Option-implied asymmetry indices in the Eurozone: the relationship with sentiment and financial stress

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Option-implied asymmetry indices in the Eurozone: the relationship with sentiment and financial stress

In this paper, we introduce novel asymmetry indices based on option prices for the Eurozone. The aim is to investigate the ability of option-implied asymmetry measures to explain sentiment dynamics and anticipate potential situations of financial stress. To achieve our objectives, we measure asymmetry in two ways. First, we decompose the *SKEW* index into its positive and negative components. Second, we introduce the Risk-Asymmetry (*RAX*) index as an alternative measure of asymmetry. Our findings suggest the importance of disentangling the information contained in the two tails of the option-implied distribution, based on calls and puts, respectively, to provide new insights into investor perceptions. In particular, the asymmetry index obtained from the right tail of the risk-neutral distribution (exploiting call option prices) embeds useful information to forecast the change of sentiment in the following month. On the other hand, in the European market it is not sufficient to rely solely on the information derived from the left tail of the distribution (put options) to anticipate periods of financial stress. Instead, a more refined measure, such as the *RAX*, is required to predict these fluctuations effectively.

Keywords: asymmetry indices; *RAX*; *SKEW*; sentiment indicators; tail risk; systemic stress; option contracts

Subject classification codes: G13, G15

1. Introduction

This paper introduces novel asymmetry indices for the Eurozone market to evaluate their effectiveness in explaining sentiment dynamics and anticipating periods of financial stress. Accurate measurement and prediction of investor sentiment and financial stress is of paramount importance for managers, policymakers, and investors. Investor sentiment captures expectations and perceptions of future cash flow and risks, often independent of available facts, reflecting confidence levels in the market for a specific asset and situation (Baker and Wurgler, 2006; 2007). Sentiment is crucial in explaining market movements during periods of panic or optimism (Reis and Pinho, 2020a) and acts as a primary force behind stock return co-movements, explaining non-fundamental return components (Frijns et al., 2017). An accurate assessment of sentiment is not only important for understanding market dynamics and assisting investors in making informed decisions but also helps regulators anticipate market shifts and potential valuation changes. In fact, investor irrationality, driven by emotions, may influence financial decisions with implications for asset prices (Benhabib et al., 2016; Piccione and Spiegler, 2014), potentially leading to excessive price movements detached from true financial instrument value and forming the basis of speculative bubbles. At the same time, negative sentiment can escalate financial stress as investors react to uncertainties with panic, leading to widespread sell-offs and sharp declines in asset prices. The prompt detection of financial stress situations has crucial importance in maintaining the stability and resilience of financial markets. This is because financial stress, characterized by increased uncertainty, market turbulence, and heightened risk aversion, may spill over to the broader economy (Chavleishvili, and Kremer, 2023). Consequently, it can contribute to an economic downturn by increasing the cost of credit and causing businesses, households, and financial institutions to be overly cautious (Hakkio and Keeton, 2009). Timely identification of these conditions allows market participants, investors, and regulators to implement effective measures to mitigate potential risks, prevent systemic issues, and restore market confidence.

In a recent study, Bevilacqua and Tunaru (2021) demonstrate a connection between option-implied asymmetry indices and sentiment, tail risk, and broader market uncertainty. This link is supported by the idea that option-implied measures like skewness reflect market expectations of future price movements and uncertainty. Moreover, Seo and Wachter (2019) find that option prices reflect the risk of rare economic events, such as consumption disasters, providing additional evidence for their importance in capturing future economic uncertainty, downside risk, and financial stress. Building on these insights, Bevilacqua and Tunaru (2021) decomposed the *SKEW* index into its positive and negative skewness components, revealing that the positive skewness index is predictive of four out of six sentiment measures examined in the U.S. market. Conversely, they found that the negative skewness component is closely related to tail risk measures.

Despite the key role assigned to option-implied skewness as a measure of risk and as a tool to monitor and forecast investor sentiment, the literature on the relationship between asymmetry indices and sentiment is scant and limited to the US (e.g. Stambaugh et al., 2012; Buraschi and Jiltsov, 2006; Han, 2008; Gârleanu et al., 2009; Friesen et al., 2012; Lemmon and Ni, 2014; Bevilacqua and Tunaru, 2021). For most of the European markets, a measure of the asymmetry in the return distribution and tail risk has yet to be introduced (Elyasiani et al., 2021); consequently, in the European context, the relationship between asymmetry indices on the one hand and sentiment and financial stress on the other, is far from being clarified.

To fill these gaps, as the Eurozone market lacks measures capturing the asymmetry of the risk-neutral distribution, we first introduce a skewness index computed exploiting EURO STOXX 50 Index options.[1] More specifically, we introduce both a

[1] The EURO STOXX 50 Index is the most widely followed benchmark for tracking equity market performance and development across the Eurozone. Developed by STOXX, an index provider owned by the Deutsche Börse Group, the index was first introduced on February 26, 1998 “to provide a blue-chip representation of Supersector leaders in the Eurozone”. It comprises fifty of the largest and most liquid stocks drawn from Austria, Belgium, Finland,

measure of asymmetry based on the *CBOE SKEW* index method (to serve as a benchmark for measuring risk-neutral skewness) and the risk-asymmetry index (*RAX*) developed by Elyasiani et al. (2018). To deal with the limited availability of option-based data for European countries that represents the main obstacle for construction of such indices in the EU (see, Elyasiani et al. 2021), we adopt a specific procedure that involves interpolation among the existing strike prices and extrapolation outside of their interval. In this way, we obtain the series of the two asymmetry measures for the standard 30-day maturity. Moreover, we resort to the methodology proposed by Bevilacqua and Tunaru (2021) to decompose the *SKEW* index into its positive and negative components: the *CALL* index, obtained by applying the *SKEW* formula to call options, and the *PUT*, index, obtained by considering only put options.

We compared and contrasted the obtained indices in explaining their contemporaneous and future relationships with sentiment and financial stress. As sentiment measures for the Eurozone, we adopt three widely used indicators: the European Sentiment index (*ESI*), the European Sentix Investor Confidence index (*SENTIX*) and the Eurozone *ZEW* Economic Sentiment (*ZEW*). Finally, financial stress is measured using the Composite Indicator of Systemic Stress (*CISS*) and three out of the five market-specific sub-indices accounting for systemic stress in bond markets, equity markets and financial intermediaries.

Our results indicate that asymmetry indices play an important role in explaining the fluctuation of economic sentiment indicators. Additionally, our findings suggest the importance of disentangling the information contained in the two tails of the option-

France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain. Its composition is reviewed annually in September.

implied distribution, since the asymmetry index obtained from the right tail of the risk-neutral distribution (call prices) provides useful information to forecast the change of sentiment in the following month. Our results also indicate that relying solely on information from the left tail of the distribution is insufficient for predicting fluctuations in financial stress indices. On the other hand, a more comprehensive measure, such as the *RAX* index, offers significant predictive information regarding future changes in systemic stress, as measured by the *CISS* indices. This makes the *RAX* index a valuable early-warning indicator for systemic stress situations, especially in the equity market. On the contrary, the behaviour of the *SKEW* and *PUT* indices seem to be affected by the investors hedging activity, making the two indices less suitable for predicting future fluctuations in sentiment or financial stress.

The remainder of the paper is structured as follows. In Section 2, we review the methodologies to obtain asymmetry measures from a cross-section of option prices. In Section 3, we introduce the dataset and the asymmetry measures. In Section 4, we empirically investigate the relationship between asymmetry indices, sentiment, and financial stress. Section 5 interprets the results and provides deeper insights. Finally, Section 6 concludes and provides some implications for investors and policy-makers.

2. Asymmetry measures based on option prices

In this section, we present the asymmetry measures computed for the European market. Subsection 2.1 focuses on the standard skewness measure (*SKEW*). Subsection 2.2 explores the decomposition of *SKEW* into its positive (*CALL*) and negative (*PUT*) components, derived from call and put options, respectively. Finally, Subsection 2.3 introduces the Risk-Asymmetry Index (*RAX*).

2.1 *The standard skewness measure for financial markets*

The standard market practice to compute risk-neutral skewness is to use the model-free skewness formula due to Bakshi et al. (2003). The *CBOE SKEW* index is designed to complement the information provided by the CBOE volatility index (*CBOE VIX*), which measures the overall risk in the 30-day S&P500 log-returns, by indicating the asymmetry of the return distribution. The following formula is commonly used in line with the CBOE procedure:

$$SK(\mathrm{t},\tau) \equiv \frac{E_t^q\left\{\left(R(\mathrm{t},\ \tau)-E_t^q\left[R(\mathrm{t},\ \tau)\right]\right)^3\right\}}{\left\{\left(E_t^q(R(\mathrm{t},\ \tau)-E_t^q\left[R(\mathrm{t},\ \tau)\right]\right)^2\right\}^{3/2}} = \frac{e^{r\tau}W(\mathrm{t},\tau)-3e^{r\tau}\mu(\mathrm{t},\tau)V(\mathrm{t},\tau)+2\mu(\mathrm{t},\tau)^3}{\left[e^{r\tau}V(\mathrm{t},\tau)-\mu(\mathrm{t},\tau)^2\right]^{3/2}} \quad (1)$$

where $R(\mathrm{t},\ \tau)$, $\left[R(\mathrm{t},\ \tau)\right]^2$ and $\left[R(\mathrm{t},\ \tau)\right]^3$ are the payoffs of the contracts at time *t* with maturity τ, based on the first, second and third moment of the distribution, respectively. Accordingly, $\mu(\mathrm{t},\tau)$, $V(\mathrm{t},\tau)$, $W(\mathrm{t},\tau)$ and $X(t,\tau)$ are the prices of the contracts, at time *t*, with maturity τ, based on the first, second, third and, fourth moment of the distribution, respectively. The prices of these contracts are obtained under the risk-neutral expectation (E_t^q). For a more detailed discussion of the contracts, see Appendix A.

2.2 *The decomposition of the SKEW index: CALL and PUT*

Despite its importance in describing the return distribution, the *CBOE SKEW* index has not gained the same level of recognition as the *CBOE VIX* index (Elyasiani et al., 2021). This may be partly due to the fact that changes in the *CBOE SKEW* index are positively correlated with changes in market returns (as shown by Liu and Faff, 2017), meaning that an increase in the *CBOE SKEW* index is associated with a simultaneous increase in market returns. Additionally, while the volatility index (*CBOE VIX*) spikes during periods of market downturn, the *CBOE SKEW* has been observed to increase during both calm and turbulent periods. This raises doubts about the effectiveness of the *CBOE SKEW* index as an indicator of fear in the US market. According to studies by Liu and Faff (2017) and Elyasiani et al. (2021), the *SKEW* index is not a reliable barometer of market fear, as it does not necessarily spike during periods of high volatility and market downturn. Therefore, existing studies have called for alternative measures of asymmetry that can better capture market fear.

