and social media, which one can obtain with higher frequency. There is still need for studies analysing the influence of global sentiment on developing and frontier markets outside of Europe and North America.

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Appendix:

Table A1. Estimation results for developed markets

Market		σ_i^2	β_i	β_i	β_i	β_i		ML			
			MCSI	GER-ES	ZEW-ES	ZEW-CS		MCSI	GER-ES	ZEW-ES	ZEW-CS
Austria	I	0.035 (0.000)	**-5.675** (0.007)	**-1.151** (0.092)	**-1.749** (0.023)	-0.273 (0.721)		**9368.82**	9366.35	9366.6	9364.04
	II	0.013 (0.000)	3.090 (0.116)	0.262 (0.765)	0.245 (0.779)	**1.167** (0.090)					
Belgiium	I	0.027 (0.000)	**-5.632** (0.002)	**-1.539** (0.025)	**-1.877** (0.007)	0.358 (0.591)		**10185.9**	10179.7	10182.3	10176.0
	II	0.009 (0.000)}	**3.440** (0.039)	0.463 (0.597)	0.769 (0.380)	**1.213** (0.047)					
Denmark	I	0.026 (0.000)	**-3.096** (0.071)	**-1.271** (0.065)	**-1.372** (0.043)	0.069 (0.918)		**10342.2**	10339.7	10341.5	10336.8
	II	0.010 (0.000)	**2.759** (0.064)	0.547 (0.473)	0.424 (0.630)	**0.961** (0.081)					
Finland	I	0.028 (0.000)	**-5.432** (0.026)	**-1.870** (0.045)	**-2.522** (0.008)	-0.830 (0.441)		**9957.2**	9954.3	9956.9	9949.62
	II	0.010 (0.000)	**3.342** (0.021)	0.784 (0.483)	0.295 (0.740)	0.364 (0.682)					
France	I	0.025 (0.000)	**-4.387** (0.026)	**-1.110** (0.084)	**-1.740** (0.019)	-0.227 (0.741)		**10184.6**	10181.5	10183.1	10180.4
	II	0.009 (0.000)	**3.041** (0.038)	0.526 (0.473)	0.174 (0.809)	**1.039** (0.067)					
Germany	I	0.026 (0.000)	**-4.709** (0.015)	**-1.456** (0.031)	**-1.984** (0.009)	-0.183 (0.824)		**10160.7**	10158.3	10160.5	10156.8
	II	0.010 (0.000)	**3.147** (0.049)	0.029 (0.973)	0.130 (0.853)	**1.014** (0.091)					
Ireland	I	0.034 (0.000)	**-5.234** (0.078)	-0.952 (0.372)	**-2.166** (0.033)	-0.395 (0.718)		**9611.72**	9609.06	9611.69	9607.99
	II	0.012 (0.000)	3.246 (0.203)	0.397 (0.786)	0.003 (0.998)	0.242 (0.813)					
Italy	I	0.031 (0.000)	**-3.605** (0.075)	-1.247 (0.111)	**-1.535** (0.041)	0.464 (0.613)		9544.94	9545.27	**9545.75**	9542.84
	II	0.012} (0.000)	1.490 (0.394)	0.493 (0.497)	0.680 (0.313)	**1.320** (0.056)					

Market		σ_i^2	β_i MCSI	β_i GER-ES	β_i ZEW-ES	β_i ZEW-CS		ML MCSI	ML GER-ES	ML ZEW-ES	ML ZEW-CS
Netherland	I	0.022 (0.000)	**-3.957 (0.025)**	**-1.634 (0.008)**	**-1.771 (0.008)**	-0.016 (0.981)		**10383.09**	10374.8	10376.7	10374.4
	II	0.008} (0.000)}	**3.822 (0.012)**	0.061 (0.950)	0.020 (0.980)	**1.309 (0.021)**					
Norway	I	0.035 (0.000)	**-3.907 (0.064)**	-0.966 (0.181)	**-2.141 (0.019)**	0.056 (0.936)		**9496.10**	9493.65	9495.34	9492.26
	II	0.012 (0.000)	3.122 (0.108)	0.097 (0.916)	0.168 (0.849)	1.013 (0.103)					
Portugal	I	0.026 (0.000)	-3.326 (0.122)	**-1.691 (0.018)**	**-1.674 (0.008)**	0.692 (0.369)		9916.08	9920.53	**9922.14**	9920.32
	II	0.011 (0.000)}	2.488 (0.145)	0.176 (0.862)	0.338 (0.621)	**1.424 (0.020)**					
Spain	I	0.029 (0.000)	**-4.543 (0.060)**	**-2.322 (0.005)**	**-3.200 (0.003)**	-0.065 (0.937)		9683.22	9685.98	**9687.84**	9684.41
	II	0.011 (0.000)	2.676 (0.150)	0.053 (0.948)	0.468 (0.599)	**1.290 (0.043)**					
Sweden	I	0.031 (0.000)	**-5.756 (0.026)**	**-1.724 (0.052)**	**-1.905 (0.039)**	-0.525 (0.617)		**9807.01**	9805.47	9806.12	9802.94
	II	0.011 (0.000)	**4.425 (0.060)**	-0.096 (0.924)	0.271 (0.786)	0.267 (0.750)					
Switzerland	I	0.022 (0.000)	**-4.350 (0.037)**	**-1.773 (0.022)**	**-1.540 (0.035)**	-0.022 (0.977)		11207.3	11206.9	**11208.2**	**11204.6**
	II	0.008 (0.000)	3.086 (0.107)	0.272 (0.780)	0.263 (0.762)	1.033 (0.113)					
UK	I	0.024 (0.000)	**-3.971 (0.047)**	-1.276 (0.360)	**-2.218 (0.009)**	-0.187 (0.776)		10588.4	10591.4	**10592.03**	10588.8
	II	0.008 (0.000)	**3.237 (0.061)**	0.543 (0.789)	0.292 (0.257)	**1.116 (0.046)**					