A proposal in this direction is due to Bevilacqua and Tunaru (2021), who show that a more refined directional construction of the implied skewness enhances information extracted from US equity index option prices. More specifically, the *SKEW* index can be decomposed into two components: a *CALL* index obtained only from S&P 500 calls, and a *PUT* index computed only from S&P 500 puts. To elaborate, in the formulas (A7)–(A9) in the Appendix A, for the computation of *CALL* (*PUT*) index, we exploit only call (put) options when $K_i \geq K_0$ $(K_i \leq K_0)$.

2.3 The Risk Asymmetry Index (RAX)

The decomposition of the *SKEW* index into its positive and negative components is not the only way to assess the risk in a specific part of the option-implied distribution. In Elyasiani et al. (2018), to account for the fact that investors like positive spikes while they dislike negative spikes in the returns, the concept of upside and downside corridor implied volatility measures is exploited to obtain an alternative indicator of asymmetry risk: the Risk-Asymmetry Index (*RAX*). The *RAX* index is a metric used to measure the asymmetry of the risk-neutral distribution. It aims to capture the pricing asymmetry of investors towards gains and losses. To calculate the *RAX* index, we follow the method used by Elyasiani et al. (2018) and combine the corridor implied volatilities for upside and downside.

The *RAX* index is then derived by measuring the difference between the upside and downside corridor implied volatilities, divided by the total volatility (for a more detailed explanation of how the *RAX* index is derived, please refer to Appendix B). In particular, the numerator is standardised by total volatility, so that the *RAX* index is not influenced by the level of volatility in bullish or bearish market periods:

$$RAX(t,\tau)=\frac{\sigma_{UP}(t,\tau)-\sigma_{DW}(t,\tau)}{\sigma_{TOT}(t,\tau)} \tag{2}$$

where $\sigma_{TOT}(t,\tau)$ is the sum of the upside and downside corridor implied volatilities and it is equal to model-free implied volatility. Downside (σ_{DW}) and upside (σ_{UP}) corridor implied volatility are the square root of downside and upside corridor implied variance and can be obtained as:

$$\sigma_{UP}(t,\tau)=\sqrt{\frac{2e^{r\tau}}{\tau}\int_{F_t}^{\infty}\frac{M(K,\tau)}{K^2}dK} \tag{3}$$

$$\sigma_{DW}(t,\tau)=\sqrt{\frac{2e^{r\tau}}{\tau}\int_{t}^{F_t}\frac{M(K,\tau)}{K^2}dK} \tag{4}$$

where $F_t = K^* e^{r\tau} * difference$, and K^* is the reference strike price (i.e. the strike at which the difference in absolute value between the at-the money call and put prices is the smallest).

Computing the *RAX* index will allow us to compare and contrast the results of measuring asymmetry based on *SKEW* with those based on corridor-implied volatilities. Additionally, the measures of risk based on corridor implied volatility have already proven to be useful in forecasting future market returns in the European market, as shown in Elyasiani et al. (2017, 2018). However, the explanatory power of these measures has primarily been established in relation to the influence of extreme values on market returns (based on Rubbaniy et al., 2014) and within specific country contexts. This narrow focus underscores the need for further research to explore the wider applicability of these potentially valuable indicators.

3. Data and methodology

Our data set includes various sources of information such as the option data required to compute the asymmetry measures, economic sentiment indicators for the Eurozone, and indicators of financial stress. The option dataset is described in subsection 3.1. The procedure adopted to obtain the asymmetry indices is outlined in Sections 3.2 and 3.3, respectively. Sections 3.4 and 3.5 provides further details on the measures of economic sentiment and financial stress adopted in our study. In Section 3.6, we discuss the descriptive statistics of the series involved in the analysis. Finally, in Section 3.7, we discuss the behaviour of the indices throughout the sample period.

3.1 The option dataset

The option dataset consists of closing prices of EURO STOXX 50 Index options, recorded from January 2010 to December 2022, based on availability. The options data set, the dividend yield and the Euribor rates are collected from OptionMetrics (IvyDB Europe). As for the underlying assets, the time series of the EURO STOXX 50 Index was obtained from Bloomberg. Options are of the European type, in the sense that they can be exercised only at the expiration date. Given that the underlying asset (S_t) of the option series pays dividend, following Elyasiani et al. (2021), we compute its adjusted value ($\hat{S}_t$) at time *t* as:

$$\hat{S}_t = S_t e^{-\delta_t \Delta t} \tag{5}$$

where δ_t is the dividend yield, and Δt is the time to maturity of the option. As a proxy for the risk-free rate, Euribor rates with maturities of one week, one month, two months, and three months are used. The appropriate yield to maturity is computed through linear interpolation.

We applied to the options dataset specific filters to remove any irregularities and opportunities for arbitrage in the prices. First, we exclude options that have a time-to-maturity of less than eight days, which is in line with the computational method used in constructing other indices, such as the *CBOE SKEW*. Second, we retain only at-the-money and out-of-the-money options, following the method used by Ait-Sahalia and Lo (1998). In-the-money options are rarely traded, and their prices can be affected by the illiquidity of the option contracts. Following Elyasiani et al. (2018), we measure the option moneyness as K/S, where K represents the strike price and S represents the index value, and consider only put options with moneyness values lower than 1.03 (i.e., $K/S < 1.03$) and call options with moneyness values greater than 0.97 (i.e., $K/S > 0.97$). Further, to establish a one-to-one relationship between strikes and implied volatilities, we take the average of the implied volatilities of options corresponding to the same strike price. Finally, we eliminate option prices that violate the standard no-arbitrage constraints and those whose closing price is less than 1 Euro, since they are frequently non-traded deep-out-of-the-money options.

3.2 The interpolation-extrapolation method

Limited availability of option-based data for European countries remains the main obstacle to constructing indices based on option prices (Elyasiani et al., 2021). The assumption of a continuum of strike prices ranging from zero to infinity, which is required for Eq. (1) and Eqs. (3-4), is not fulfilled in the reality of the options market. While this assumption can be mitigated for the US market due to the high number of option prices traded (usually more than 100 per day), it can represent a significant issue for European markets, which are characterised by a limited number of strike prices traded (Elyasiani et al., 2021), leading to truncation and discretization errors.

To overcome the limitations of infrequent option trades and assess the reliability of the *SKEW* index estimates, we resort to a procedure that allows us to nearly eliminate truncation and discretization errors and greatly improves the precision of the skewness estimate. The procedure involves the following steps. After applying the filters described above, we create a table of available strike prices and implied volatilities, which serves as our initial input. To achieve a sufficient number of strike prices, we follow an interpolation-extrapolation method (as described in Jiang and Tian, 2005). Implied volatilities are interpolated between two adjacent knots using cubic splines to keep the function smooth in the knots and extrapolated outside the traded domain of strike prices. Specifically, we assume constant volatility for strike prices higher than the maximum strike price traded and lower than the minimum strike price traded. The constant volatility used in the left (right) part of the extended smile is set to be equal to the volatility of the lowest (highest) strike price traded. This ensures that we avoid negative implied volatilities (as recommended by Muzzioli et al., 2018). Finally, we compute missing implied volatility and strike prices from the interpolated-extrapolated smile by using a specific space interval ΔK to ensure insignificant truncation errors. On the other hand, truncation errors are mitigated by computing a matrix of strike prices and implied volatility in the interval $S/(1+u) \leq K \leq S(1+u)$, where S is the underlying asset value, and u is a parameter equal to 2, in line with Elyasiani et al. (2021). Descriptive statistics for maturities, the number of options, and the number of strike prices derived from the interpolation-extrapolation procedure are reported in Table 1.

As a last step, after obtaining the implied volatilities, we convert them into option prices and by applying equations (A7-A9) we obtain three measures of asymmetry: i) the *SKEW* index by considering all the options; the *CALL* index by exploiting only call options, and the *PUT* index by using only put options. Therefore, our procedure is designed to follow the CBOE method as closely as possible, with the exception of the interpolation-extrapolation step. The interpolation-extrapolation procedure will be used also for the construction of the risk-asymmetry index. In particular, following Elyasiani et al. (2018), corridor implied volatilities are computed as a discrete version of equations. (3)-(4) with integration domain equal to [$K_{\min}$, F] and [F, $K_{\max}$], where $K_{\min}$ and $K_{\max}$ correspond to the minimum and maximum strike price of our interpolated-extrapolated volatilities, thus ensuring an insignificant truncation error (for more details see Muzzioli, 2015).

3.2 The final skewness index

Applying the formulas described in the previous section to a cross-section of option prices, we obtain a measure of asymmetry that refers to the expiration dates of the options used, and therefore, varies each day. To obtain a measure with a fixed 30-day maturity, following the CBOE procedure (CBOE, 2010), we exploit two different option series. Specifically, a first option series with a maturity of less than 30 days and a second option series with time to maturity greater than 30 days, are used:

$$M_{30} = wM_{near} + \left(1-w\right)M_{next} \tag{6}$$

with $w=(T_{next}-30)/(T_{next}-T_{near})$, where T_{near} (T_{next}) is the time to expiration of the near (next term) options, and M_{near} and M_{next} are the estimated measures of asymmetry, which refer to the near and next term options, respectively.

In line with the CBOE procedure (CBOE, 2010), we calculate the final value of the asymmetry indices as:

$$SKEW = 100 - 10 \times M_{30} \tag{7}$$

where M_{30} is obtained in equation (6). As the risk-neutral skewness attains typically negative values for equity indices, formula (7) enhances the interpretation of a skewness index. For symmetric distributions, risk-neutral skewness is equal to zero, and the skewness index will be equal to 100. On the other hand, values higher (lower) than 100 for the skewness index point to a left (right) skewed risk-neutral distribution. The higher the risk, the higher the perceived risk related to negative returns will be. Moreover, a high value of the *SKEW* index indicates that buying protection against market downturns (put options) is more expensive.

To obtain a constant 30-day measure for the skewness index, following Elyasiani et al. (2018), the *RAX* index is constructed by using 30-day volatility measures obtained with the same linear interpolation procedure of the near- and next-term options adopted for the *SKEW* (equation (6)). Moreover, the transformation in equation (7) is applied to the daily values of the *RAX* index for ease of comparison with the *SKEW* index. As a result, a value of the *RAX* higher than 100 indicates that the volatility of the left side of the distribution (σ_{DW}) is higher than the one of the right side (σ_{UP}), indicating that investors attach a higher (risk-neutral) probability to negative returns.

Finally, in order to make the asymmetry indices comparable to the economic sentiment indices (which are computed on a monthly frequency), we average the daily estimates for each month to obtain the monthly series that will form our final dataset.

3.4 Economic sentiment indicators

To assess the relationship between asymmetry indices and sentiment measures, we employed three different sentiment indicators for the Eurozone as a whole. The first indicator is the Economic Sentiment Indicator (*ESI*). It is a composite index measuring the level of confidence in the Euro area. The index is computed monthly by the European Commission's Directorate-General for Economic and Financial Affairs, which regularly conducts harmonised surveys for various sectors of the European Union and candidate countries' economies. The *ESI* is obtained from surveys addressed to representatives of the manufacturing industry, services, retail trade, construction, and consumers. These surveys allow for the comparison of economic cycles across different countries and have become an indispensable tool for monitoring the evolution of the EU and Euro area economies, as well as developments in candidate countries. The index is generated by calculating the weighted average of the scores from each survey, which is subsequently normalised to ensure a long-term average of 100 and a standard deviation of 10. Values above 100 indicate economic sentiment above average, while values below 100 indicate a position below the average. Assuming an approximately normal distribution, setting the standard deviation to 10 implies that, in about 68% of cases, the *ESI* falls within the 90-110 range.

The second indicator is the European Sentix Investor Confidence, also known as *SENTIX*. It is an index that evaluates the economic situation and prospects for the euro area for the next six months. The index calculation is based on information processed through a monthly survey conducted with around 5,500 investors and analysts. These participants are interviewed about their estimates regarding the 14 financial markets under analysis. If the reading is above zero, it indicates optimism, while a reading below zero indicates pessimism.

The Eurozone *ZEW* Economic Sentiment (referred to as *ZEW*) is the third indicator that is used to assess the economic outlook for the Eurozone over the next six months. It is a monthly index that is based on the *ZEW* Financial Market Test, where 300 experts from banks, insurance companies, and financial departments of selected companies are interviewed every month. These experts are questioned about their assessments and forecasts on important international financial market data, including the economy, inflation rates, interest rates, stock markets, and exchange rates. Their expectations for the next six months are recorded and used to form the *ZEW* index.

To facilitate the comparison between the *ESI* and the asymmetry indices (characterised by a baseline level of 100), we have added 100 to both the *SENTIX* and the *ZEW*. This adjustment was made to align the sentiment indices with the asymmetry indices without changing their essential meaning. It is crucial to note that an index above 100 still indicates a positive sentiment, while an index below 100 still connotes a negative sentiment.

3.5 Indicators of financial stress

Measuring financial stress is crucial as it provides a real-time barometer for the health and stability of financial markets. It allows policymakers, investors, and regulators to identify potential vulnerabilities, assess systemic risks, and implement timely interventions. For the European area, the Composite Indicator of Systemic Stress (*CISS*) is the main financial metric designed to assess and quantify the overall stability and health of the financial system. It serves as a comprehensive tool for monitoring potential systemic risks by aggregating various indicators and variables that reflect the conditions of financial markets. In particular, the *CISS*, proposed by Holló et al. (2012), is meant to measure the systemic risk that has already materialised, whereas the systemic risk can be defined as the risk that financial crisis or instability become so widespread as to reach and affect the real economy. The index includes 15 variables aggregated at the European level in five sub-indices that measure financial stress in the money market, bond market, equity market, financial intermediaries, and foreign exchange market. The *CISS* index considers factors such as market volatility, credit spreads, and liquidity conditions, among others, to provide a holistic view of the systemic stress levels.

To investigate the relationship between asymmetry indices and financial stress, we obtained from the ECB data portal[2] the monthly series of the Composite Indicator of Systemic Stress (*CISS*) and three out of the five market-specific sub-indices accounting for systemic stress in bond markets, equity markets and financial intermediaries, respectively.[3] As the *CISS* value varies between 0 and 1, with higher values indicating higher systemic stress in financial markets, we multiply the indices by 100 in order to facilitate the comparison with the asymmetry indices.

3.6 Descriptive statistics

Table 2 presents the descriptive statistics for our asymmetry indices, alongside sentiment indicators and financial stress measures. Examining the asymmetry measures, we find that three out of four indices (*PUT*, *SKEW*, and *RAX*) exhibit average values above 100. This indicates a left-skewed option-implied distribution for the EURO STOXX 50 Index, in line with previous evidence in the European (e.g. Muzzioli and Gambarelli, 2019) and US markets (Bevilacqua and Tunaru, 2021). In simpler terms, the market participants attribute a higher probability to negative returns compared to positive returns. Conversely, the *CALL* index, calculated using only call option prices, displays an average value below 100, suggesting a right-skewed distribution. This is expected given the characteristic V-shaped volatility smile, where out-of-the-money calls are generally priced with less implied volatility than out-of-the-money puts.[4]

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[2] https://data.ecb.europa.eu/data

[3] In our analysis, we exclude CISS sub-indices related to the money market and foreign exchange market, as they are unlikely to be significantly affected by the same source of risk captured by the asymmetry indices.

[4] The "smile" is a graphical representation of implied volatility, which is calculated by inverting the Black-Scholes formula, plotted against the strike price. The curve of the smile can either

Further analysis of normality reveals that the *CALL* index is approximately normally distributed, as evidenced by the failure to reject the null hypothesis in the Jarque-Bera test. In contrast, the *PUT*, *SKEW*, and *RAX* indices exhibit positive skewness and deviate significantly from a normal distribution. This points to a heavier left tail in their distributions, likely driven by investors using put options for downside protection, which impacts their pricing. Similar positive skewness and non-normality are observed for financial stress indices, suggesting a tendency towards positive spikes rather than crashes. Conversely, economic sentiment indices show negative skewness, implying a higher likelihood of significant decreases in sentiment than increases.

Panel B of Table 2 reports statistics for monthly changes in the indices. These series show lower skewness compared to the level series, indicating a more symmetric distribution. Nevertheless, they exhibit pronounced fat tails, as reflected by the high kurtosis values, especially for *ESI* and *ZEW*. The last two rows of each panel include test statistics for the augmented Dickey-Fuller (ADF) test. The ADF test examines whether a series has a unit root (i.e., non-stationary) or not. The results of the test are crucial and will be discussed in Sections 4.1 and 4.2.

The correlation coefficients between the indices in our sample are presented in Table 3. Surprisingly, we found that there is a positive relationship between asymmetry and sentiment indices when analysed in terms of levels (Panel A). This suggests that high market sentiment often aligns with increased asymmetry in the EURO STOXX 50 Index risk-neutral distribution. This unexpected finding merits further investigation in Section

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resemble an upward smile (when the implied volatility is higher for out-of-the-money options than it is for at-the-money options) or a smirk (when the implied volatility is higher for put prices and lower for call prices).

4.1. Among the asymmetry indices, the *CALL* index shows a weak correlation with *SKEW*, while the association between *PUT* and *SKEW* is strong. This indicates that the *SKEW* index's fluctuations are primarily influenced by the skewness captured by put options. Moreover, *SKEW* and *RAX*, measuring asymmetry across the entire distribution, are highly correlated. In terms of levels, financial stress indices negatively correlate with both asymmetry and sentiment indices. Additionally, these stress indices exhibit a strong positive correlation among themselves.

Correlation coefficients generally weaken when examining our series in terms monthly changes (Table 3, Panel B). However, strong relationships within the respective groups (asymmetry, sentiment, and financial stress indices) persist, highlighting consistent dynamics within these categories. Specifically, the *SKEW* index remains highly correlated with *PUT* (0.827) and *RAX* (0.795) even in monthly changes. Notably, *RAX* uniquely shows a moderate correlation with *CALL* (0.365), suggesting that unlike *SKEW*, *RAX* incorporates information from both call and put options to provide a broader perspective on market asymmetry. Conversely, inter-group correlations are weak, suggesting that contemporaneous fluctuations in asymmetry, sentiment, and financial stress indices are largely decoupled. An exception is represented by the *PUT* and *SKEW* indices, which are negatively correlated with financial stress indices. This result will be better investigated in Section 4.2.

3.7 Indices behaviour over the sample period

Figures 1-3 illustrate the behaviour of our series over time. Figure 1 depicts the *PUT*, *SKEW*, *RAX*, and *CALL* indices on different scales for clearer comparisons, emphasizing relative movement rather than absolute levels. The *PUT* and *SKEW* indices follow a very similar trajectory, characterized by pronounced fluctuations during periods of high market stress, such as the European debt crisis, the COVID-19 outbreak, and the 2022 energy crisis. This reflects the use of put options for downside protection during these turbulent times. The *RAX* index shows fewer spikes, particularly in the initial period, but exhibits an upward trend in 2021, with a subsequent slight decline in 2022. In contrast, the *CALL* index remains relatively stable, suggesting lower sensitivity to extreme market events.

Also, the sentiment indices (*ZEW*, *SENTIX*, and *ESI*), shown in Figure 2, display considerable variation over the sample period, reflecting major economic and financial events. Low sentiment periods occurred during the European debt crisis (2011-2012), the COVID-19 outbreak (2020), and the energy crisis of 2022. Conversely, high sentiment periods were particularly observed during the economic recovery following the debt crisis (2014-2018) and during the post-pandemic recovery (2020-2021).

Finally, Figure 3 shows the composite *CISS* index and its components (*COMP*, *BOND*, *FINI*, and *EQUI*). High levels of financial stress generally align with low sentiment periods, as seen during the European debt crisis, the COVID-19 outbreak, and 2022. The 2016 increase in financial stress likely resulted from global uncertainties such as Brexit, slower global growth, and instability in emerging markets.

4. The relationship between asymmetry indices, sentiment and financial stress

In this section, we aim to explore the relationship between asymmetry indices based on option prices and both sentiment and financial stress indicators. In particular, Subsection 4.1 examines the relationship between asymmetry indices and sentiment, while Subsection 4.2 explores the relationship between asymmetry indices and financial stress indicators.

4.1 The relationship between sentiment and asymmetry indices

While a substantial body of research has investigated the relationship between sentiment and risk-neutral skewness in the US market (e.g., Stambaugh et al., 2012; Buraschi and Jiltsov, 2006; Han, 2008; Garleanu et al., 2009; Friesen et al., 2012; Lemmon and Ni, 2014; Bevilacqua and Tunaru, 2021), there remains a notable paucity of evidence regarding this relationship within the European context. Given the distinct institutional characteristics of the European market, it is crucial to address this research gap. For instance, the European market is characterised by a more prominent financial sector and a less dominant technology sector, a composition that contrasts sharply with the US market.