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Note: α_i and $\beta_i$are the parameter from the transition probability matrix, given in the equation (2) Parameters significant at 10% level and the highest log-likelihood values for a given market are written in bold.

Source: own study.

Table A2. Estimation results for emerging and frontiers markets

Market		σ_i^2	β_i MCSI	β_i GER-ES	β_i ZEW-ES	β_i ZEW-CS		ML MCSI	ML GER-ES	ML ZEW-ES	ML ZEW-CS
Emerging markets											
Czech R.	I	0.036 (0.000)	-4.629 (0.101)	**-1.969 (0.033)**	**-1.942 (0.045)**	-0.377 (0.729)		10111.63	10112.8	**10113.7**	10108.91
	II	0.011 (0.000)	3.330 (0.187)	0.811 (0.569)	0.971 (0.459)	1.208 (0.178)					
Greece	I	0.044 (0.000)	-1.281 (0.687)	-0.328 (0.597)	-0.802 (0.211)	1.142 (0.377)		8119.86	8120.09	**8120.89**	8115.067
	II	0.017 (0.000)	1.128 (0.440)	0.526 (0.387)	0.191 (0.746)	1.388 (0.412)					
Hungary	I	0.038 (0.000)	**-5.538 (0.022)**	**-1.643 (0.087)**	**-1.292 (0.085)**	-0.072 (0.907)		**9043.59**	9041.49	9041.98	9042.42
	II	0.013 (0.000)	**3.326 (0.056)**	0.111 (0.907)	0.419 (0.635)	**1.732 (0.004)**					
Poland	I	0.034 (0.000)	**-6.355 (0.013)**	**-1.415 (0.076)**	**-1.389 (0.091)**	0.441 (0.665)		9395.95	9396.34	**9397.33**	9397.17
	II	0.013 (0.000)	2.664 (0.259)	0.052 (0.430)	0.284 (0.778)	**1.527 (0.060)**					
Russia	I	0.014 (0.000)	**-4.092 (0.040)**	**-1.405 (0.041)**	**-1.541 (0.075)**	-0.785 (0.267)		9135.76	9131.33	**9138.47**	9136.59
	II	0.044 (0.000)	2.186 (0.302)	0.357 (0.734)	0.232 (0.807)	0.874 (0.186)					
Turkey	I	0.038	-2.129	-0.628	-0.185	-0.005		8805.83	**8808.3**	8807.71	8802.48

Market		σ_i^2	β_i	β_i	β_i	β_i		ML			
			MCSI	GER-ES	ZEW-ES	ZEW-CS		MCSI	GER-ES	ZEW-ES	ZEW-CS
		(0.000)	(0.266)	(0.250)	(0.743)	(0.995)					
	II	0.016 (0.000)	1.084 (0.587)	**1.238** (0.070)	**1.650** (0.014)	0.507 (0.497)					
Frontier markets											
Croatia	I	0.026 (0.000)	**-5.662** (0.009)	**-1.665** (0.018)	**-1.771** (0.015)	-0.065 (0.932)		**11416.55**	11412.8	11412.9	11406.8
	II	0.007 (0.000)	**3.250** (0.096)	0.489 (0.470)	1.098 (0.194)	**1.015** (0.094)					
Estonia	I	0.028 (0.000)	**-3.701** (0.017)	-0.411 (0.333)	-0.712 (0.686)	0.058 (0.928)		**10242.1**	10219.7	10221.2	10217.1
	II	0.008 (0.000)	**3.566** (0.004)	0.181 (0.724)	0.321 (0.501)	**1.111** (0.069)					
Kazakhstan	I	0.032 (0.000)	-0.929 (0.451)	**-0.783** (0.094)	-0.695 (0.110)	-0.092 (0.790)		9212.89	**9215.8**	9215.65	9208.83
	II	0.008 (0.000)	0.761 (0.540)	0.207 (0.664)	0.372 (0.397)	0.450 (0.268)					
Lithuania	I	0.036 (0.000)	**-4.319** (0.047)	-0.126 (0.811)	-0.126 (0.628)	-0.979 (0.139)		**11121.11**	11109.5	11110	11112.4
	II	0.011 (0.000)	**3.979** (0.013)	0.654 (0.316)	**1.121** (0.058)	0.587 (0.332)					
Romania	I	0.033 (0.000)	**-4.002** (0.065)	-0.479 (0.440)	-0.660 (0.296)	-0.353 (0.621)		**9886.94**	9881.17	9882.6	9882.31
	II	0.010 (0.000)	**3.826** (0.013)	0.973 (0.260)	1.033 (0.198)	0.838 (0.187)					
Serbia	I	0.033 (0.000)	**-4.799** (0.003)	**-1.252** (0.017)	**-1.096** (0.038)	-0.227 (0.775)		**10338.9**	10334.2	10336.2	10330.1
	II	0.008 (0.000)	**3.199** (0.012)	**1.399** (0.013)	**1.283** (0.018)	0.971 (0.021)					
Slovenia	I	0.027 (0.000)	**-4.263** (0.016)	**-2.196** (0.000)	**-1.754** (0.041)	-0.133 (0.807)		**10633.51**	10629.3	10632.2	10623.3
	II	0.009 (0.000)	**2.552** (0.093)	0.819 (0.230)	0.720 (0.186)	**0.948** (0.082)					

Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Note: α_i and β_i are the parameter from the transition probability matrix, given in the equation (2) Parameters significant at 10% level and the highest log-likelihood values for a given market are written in bold.

Source: own study.

Table A3. Estimation results for AR(1)-GJR-GARCH model (up to 2019)

Sentiment		μ	ϕ	β_{mean}	ω	α	β	γ	β_{var}
Panel A: Developed markets									
MCSI	Estimate	0.001*	0.003	**-0.001***	0.000	0.011	0.900***	0.151***	0.000
	p-value	0.038	0.890	**0.041**	0.257	0.523	0.000	0.000	**0.997**
ZEW-ES	Estimate	0.000	0.002	**0.000**	0.000.	0.020***	0.902***	0.138***	**9.63E-09*** **
	p-value	0.515	0.934	**0.445**	0.086	0.000	0.000	0.000	**0.000**
ZEW-CS	Estimate	0.000	0.001	**-0.001***	0.000	0.015**	0.901***	0.145***	**0.000**
	p-value	0.624	0.945	**0.016**	0.110	0.007	0.000	0.000	**0.996**
GER-ES	Estimate	0.001.	0.005	**-0.001.**	0.000	0.026**	0.888***	0.137***	**0.000**
	p-value	0.063	0.228	**0.081**	0.166	0.006	0.000	0.000	**0.973**
Panel B: Emerging markets									
MCSI	Estimate	0.000	0.058**	**0.000**	0.000	0.012.	0.939***	0.080***	**0.000**
	p-value	0.604	0.002	**0.305**	0.120	0.062	0.000	0.000	**0.951**
ZEW-ES	Estimate	0.000	0.059**	**0.000**	0.000	0.015	0.938***	0.079***	**1.26E-08*** **
	p-value	0.955	0.002	**0.291**	0.479	0.427	0.000	0.000	**0.000**
ZEW-CS	Estimate	0.000	0.059***	**0.000**	0.000	0.014*	0.939***	0.079***	**0.000**
	p-value	0.783	0.001	**0.896**	0.145	0.034	0.000	0.000	**0.978**
GER-ES	Estimate	0.000	0.056**	**0.000**	0.000.	0.000	0.956***	0.068***	**1.11E-08*** **
	p-value	0.599	0.007	**0.487**	0.081	0.994	0.000	0.000	**0.000**

Sentiment		μ	ϕ	β_{mean}	ω	α	β	γ	β_{var}
Panel C: Frontier markets									
MCSI	Estimate	0.000	0.036.	**0.000**	0.000.	0.034***	0.911***	0.061***	**0.000**
	Estimate	0.442	0.061	**0.613**	0.052	0.000	0.000	0.000	**0.997**
ZEW-ES	Estimate	0.000	0.036.	**0.000**	0.000*	0.035***	0.911***	0.060***	**1.07E-08*** **
	p-value	0.537	0.064	**0.758**	0.017	0.000	0.000	0.000	**0.000**
ZEW-CS	Estimate	0.000	0.037.	**0.000**	0.000*	0.035***	0.911***	0.060***	**0.000**
	p-value	0.832	0.061	**0.480**	0.027	0.000	0.000	0.000	**0.999**
GER-ES	Estimate	0.000	0.033	**0.000**	0.000***	0.001	0.934***	0.058***	**0.97E-08*** **
	p-value	0.257	0.115	**0.369**	0.000	0.397	0.000	0.000	**0.000**

Significant codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1.
Source: own study.

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Contribution share: Czapkiewicz – 30%: conceptualisation, literature review, calculations, writing, Choczyńska – 40%: conceptualisation, literature review, calculations, writing, Machno – 30%: calculations, writing.

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Use of Artificial Intelligence

Authors declare the use of AI tools DeepL Write and ChatGPT for proofreading the manuscript.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.