4.1.1 Contemporaneous fluctuations in sentiment and asymmetry indices

In their study, Bevilacqua and Tunaru (2021) explored the relationship between sentiment and asymmetry indices by regressing sentiment indicators on asymmetry indices in terms of levels. However, the results presented in Table 2 for the ADF test indicate that some indices, namely the *RAX* and the *SKEW* indices, are affected by non-stationarity. In fact, the null hypothesis of a unit root being present in a time series cannot be rejected at the 5% level.[5] In this paper, we delve into the rationale behind employing first differences as a methodological approach to enhance the validity of time series analyses in the face of non-stationarity. To further support our choice, we carried out the ADF test again on the first differences of the series (the test statistics are reported in Table

[5] In time series analysis, it is important to recognize the inherent non-stationarity present in certain series that yield traditional analyses based on levels inappropriate. Non-stationary time series have a dynamic nature that introduces trends, seasonality, and other structural shifts that can make it difficult to establish meaningful relationships. As a result, researchers often use transformation techniques, such as differencing, to mitigate these issues. By taking the first differences of the series, temporal dependencies and non-stationary components are effectively reduced, allowing for a more accurate exploration of relationships between variables. This transformation not only helps achieving stationarity but also enables the extraction of underlying patterns and meaningful insights that may be obscured in the original level-based analysis.

2, Panel B). As a result, we found that the null hypothesis is now rejected at the 1% level for all the indices, when considered in terms of monthly changes. This indicates that the first difference of the series are stationary, which means that our indices are I(1). Consequently, to shed light on the relationship between sentiment and asymmetry indices fluctuations, we perform the following regression model:

$$\Delta SENT_t = \alpha + \beta \Delta asymmetry_t + \varepsilon_t \tag{8}$$

where $\Delta SENT_t$ is the monthly change of the sentiment index and is proxied alternatively by changes in *ESI*, *SENTIX* and *ZEW*, and $\Delta asymmetry_t$ is the monthly change of option-implied asymmetry measured alternatively by monthly changes in *CALL*, *PUT*, *SKEW*, and *RAX* indices. The output of the regression model is reported in Table 4.

The output of the model indicates a positive association between asymmetry and sentiment indices fluctuations in almost all cases, with the exception of the *ESI* index, which is significantly associated in terms of monthly changes only with the *CALL* index. Another exception is the relationships between the *CALL* and the *ZEW*, which is not statistically significant. It is worth noting that no single asymmetry index is found to be superior to others in explaining sentiment indices in all cases. In fact, the *CALL* index is the most effective in explaining the *ESI* sentiment index. Meanwhile, *SKEW* and *PUT* are better suited to explain the *SENTIX* and *ZEW* economic sentiment indices. The reason for the dissimilarity could be related to the different measurement of sentiment provided by the three indicators. The *ESI* is obtained from surveys addressed to representatives of the manufacturing industry, services, retail trade, construction, and consumers. On the other hand, *SENTIX* and the *ZEW* indices consider sentiment obtained from investors and analysts, and experts from financial intermediaries, respectively.

The different types of sentiment indicators adopted in our analysis could be at the basis of the difference between our results and those obtained in Bevilaqua and Tunaru

(2021). According to their findings, the *SKEW* and the asymmetry index obtained using put options were characterised by a negative relationship with sentiment indices. On the other hand, a positive association with sentiment indices was detected only for asymmetry obtained from call option prices. Moreover, it is worth noting that the sentiment indices used in their study are mainly market-based sentiment indicators, often obtained by combining financial variables. On the other hand, sentiment indicators available for the Eurozone are based on surveys, thus conveying different information content. The comparison with Bevilaqua and Tunaru (2021) may be more appropriate by looking at the results for the University of Michigan Consumer Sentiment index, which is a monthly survey of consumer confidence levels in the United States conducted by the University of Michigan. However, their results on the association between asymmetry indices and the University of Michigan Consumer Sentiment index point to an overall weak relationship (R-squared around 1%), significant only for the index obtained using call option prices.

In summary, our findings suggest that all the asymmetry indices play a significant role in explaining fluctuations in sentiment indicators for the Eurozone. In terms of index selection, the index that measures asymmetry accounting only for call option prices (*CALL*) is more appropriate for representing economic sentiment of the manufacturing industry, services, retail trade, construction and consumers. On the other hand, the indices that also consider put options are better suited to capture the sentiment of investors and analysts, and of financial intermediaries.

4.1.2 The predictive power of asymmetry indices on sentiment indicators

Among the different methodologies adopted in the literature to construct sentiment indices (see González-Sánchez and Morales de Vega, 2021), some indices could be more responsive to incorporating changes in sentiment than others. In particular, indices based on option prices, could incorporate investors' expectation about future sentiment fluctuations. In order to further investigate the relationship between asymmetry indices and sentiment, we test whether indices based on option prices have some predictive power on sentiment indicators based on surveys by running the following model:

$$\Delta SENT_t = \alpha + \beta\,\Delta asymmetry_{t-1} + \varepsilon_t \tag{9}$$

where $\Delta SENT_t$ is the monthly change of the sentiment index at month t and is proxied alternatively by ΔESI, $\Delta SENTIX$ and ΔZEW, and $\Delta asymmetry_t$ is the monthly change in option-implied asymmetry measured alternatively by the $\Delta CALL$, ΔPUT, $\Delta SKEW$, and ΔRAX, recorded in the previous month (t-1). The output of the regression model is reported in Table 5, Panel A.

The findings presented in Panel A reveal that there is a weak association between monthly changes in option-implied asymmetry indices and future fluctuation in sentiment indicators and the sign is mixed. In particular, while changes in the *CALL* index negatively predict changes in *SENTIX*, the opposite holds for the *PUT* index. Moreover, the adjusted R-squared of the models is low, suggesting a weak explanatory power of asymmetry fluctuations on future sentiment fluctuations.

A possible explanation is related to the fact that important variables to explain future sentiment fluctuations are omitted in the model. Therefore, to provide a better understanding of the relationship between future sentiment fluctuations and changes in option-implied asymmetry, we take an additional step with respect to the model proposed in Bevilaqua and Tunaru's (2021) study. In particular, we also tested the relationship between asymmetry indices' changes and sentiment fluctuations after controlling for past sentiment changes, by running the following regression model:

$$\Delta SENT_t = \alpha + \beta_1\,\Delta asymmetry_{t-1} + \beta_2\,\Delta SENT_{t-1} + \varepsilon_t \tag{10}$$

where $\Delta SENT_t$ is the monthly change of the sentiment index at month t and is proxied alternatively by ΔESI, $\Delta SENTIX$ and ΔZEW. $\Delta SENT_{t-1}$ represents the change in the corresponding sentiment index recorded in the previous month, and $\Delta asymmetry_{t-1}$ is the change in option-implied asymmetry measured alternatively by $\Delta CALL$, ΔPUT, $\Delta SKEW$, and ΔRAX, observed in the previous month (t-1).

The results, presented in Panel B, indicate that the model's explanatory power significantly increases when past changes in sentiment are considered as a regressor. This also reduces the importance of option-implied asymmetry indices that consider put options. On the other hand, changes in the *CALL* index show a negative relationship with future sentiment fluctuations for all the sentiment indices considered in the analysis. While the relationship between changes in the *CALL* index and future changes in the *ZEW* sentiment indicator is only marginally significant, the association between changes in the *CALL* index on the one side and future changes in *ESI* and *SENTIX* on the other, is significant at the 5% and at the 1% level, respectively. The result suggests that the *CALL* index embeds significant information content to predict future sentiment fluctuations. In particular, the negative sign indicates that an increase in the *CALL* index is generally reflected in a decrease in sentiment in the following month. On the other hand, indices that also consider put options (*PUT*, *SKEW*, *RAX*) do not provide useful information to predict future fluctuation in sentiment.

Our findings differ from those presented in Bevilaqua and Tunaru (2021) research. They found a strong positive correlation between the asymmetry index obtained from call options and the future levels of the University of Michigan Consumer Sentiment index, while we find a negative relation between *CALL* index and future changes in *ESI* and *SENTIX*. Similarly to Bevilaqua and Tunaru (2021), the other asymmetry indices were not able to accurately forecast the sentiment indices. We acknowledge that the difference in models' outcomes could be also motivated by the different computation methodology of the sentiment indicator being analysed, as well as the different periods considered (our study focused on 2010-2022, while their study analysed 1996-2017). Furthermore, the distinct institutional characteristics of the markets being analysed may also have contributed to the different results.

4.2 The relationship between asymmetry indices and of financial stress

Although the *CISS* (Composite Indicator of Systemic Stress) is a crucial risk indicator, it assesses the risk that has already materialised, making it unsuitable for predictive purposes (i.e. the indicator is backward-looking for construction). For this reason, we are interested in understanding whether risk indices based on options (that are forward-looking indicators) can provide valuable insights into the evolution of the financial stress measured by the *CISS*. Moreover, since the *CISS* captures various dimensions of financial stress, it is interesting to understand whether asymmetry indices are better able to capture specific types of risk among those captured by the *CISS*, such as financial stress accumulated in the bond market, the stock market, or systemic stress related to financial intermediaries.

4.2.2 The predictive power of asymmetry indices on financial stress

We firstly investigate whether financial stress indices are associated to asymmetry indices by exploiting the following regression model:

$$\Delta CISS_t = \alpha + \beta \Delta asymmetry_t + \varepsilon_t \tag{11}$$

where $\Delta CISS_t$ is the monthly change in the financial stress index at month t and is proxied alternatively by $\Delta COMP$, $\Delta BOND$, $\Delta FINI$, and $\Delta EQUI$; $\Delta asymmetry_t$ is the monthly change in option-implied asymmetry indices measured alternatively by $\Delta CALL$, ΔPUT, $\Delta SKEW$, and ΔRAX.

The regression results reported in Table 6 show that the *PUT* and *SKEW* indices are significantly and negatively associated with the *CISS* index and its main components. In other words, as financial stress declines, the *PUT* and *SKEW* indices tend to rise. In contrast, the *RAX* and *CALL* indices do not exhibit any significant contemporaneous relationship with financial stress. This pronounced association with the *PUT* and *SKEW* indices could be attributed to investors' hedging behaviours. Specifically, when financial stress diminishes, investors may find it more advantageous to purchase relatively inexpensive out-of-the-money put options, thereby increasing the values of these indices, which are sensitive to such demand for downside protection. By comparison, the absence of a significant contemporaneous relationship between *RAX* and financial stress suggests that the *RAX* index is less affected by immediate hedging activities. Nonetheless, the *RAX* may still provide valuable information for forecasting future fluctuations in financial stress levels.

4.2.2 Contemporaneous fluctuations in asymmetry indices and financial stress

To investigate the relationship between changes in financial stress and past changes in option-implied asymmetry measures, we run the following regression model:

$$\Delta CISS_t = \alpha + \beta \Delta asymmetry_{t-1} + \varepsilon_t \qquad (12)$$

where $\Delta CISS_t$ is the monthly change in the financial stress index at month t and is proxied alternatively by change in *COMP*, *BOND*, *EQUI*, and *FINI*, which represent the Composite *CISS* indicator and three out of the five market-specific sub-indices accounting for systemic stress in bond markets, equity markets and financial intermediaries, respectively. $\Delta asymmetry_t$ is the monthly change in option-implied asymmetry measured alternatively by Δ*CALL*, Δ*PUT*, Δ*SKEW*, and Δ*RAX*, recorded in the previous month (t-1). The output of the model is reported in Table 6, Panel A.

To assess the robustness of the results to the inclusion of lagged changes in *CISS* indices during the previous month, we also estimate the following regression model, and we report the results of the β_1 coefficient for asymmetry indices in Table 6, Panel B:

$$\Delta CISS_t = \alpha + \beta_1 \Delta asymmetry_{t-1} + \beta_2 \Delta CISS_{t-1} + \varepsilon_t \tag{13}$$

where $\Delta CISS_{t-1}$ is proxied alternatively by *ΔCISS_COMP*, *ΔCISS_BOND*, *ΔCISS_EQUI*, and *ΔCISS_FINI*, recorded in the previous month.

The results of the models show that the *RAX* index is the only asymmetry index that embed significant information content to predict future fluctuations in systemic stress measured by the *CISS* indices. Past changes in the *RAX* index are statistically significant even when controlling for past changes in *CISS* indices. Moreover, the positive sign indicates that an increase in the asymmetry of the option-implied distribution (i.e. when bad volatility increases relative to good volatility) is associated with an increase in systemic risk measured by the *CISS.*

To assess the robustness of the relationship between the *RAX* index and financial stress indices, we augment our model (equation 13) with additional regressors that incorporate market returns, market volatility, and the European Economic Policy Uncertainty (*EPU*) Index, as follows:

$$\Delta CISS_t = \alpha + \beta_1 \Delta RAX_{t-1} + \beta_2 \Delta CISS_{t-1} + \beta_3 R_{t-1} + \beta_3 \Delta VOL_{t-1} + \beta_3 \Delta EPU_{t-1} + \varepsilon_t \tag{14}$$

where $\Delta CISS_t$ is the monthly change in the financial stress index at month *t* and is proxied alternatively by $\Delta COMP$, $\Delta BOND$, $\Delta FINI$, and $\Delta EQUI$. $\Delta CISS_{t-1}$ represents the financial stress index change in the previous month, ΔRAX_{t-1} is the monthly change in the *RAX* index recorded in the previous month (t-1), R_{t-1} is the market log-return over the past month, and ΔVOL_{t-1} are ΔEPU_{t-1} are the past monthly changes in option-implied volatility (computed as the denominator of equation 2) and in the *EPU* index, respectively.

The results shown in Table 8 confirm the significant role of the *RAX* index in predicting fluctuations in the composite financial stress index (*COMP*) and its individual components (*BOND*, *FINI*, *EQUI*). Additionally, the model demonstrates the strongest explanatory power for financial stress accumulated in the stock market (*EQUI*). This result is somewhat expected, since asymmetry indices, which are calculated using options on the EURO STOXX 50 Index, may incorporate valuable information regarding perceived risk in the equity market. Additionally, the monthly changes in the *RAX* index can also predict monthly changes in financial stress dimensions related to the bond market and financial intermediaries. Therefore, we believe that the *RAX* index can be a valuable tool to support regulators and investors in their policy and investment choices. It may also serve as an early-warning indicator for systemic stress situations, particularly concerning the equity market. Regarding the included control variables, market returns also significantly contribute to the predictive power of the model. This suggests that financial stress is generally preceded by negative stock market performance over the previous month. In contrast, past changes volatility (*VOL*) and Economic Policy Uncertainty (*EPU*) indices do not appear to have a significant predictive impact.

To further enhance the robustness of our analysis, we estimated the model with the inclusion of monthly and annual dummy variables (results available upon request) to account for unobserved seasonal patterns, periodic macroeconomic cycles, and other time-specific shocks that could affect the results. After incorporating these time dummies, our main findings remain largely consistent; however, we did observe a slight decline in the adjusted R-squared value due to the addition of numerous dummy variables.

5. Discussion of the results

The results presented in Sections 4.1–4.2 reveals that asymmetry indices play a significant role in explaining both current and future shifts in economic sentiment and financial stress. Notably, monthly changes in the *CALL* index, which is sensitive to call option prices, are negatively correlated with sentiment indicators. This suggests that a positive change in the asymmetry of the option-implied distribution (out-of-the-money calls become more expensive that at-the-money ones, and hence a decrease of the *CALL* index), is associated with an increase of sentiment indicators. This result is consistent with investors' inclination to anticipate potential sentiment changes by purchasing call options to capitalise on a potential market upturn associated with improved sentiment. Conversely, it is more challenging to understand the negative contemporaneous relationship observed between certain asymmetry indices (*SKEW*, *PUT*) and fluctuations in both sentiment and financial stress indicators.

A possible explanation for this result is that investors may be inclined to pay for hedging their gains in an environment of rising sentiment and declining financial stress. Specifically, institutional investors might find it advantageous to purchase cheaper out-of-the-money put options to protect their portfolios. This behaviour would shift the risk-neutral distribution to the left, thereby increasing the asymmetry indices. This phenomenon can also be linked to the "bubble theory", which suggests that high past returns may indicate that a bubble is inflating, and a large drop can be expected when the bubble bursts. Harvey and Siddique (2000) found that when past returns were high in the US market, the investors' forecast of skewness became more negative (more skewed towards the left). Similarly, Xiong et al. (2016) found that high-priced stock markets are characterised by highly negative risk-neutral skewness, while stocks that have already fallen in price tend to be more positively skewed. Similarly, Elyasiani et al. (2021) found in the Italian market that asymmetry indices tend to be positively associated with returns and are on average higher during periods of market optimism. Similarly, the apparent lack of predictive power for future sentiment and financial stress fluctuations by *PUT* and

SKEW indices might be due to the fact that these indices are significantly influenced by investor hedging activities. The focus on the left-tail risk embedded in put option pricing, that characterised these indices, might obscure broader sentiment-related information.

Conversely, the *RAX* index, by effectively integrating information from both the right (call options) and left (put options) tails of the distribution – as evidenced by its significant correlation with both *CALL* and *PUT* indices – appears better positioned to capture predictive signals related to changes in financial stress.

6. Conclusion

The Eurozone market lacks established measures for capturing option-implied asymmetry (Elyasiani et al., 2021), leaving a gap in our understanding of how these measures relate to sentiment and financial stress.

To address this gap, we introduced four novel asymmetry indices derived from option prices. First, we obtained a skewness index based on the CBOE procedure as a benchmark to measure risk-neutral skewness. Second, we followed the approach of Bevilacqua and Tunaru (2021) to decompose the *SKEW* index into its positive and negative components by considering call and put prices, respectively. This allowed us to obtain two indices, *CALL* and *PUT*, that account for asymmetry in specific parts of the option-implied distribution. Finally, we included the Risk-Asymmetry Index (*RAX*) developed by Elyasiani et al. (2018), which has proven to be a useful measure of risk in the Italian stock market.

Our analysis of the contemporaneous relationships between asymmetry indices and sentiment/financial stress measures generally indicates that option-implied asymmetry tends to increase alongside rising market sentiment and declining financial stress. A plausible explanation is that investors are more likely to hedge their portfolios with put options during periods of positive market sentiment and low stress. The reduced relative cost of these options in such conditions encourages their use as protective instruments, thus contributing to the observed increase in market asymmetry.

Our findings also underscore the importance of disentangling the information contained in the two tails of the option-implied distribution, based calls and puts, respectively, to obtain information about future sentiment fluctuations. In particular, the asymmetry index obtained from the right tail of the risk-neutral distribution (exploiting call option prices) embeds useful information to forecast the change of sentiment in the following month. The *CALL* index has the highest forecasting power among the option-implied asymmetry indices, suggesting that investors anticipate potential sentiment changes by purchasing call options to capitalise on a potential market upturn associated with improved sentiment.

However, unlike the findings of Bevilacqua and Tunaru (2021) for the U.S. market, relying solely on left-tail information (put options) is not sufficient to predict financial stress in the European market. Instead, a more comprehensive measure, such as the *RAX* index, is necessary. Among the asymmetry indices studied, only *RAX* offers significant predictive power for future fluctuations in financial stress measured by the *CISS* index. Specifically, we find that an increase in option-implied asymmetry, as measured by *RAX*, is associated with an increase in *CISS*-measured financial stress in the subsequent period. Furthermore, the predictive power of *RAX* is particularly strong when analysing the relationship with the equity component of the *CISS*, suggesting its relevance as a leading indicator of stock market stress. Thus, the *RAX* index may be a valuable resource for both regulators and investors in their decision-making, serving as a potential early warning indicator for systemic stress, especially in the equity market. These results also suggest a deeper need to investigate cross-market differences when analysing option-implied measures.

While our results challenge the direct applicability of Bevilacqua and Tunaru's (2021) findings to the Eurozone market, we identify two compelling parallels. First, indices based on call options appear to be more suitable for capturing investor sentiment fluctuations. Second, indices that include also information from put options, particularly the *RAX*, seem better suited as early warning signals for risk or financial stress. Given that accurate measurement and prediction of investor sentiment and financial stress are paramount for managers, policymakers, and investors, our results hold significant value for a broad range of stakeholders. Managers can utilize this understanding to better grasp market dynamics and to make better strategic investment decisions. Policymakers can leverage these analyses to anticipate market trends and adapt regulatory frameworks to promote stability and growth. For investors, a reliable assessment of sentiment and financial stress is crucial for risk management and portfolio optimization, empowering them to make well-informed decisions in dynamic markets.

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Appendix A. The Bakshi et al. (2003) model-free skewness formula, the SKEW index and its decomposition

In this section we provide further details about the model-free formula proposed in Bakshi et al. (2003) in order to compute the *SKEW* index and its components based on call and put options. According to Bakshi et al. (2003) model-free skewness is obtained from the following equation as:

$$SK(\mathrm{t},\tau) \equiv \frac{E_t^q\left\{\left(R(\mathrm{t},\ \tau)-E_t^q\left[R(\mathrm{t},\ \tau)\right]\right)^3\right\}}{\left\{\left(E_t^q(R(\mathrm{t},\ \tau)-E_t^q\left[R(\mathrm{t},\ \tau)\right]\right)^2\right\}^{3/2}} = \frac{e^{r\tau}W(\mathrm{t},\tau)-3e^{r\tau}\mu(\mathrm{t},\tau)V(\mathrm{t},\tau)+2\mu(\mathrm{t},\tau)^3}{\left[e^{r\tau}V(\mathrm{t},\tau)-\mu(\mathrm{t},\tau)^2\right]^{3/2}} \quad \text{(A1)}$$

where $\mu(\mathrm{t},\tau)$, $V(\mathrm{t},\tau)$, $W(\mathrm{t},\tau)$ and $X(t,\tau)$ are the prices of the contracts, at time t with maturity τ, based on first, second, third and fourth moment of the distribution, respectively; their values are can be obtained from a cross-section of call and put option prices as:

$$\mu(t,\tau) \equiv E^q \ln\left[S(t+\tau)/S(t)\right] = e^{r\tau}-1-\frac{e^{r\tau}}{2}V(t,\tau)-\frac{e^{r\tau}}{6}W(t,\tau)-\frac{e^{r\tau}}{24}X(t,\tau) \quad \text{(A2)}$$

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2\left(1-\ln\left[K/S(t)\right]\right)}{K^2}C(t,\tau;K)dK + \int_0^{S(t)} \frac{2(1+ln\left[S(t)/K\right]}{K^2}P(t,\tau;K)dK \quad \text{(A3)}$$

$$\begin{aligned} W(t,\tau) = &\int_{S(t)}^{\infty} \frac{6\ln\left[K/S(t)\right]-3\left(\ln\left[K/S(t)\right]\right)^2}{K^2}C(t,\tau;K)dK \\ &-\int_0^{S(t)} \frac{6\ln[S(t)/K]+3\left(\ln\left[S(t)/K\right]\right)^2}{K^2}P(t,\tau;K)dK \end{aligned} \quad \text{(A4)}$$

$$\begin{aligned} X(t,\tau) = &\int_{S(t)}^{\infty} \frac{12\left(\ln\left[K/S(t)\right]\right)^2-4\left(\ln\left[K/S(t)\right]\right)^3}{K^2}C(t,\tau;K)dK + \\ &\int_0^{S(t)} \frac{12\left(\ln\left[S(t)/K\right]\right)^2+4\left(\ln\left[S(t)/K\right]\right)^3}{K^2}P(t,\tau;K)dK \end{aligned} \quad \text{(A5)}$$

where $C(t,\tau;K)$ and $P(t,\tau;K)$ are the prices of a call and a put option at time t with maturity τ and strike K, respectively, $S(t)$ is the underlying asset price at time t.

To obtain the daily estimate of the *SKEW* index based on the CBOE (2010) methodology, SK is computed starting from a portfolio of options with payoff reflecting the skewness payoff:

$$SK = \frac{\mathrm{E}[R^3] - 3\mathrm{E}[R]\mathrm{E}[R^2] + 2\mathrm{E}[R]^3}{([R^2] - \mathrm{E}^2[R])^{3/2}} \tag{A6}$$

For simplicity, *SK* can be written as $SK = \frac{P_3 - 3P_1P_2 + 2P_1^3}{(P_2 - P_1^2)^{3/2}}$, where P_1, P_2, and P_3, can be obtained as follows (CBOE, 2010):

$$P_1 = \mu = \mathrm{E}\,[R_\tau] = e^{r\tau}\left(-\sum_i \frac{1}{K_i^2} Q_{K_i}\,\Delta_{K_i}\right) + \varepsilon_1 \tag{A7}$$

$$P_2 = \mu = \mathrm{E}[\![R_\tau^2] = e^{r\tau}\left(\sum_i \frac{2}{K_i^2}\left(1 - \ln\left(\frac{K_i}{F_0}\right)\right) Q_{K_i}\,\Delta_{K_i}\right) + \varepsilon_2 \tag{A8}$$

$$P_3 = \mu = \mathrm{E}[\![R_\tau^3] = e^{r\tau}\left(\sum_i \frac{3}{K_i^2}\left\{2\ln\left(\frac{K_i}{F_0}\right) - \ln^2\left(\frac{K_i}{F_0}\right)\right\} Q_{K_i}\,\Delta_{K_i}\right) + \varepsilon_3 \tag{A9}$$

where F_0 denotes the forward price of the underlying index calculated from the put-call parity as $F_0 = e^{r\tau}\left[c(K,\tau) - p(K,\tau)\right] + K$, K_0 is the reference price, the first exercise price less or equal to the forward level $F_0(K \le F_0)$, K_i is the strike price of i-th out-of-the-money options used in the calculation, *r* is the risk-free rate with expiration τ, Δ_{K_i} is the sum divided by two of the two nearest prices to the exercise price *K*, Q_{K_i} is a generic price of a European call (resp. put) option with strike price above (resp. below) K_0. Finally, ε_1, ε_2, and ε_3 represent the adjustments for the difference between K_0 and F_0 and can be obtained as:

$$\varepsilon_1 = -\left(1 + \ln\left(\frac{F_0}{K_0}\right) - \frac{F_0}{K_0}\right) \tag{A10}$$

$$\varepsilon_2 = 2\ln\left(\frac{K_0}{F_0}\right)\left(\frac{F_0}{K_0} - 1\right) + \frac{1}{2}\ln^2\left(\frac{K_0}{F_0}\right) \tag{A11}$$

$$\varepsilon_3 = 3\ln^2\left(\frac{K_0}{F_0}\right)\left(\frac{1}{3}\ln\left(\frac{K_0}{F_0}\right) - 1 + \left(\frac{F_0}{K_0}\right)\right) \tag{A12}$$

Appendix B. Alternative measures of risk: the RAX index

Given the importance of disentangling positive and negative shocks to volatility, which are seen by investors, as good or bad news respectively, the information on upside and downside corridor implied volatilities is exploited in Elyasiani et al. (2018) in order to measure the asymmetry of the return distribution. Upside and downside corridor implied volatilities are aggregated into the risk-asymmetry index (*RAX*), which measures the difference between upside and downside corridor implied volatilities standardised by total volatility. The *RAX* index is meant to measure the investors' pricing asymmetry towards upside gains and downside losses.

Corridor implied volatility can be computed as the square root of corridor implied variance (*CIV*), that is obtained from model-free implied variance, due to Britten-Jones and Neuberger (2000) by truncating the integration domain between two barriers (see Carr and Madan, 1998; Andersen and Bondarenko, 2007):

$$\hat{E}\left[CIV\left(t,\tau\right)\right]=\hat{E}\left[\frac{1}{T}\int_{t}^{T}\sigma^{2}\left(t,\ldots\right)I_{t}\left(B_{1}B_{2}\right)dt\right] \quad \text{(B1)}$$

where $I_t\left(\ldots\right)$ is an indicator function that accumulates variance only if the underlying asset lies between the two barriers (B_1 and B_2). According to Demeterfi et al. (1999) and Britten-Jones and Neuberger (2000), it is possible to compute the expected value of corridor implied variance (CIV), under the risk-neutral probability measure, by using a portfolio of options with strikes ranging from B_1 to B_2, as:

$$\hat{E}\left[CIV\left(t,\tau\right)\right]=\frac{2e^{r\tau}}{\tau}\int_{B_1}^{B_2}\frac{M\left(K,\tau\right)}{K^{2}}dK \quad \text{(B2)}$$

where $M\left(K,\tau\right)$ is the minimum between a call or put option price with strike price K and maturity τ, r is the risk-free rate, and B_1 and B_2 are the barrier levels within which the variance is accumulated. Downside corridor implied variance is obtained by setting

B_1 equal to zero and B_2 equal to the forward price, F_t, on the other hand, upside corridor implied variance is computed by setting B_1 equal to the forward price, F_t, and B_2 equal to infinity (∞). Downside (σ_{DW}) and upside (σ_{UP}) corridor implied volatility are the square root of downside and upside corridor implied variance, respectively:

$$\sigma_{DW}(t,\tau)=\sqrt{\frac{2e^{r\tau}}{\tau}\int_{t}^{F_t}\frac{M(K,\tau)}{K^2}dK} \tag{B3}$$

$$\sigma_{UP}(t,\tau)=\sqrt{\frac{2e^{r\tau}}{\tau}\int_{F_t}^{\infty}\frac{M(K,\tau)}{K^2}dK} \tag{B4}$$

and $F_t = K^* e^{r\tau} * difference$, where K^* is the reference strike price (i.e. the strike at which the $difference$ in absolute value between the at-the money call and put prices is the smallest).

Following Elyasiani et al. (2018), we aggregate upside and downside corridor implied volatilities into the risk-asymmetry index (*RAX*), which measures the difference between upside and downside corridor implied volatilities standardised by total volatility. The numerator is standardised by total volatility so that the *RAX* index is not influenced by the level of volatility in bullish or bearish market periods:

$$RAX(t,\tau)=\frac{\sigma_{UP}(t,\tau)-\sigma_{DW}(t,\tau)}{\sigma_{TOT}(t,\tau)} \tag{B5}$$

where $\sigma_{TOT}(t,\tau)$ is the sum of the upside and downside corridor implied volatilities and coincides with model-free implied volatility.

Table 1. Descriptive statistics for the option series used in the asymmetry indices calculation

	First option series	Second option series
Min. maturity	8 days	35 days
Max. maturity	43 days	71 days
Avg. maturity	22.4 days	52.6 days
Min. num. of options	8	20
Max. num. of options	97	121
Avg. num. of options	34.6	52.4
Min. num. of interpolated-extrapolated strikes	2129.0	2129.0
Max. num. of interpolated-extrapolated strikes	4693.0	4690.0
Avg. num. of interpolated-extrapolated strikes	3406.5	3402.5

Note: the table presents descriptive statistics for maturities, the number of options, and the number of strike prices derived from the interpolation-extrapolation procedure. The statistics summarize the average, minimum, and maximum values for each metric across the first and second option series used to obtain the 30-day measures of asymmetry.

Table 2. Descriptive statistics for the option-implied asymmetry indices, sentiment indicators, and financial stress measures.

	CALL	*PUT*	*SKEW*	*RAX*	*ESI*	*SENTIX*	*ZEW*	*COMP*	*BOND*	*EQUI*	*FINI*
Panel A: indices in terms of levels											
Mean	79.42	138.52	118.65	102.58	100.68	101.81	117.40	16.67	5.37	4.03	11.46
Median	79.45	137.52	117.33	102.49	102.05	105.30	122.10	11.89	5.06	3.64	10.35
Minimum	77.19	128.95	110.88	101.62	59.70	57.13	39.30	3.09	1.75	0.47	3.66
Maximum	81.46	163.53	142.29	104.40	118.70	133.97	184.00	57.99	11.81	11.38	23.53
Std. dev.	0.88	6.25	6.13	0.56	9.19	17.03	33.88	12.81	2.33	2.18	4.81
Skewness	0.00	1.24	1.55	0.96	-0.93	-0.36	-0.37	1.15	0.82	0.55	0.53
Kurtosis	2.58	4.91	5.76	3.71	5.82	2.49	2.51	3.40	3.12	2.79	2.39
Jarque-Bera	1.12	63.75	122.03	27.09	74.11	5.12	6.18	35.42	17.57	8.12	9.81
	(0.57)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.08)	(0.00)	(0.00)	(0.02)	(0.01)
ADF test	-7.11	-5.00	-2.82	-2.83	-3.49	-3.18	-2.84	-2.45	-2.90	-3.37	-2.70
	(0.00)	(0.00)	(0.06)	(0.06)	(0.01)	(0.02)	(0.05)	(0.13)	(0.05)	(0.01)	(0.079
Panel B: indices in terms of monthly changes											
Mean	0.00	0.02	0.02	0.00	0.02	-0.11	-0.45	0.04	0.04	-0.01	0.01
Median	-0.08	-0.16	0.01	0.00	0.10	0.62	0.80	-0.52	-0.06	-0.23	-0.45
Minimum	-2.262	-14.20	-9.23	-0.78	-34.10	-25.72	-87.30	-9.53	-2.16	-6.74	-4.77
Maximum	2.87	17.95	9.53	0.99	11.10	17.07	74.70	20.35	5.75	8.10	9.96
Std. dev.	0.87	4.72	3.51	0.31	3.57	6.39	15.51	4.47	1.13	2.52	2.03
Skewness	0.34	-0.09	-0.07	0.21	-5.57	-0.95	-0.80	1.30	1.33	0.50	1.21
Kurtosis	3.58	4.29	3.06	2.97	56.25	5.78	12.38	6.78	7.02	3.73	6.35
Jarque-Bera	5.21	10.89	0.17	1.12	19116.53	73.23	585.12	135.66	149.87	10.03	105.88
	(0.07)	(0.00)	(0.92)	(0.57)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
ADF test	-10.88	-16.23	-16.72	-16.41	-8.97	-9.23	-12.51	-10.90	13.21	-14.84	14.54
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: The table shows the descriptive statistics of the monthly indices adopted in our study. *SKEW* is the index we compute using the CBOE method, *CALL* and *PUT* are obtained by applying the *CBOE SKEW* formula only to call and put option prices, respectively (see Appendix A for a detailed description). *RAX* is the risk-asymmetry index based on Elyasiani et al. (2018) (see Appendix B). The *ESI* is obtained from surveys addressed to representatives of the manufacturing industry, services, retail trade, construction, and consumers of the Euro area economies. *SENTIX* is the European Sentix Investor Confidence, based on information processed through a monthly survey conducted with around 5,500 investors and analysts. *ZEW* is the Eurozone *ZEW* Economic Sentiment, a monthly index based on the *ZEW* Financial Market Test, where 300 experts from banks, insurance companies, and financial departments of selected companies are interviewed every month about their assessments and forecasts on important international financial market data over the next six months. In order to enhance the comparison with the *ESI* and the asymmetry indices (characterised by a baseline level of 100), we have added 100 to both the *SENTIX* and the *ZEW*. *COMP*, *BOND*, *EQUI*, and *FINI* are the Composite Indicator of Systemic Stress and three out of the five market-specific sub-indices accounting for systemic stress in bond markets, equity markets and financial intermediaries, respectively. Their value is multiplied by 100 in order to enhance the comparison with the other indices. In the last two rows we reported the test statistics and the related p-values for the augmented Dickey–Fuller test (ADF), for the null hypothesis that a unit root is present in a time series sample.

Table 3. Correlation matrix

	CALL	*PUT*	*SKEW*	*RAX*	*ESI*	*SENTIX*	*ZEW*	*COMP*	*BOND*	*EQUI*	*FINI*
Panel A: indices in terms of levels											
CALL	1.000										
PUT	0.117	1.000									
SKEW	0.200	0.905	1.000								
RAX	0.410	0.702	0.921	1.000							
ESI	0.213	0.337	0.400	0.392	1.000						
SENTIX	0.200	0.329	0.313	0.264	0.797	1.000					
ZEW	0.133	0.373	0.299	0.205	0.051	0.507	1.000				
COMP	-0.215	-0.410	-0.389	-0.323	-0.485	-0.650	-0.565	1.000			
BOND	-0.075	-0.468	-0.334	-0.170	-0.225	-0.529	-0.712	0.789	1.000		
EQUI	-0.039	-0.478	-0.369	-0.204	-0.397	-0.585	-0.530	0.832	0.816	1.000	
FINI	-0.117	-0.457	-0.419	-0.314	-0.498	-0.652	-0.551	0.922	0.787	0.858	1.000
Panel B: indices in terms of monthly changes											
CALL	1.000										
PUT	0.005	1.000									
SKEW	0.031	0.827	1.000								
RAX	0.365	0.399	0.795	1.000							
ESI	0.161	-0.002	0.003	0.056	1.000						
SENTIX	0.183	0.235	0.246	0.219	0.659	1.000					
ZEW	0.069	0.272	0.252	0.174	-0.001	0.519	1.000				
COMP	-0.056	-0.370	-0.293	-0.124	-0.259	-0.518	-0.503	1.000			
BOND	-0.034	-0.405	-0.296	-0.089	-0.161	-0.404	-0.458	0.810	1.000		
EQUI	0.072	-0.382	-0.306	-0.091	-0.093	-0.374	-0.436	0.782	0.768	1.000	
FINI	0.066	-0.440	-0.374	-0.152	-0.140	-0.423	-0.480	0.851	0.838	0.795	1.000

Note: the table reports the correlation between the monthly series of the indices. For a definition of the measures, see Table 2.

Table 4. Regression output for linear regression model in equation (8)

	ESI		*SENTIX*		*ZEW*	
CALL	0.659^{**} (2.057)	1.96%	1.336^{**} (2.574)	2.70%	1.222 (1.002)	0.00%
PUT	-0.002 (-0.036)	0.00%	0.319^{**} (3.181)	4.91%	0.893^{**} (2.352)	6.78%
SKEW	0.003 (0.046)	0.00%	0.449^{***} (3.542)	5.45%	1.115^{**} (2.521)	5.75%
RAX	0.639 (1.475)	0.00%	4.507^{***} (3.185)	4.18%	8.672^{***} (2.720)	2.39%

Note: the table presents the estimated output of the following regressions:

$$\Delta SENT_t = \alpha + \beta \Delta asymmetry_t + \varepsilon_t \tag{8}$$

where $\Delta SENT_t$ is the monthly change of the sentiment index and is proxied alternatively by ΔESI, $\Delta SENTIX$ and ΔZEW, and $\Delta asymmetry_t$ is the change in option-implied asymmetry measured alternatively by the $\Delta CALL$, ΔPUT, $\Delta SKEW$, and ΔRAX. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). For the definition of the measures see Table 2. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 5. Regression output for linear regression model in equations (9-10)

	ESI		*SENTIX*		*ZEW*	
Panel A: regression output for model in equation (9)						
CALL	-0.172 (-1.240)	0.00%	-0.849^{**} (-2.151)	0.68%	-1.403 (-1.637)	0.00%
PUT	0.169 (1.571)	4.35%	0.278^{**} (2.158)	3.60%	0.532^{*} (1.659)	1.98%
SKEW	0.199^{*} (1.768)	3.16%	0.300^{*} (1.749)	2.07%	0.473 (1.128)	0.49%
RAX	0.548 (1.330)	0.00%	-0.005 (-0.003)	0.00%	-1.301 (-0.381)	0.00%
Panel B: regression output for model in equation (10)						
CALL	-0.374^{**} (-2.283)	8.41%	-1.228^{***} (-2.694)	9.02%	-1.490^{*} (-1.717)	1.27%
PUT	0.170 (1.475)	12.69%	0.203 (1.634)	8.44%	0.501^{*} (1.691)	1.44%
SKEW	0.199 (1.635)	11.44%	0.191 (1.139)	7.32%	0.415 (1.042)	0.10%
RAX	0.369 (0.948)	7.70%	-1.253 (-0.841)	6.64%	-1.998 (-0.611)	0.00%

Note: the table presents the results for the β_1 coefficient of the following regressions:

Panel A Model: $\Delta SENT_t = \alpha + \beta_1 \Delta asymmetry_{t-1}$ (9)

Panel B Model: $\Delta SENT_t = \alpha + \beta_1 \Delta asymmetry_{t-1} + \beta_2 \Delta SENT_{t-1} + \varepsilon_t$ (10)

where $\Delta SENT_t$ is the monthly change in the sentiment index at month *t* and is proxied alternatively by ΔESI, $\Delta SENTIX$ and ΔZEW. $\Delta SENT_{t-1}$ represents the sentiment index change in the previous month, and $\Delta asymmetry_{t-1}$ is the monthly change in option-implied asymmetry measured alternatively by the $\Delta CALL$, ΔPUT, $\Delta SKEW$, and ΔRAX indices, recorded in the previous month (t-1). All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). For the definition of the measures see Table 2. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 6. Regression output for linear regression model in equations (11)

	COMP		*BOND*		*EQUI*		*FINI*	
CALL	0.041 (0.102)	0.00%	-0.043 (-0.438)	0.00%	0.209 (0.824)	0.00%	0.154 (0.975)	0.00%
PUT	-0.351*** (-3.642)	13.12%	-0.097*** (-3.690)	15.86%	-0.204*** (-3.929)	14.01%	-0.190*** (-4.002)	18.96%
SKEW	-0.374*** (-3.931)	8.01%	-0.095*** (-3.193)	8.15%	-0.220*** (-3.931)	8.79%	-0.217*** (-4.411)	13.44%
RAX	-1.779 (-1.443)	0.88%	-0.323 (-0.949)	0.14%	-0.739 (-1.046)	0.19%	-0.994* (-1.742)	1.67%

Note: the table presents the estimated output of the following regression model:

$$\Delta CISS_t = \alpha + \beta\, \Delta asymmetry_t + \varepsilon_t \qquad (11)$$

where $\Delta CISS_t$ is the monthly change in the financial stress index at month *t* and is proxied alternatively by $\Delta COMP$, $\Delta BOND$, $\Delta FINI$, and $\Delta EQUI$; $\Delta asymmetry_t$ is the monthly change in option-implied asymmetry measured alternatively by $\Delta CALL$, ΔPUT, $\Delta SKEW$, and ΔRAX. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). For the definition of the measures see Table 2. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 7. Regression output for linear regression model in equations (12-13)

	COMP		*BOND*		*EQUI*		*FINI*	
Panel A: regression output for model in equation (11)								
CALL	0.631		0.172		0.233		0.334	
	(1.342)	0.85%	(1.354)	1.09%	(1.021)	0.35%	(1.106)	0.68%
PUT	-0.016		0.007		0.022		0.034	
	(-0.211)	0.00%	(0.306)	0.00%	(0.513)	0.00%	(0.646)	0.00%
SKEW	0.102		0.043		0.085*		0.132***	
	(1.218)	0.00%	(1.604)	1.13%	(1.865)	1.51%	(2.620)	2.74%
RAX	2.943***		0.899***		1.494***		2.379**	
	(2.910)	3.53%	(3.461)	5.47%	(3.095)	4.61%	(3.677)	8.00%
Panel B: regression output for model in equation (12)								
CALL	0.660		0.169		0.262		0.376	
	(1.356)	1.73%	(1.370)	0.86%	(1.206)	2.56%	(1.363)	3.75%
PUT	0.029		0.000		-0.011		-0.004	
	(0.342)	0.15%	(0.009)	0.00%	(-0.252)	1.34%	(-0.078)	2.05%
SKEW	0.159*		0.040		0.058		0.101*	
	(1.708)	1.51%	(1.431)	0.58%	(1.187)	2.18%	(1.911)	3.88%
RAX	3.184***		0.884***		1.368***		2.265**	
	(3.135)	4.94%	(3.379)	5.07%	(2.775)	5.64%	(3.522)	9.89%

Note: the table presents the results for the β_1 coefficient of the following regressions:

Panel A Model: $$\Delta CISS_t = \alpha + \beta_1 \Delta asymmetry_{t-1} \tag{12}$$

Panel B Model: $$\Delta CISS_t = \alpha + \beta_1 \Delta asymmetry_{t-1} + \beta_2 \Delta CISS_{t-1} + \varepsilon_t \tag{13}$$

where $\Delta CISS_t$ is the monthly change in the financial stress index at month t and is proxied alternatively by $\Delta COMP$, $\Delta BOND$, $\Delta FINI$, and $\Delta EQUI$. $\Delta CISS_{t-1}$ represents the financial stress index change in the previous month, and $\Delta asymmetry_t$ is the monthly change in option-implied asymmetry measured alternatively by $\Delta CALL$, ΔPUT, $\Delta SKEW$, and ΔRAX, recorded in the previous month (t-1). All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). For the definition of the measures see Table 2. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Table 8. Regression output for linear regression model in equations (14)

	COMP	*BOND*	*EQUI*	*FINI*
α	0.079	0.058	0.009	0.004
	(0.246)	(0.759)	(0.059)	(0.032)
RAX_{t-1}	2.997***	0.807***	2.124***	1.321***
	(2.860)	(3.058)	(3.389)	(2.681)
$COMP_{t-1}$	0.029	-0.195**	-0.316***	-0.226***
	(0.235)	(-2.249)	(-3.046)	(-2.818)
R_{t-1}	-29.764***	-7.959***	-17.374***	-14.792***
	(-3.156)	(-3.022)	(-3.742)	(-3.433)
VOL_{t-1}	0.122	0.051*	0.093	0.040
	(1.090)	(1.911)	(1.301)	(0.842)
EPU_{t-1}	0.009	0.002	0.006	0.005
	(0.801)	(0.822)	(1.161)	(1.099)
Adj. R^2	16.06%	20.62%	23.70%	18.84%

Note: the table presents the results for the β_1 coefficient of the following regression:

Model: $$\Delta CISS_t = \alpha + \beta_1 \Delta RAX_{t-1} + \beta_2 \Delta CISS_{t-1} + \beta_3 R_{t-1} + \beta_3 \Delta VOL_{t-1} + \beta_3 \Delta EPU_{t-1} + \varepsilon_t \quad (14)$$

where $\Delta CISS_t$ is the monthly change in the financial stress index at month t and is proxied alternatively by $\Delta COMP$, $\Delta BOND$, $\Delta FINI$, and $\Delta EQUI$. $\Delta CISS_{t-1}$ represents the financial stress index change in the previous month, ΔRAX_{t-1} is the monthly change in the *RAX* index recorded in the previous month (t-1), R_{t-1} is the market log-return over the past month, and ΔVOL_{t-1} are ΔEPU_{t-1} are the past monthly changes in option-implied volatility (obtained as in equation 2) and in the *EPU* index, respectively. All the regressions are run by using the Ordinary Least Squares (OLS), with the Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix (t-stats in parentheses). For the definition of the measures see Table 2. Significance at the 1% level is denoted by ***, at the 5% level by **, and at the 10% level by *.

Figure 1. Overview of the asymmetry indices during the sample period

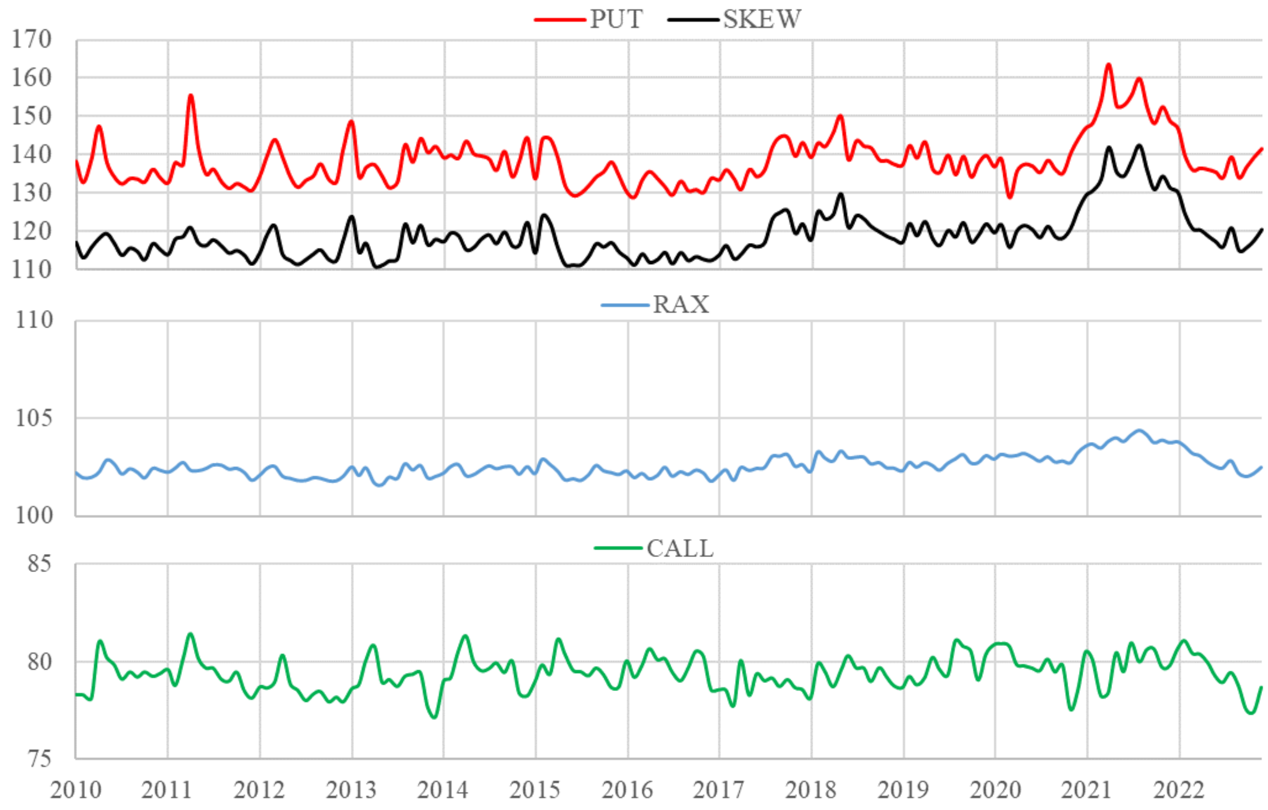

Figure 2. Overview of the sentiment indices during the sample period

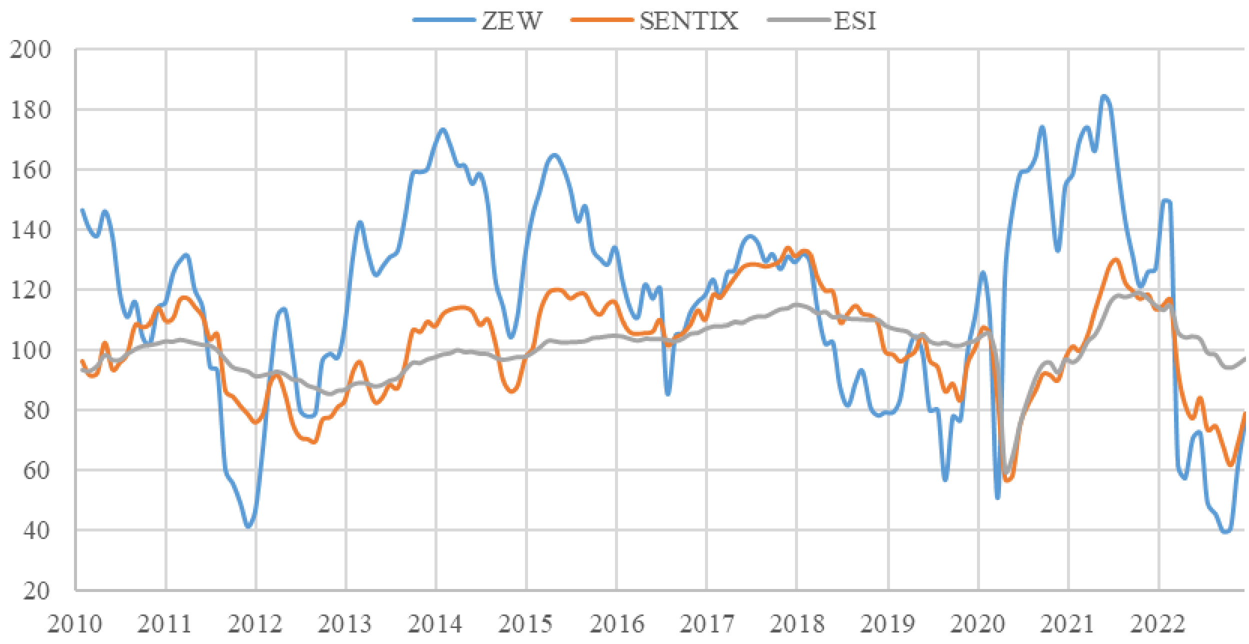

Figure 3. Overview of the financial stress indices during the sample period