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The impact of investor sentiment on the STOXX Europe 600 Banks Index between 2022 and April 2023

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Católica Porto Business School
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To those who are no longer with us, to those who've been here from the start, to those I've lost, and to those I've gained.

To my grandparents, I carry you with me every step of the way.

To my parents, for your unconditional love and support—thank you for letting me fly even when all you wanted was to keep me close. Your sacrifices and hard work have never gone unnoticed.
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To my father, for never letting me give up.

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Abstract

This study explores the impact of investor sentiment on the stock returns of banks in the STOXX Europe 600 Banks Index during the Russia-Ukraine war from January 1, 2022 to April 20, 2023. Investor sentiment is measured using RUWESsent, a conflict-specific index, capturing war-related sentiment. Employing a random effects panel data model, the analysis finds that overall investor sentiment had a statistically significant but modest negative effect on bank returns. When sentiment is disaggregated, war- and sanction-related sentiment exhibited positive effects, potentially reflecting investor confidence in institutional responses. In contrast, media-driven sentiment had a negative influence, amplifying the role of public attention during crises. Country-level analysis revealed heterogeneity in sentiment effects, with weaker sentiment responses in less speculative markets. These findings support behavioral finance perspectives on the influence of sentiment during crises, emphasizing the conditional nature of its impact depending on the source of sentiment and market context.

Keywords: investor sentiment, RUWESsent, STOXX Europe 600 Banks Index, Russia-Ukraine war, banks returns, behavioral finance .

Resumo

Este estudo explora o impacto do sentimento dos investidores nos retornos das ações dos bancos que compõem o índice STOXX Europe 600 Banks durante a guerra entre a Rússia e a Ucrânia, no período de 1 de janeiro de 2022 a 20 de abril de 2023. O sentimento dos investidores é medido através do RUWESsent, um índice específico para conflitos, que capta o sentimento relacionado à guerra. Utilizando um modelo de dados em painel com efeitos aleatórios, a análise revela que o sentimento geral dos investidores teve um efeito negativo estatisticamente significativo, porém modesto, sobre os retornos dos bancos. Quando desagregado, o sentimento relacionado à guerra e às sanções apresentou efeitos positivos, possivelmente refletindo a confiança dos investidores nas respostas institucionais. Em contraste, o sentimento impulsionado pela media teve uma influência negativa, ressaltando o papel da atenção pública durante crises. A análise ao nível dos países revelou heterogeneidade nos efeitos do sentimento, com respostas mais fracas em mercados menos especulativos. Esses resultados apoiam as perspetivas da finança comportamental sobre a influência do sentimento em períodos de crise, enfatizando a natureza condicional do seu impacto, dependendo da fonte do sentimento e do contexto de mercado.

Palavras-chave: sentimento dos investidores, RUWESsent, índice STOXX Europe 600 Banks, guerra Rússia-Ucrânia, retornos bancários, finanças comportamentais.

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Chapter 1

Introduction

1. General Framework

Samuelson (1965) argued that anticipated prices fluctuate randomly, aligning with the view that price changes follow a random walk, reflecting the unpredictability of new information. This underpins the Efficient Market Hypothesis (EMH), which assumes that stock prices fully incorporate all available information at any point in time (Fama, 1970). Osborne (1959) similarly supported the random walk hypothesis but acknowledged that both behavioral and structural factors could lead to deviations from perfect efficiency. Building on this, Kahneman and Tversky (1979) challenged the assumption of investor rationality, highlighting the influence of psychological biases on decision-making. Behavioral finance emerged in response, recognizing that investors are not always rational and are instead influenced by systematic cognitive and emotional biases.

Investor sentiment became a key concept within behavioral finance as researchers sought to understand how investors' attitudes and emotions could influence asset prices, contradicting the EMH's premise of rational markets. This perspective holds that financial markets are shaped not only by fundamentals but also by psychological factors, which can lead to temporary mispricings (Brown and Cliff, 2004; Baker and Wurgler, 2006). Sentiment captures the collective mood or outlook of market participants, affecting how information is interpreted and how decisions are made. In recent years, alternative sentiment measures have gained traction, including those based on social media (Lachana and Schröder, 2023; Vamossy, 2024), Google search trends (Hamadou et al., 2024; Zhu et al., 2023), and machine learning-driven textual analysis (Obaid and Pukthuanthong, 2022). Growing evidence also highlights the sensitivity of investor sentiment to geopolitical risk, particularly during wars. He (2023) shows that such crises trigger sharp declines in sentiment and market reactions, while Klein (2024) highlights that investors react instantaneously to increases in geopolitical risk.

The STOXX Europe 600 Banks Index, which includes major banks across 17 European countries, is a key indicator of the region's financial health. With significant exposure to countries like the UK, Spain, and Italy, the index's sensitivity to economic fluctuations makes it particularly relevant for analyzing the impact of the Russia-Ukraine war, which disrupted markets and affected bank valuations (Ahmed et al., 2023; Martins et al., 2023). By exploring how investor sentiment, shaped by the Russia-Ukraine conflict, influences the financial performance of banks within this index, this study aims to provide valuable insights into the complex interplay between geopolitical crises, investor behavior, and market stability.

2. Research Gaps

Research on behavioral finance highlights the influence of psychological and cognitive factors on financial decisions. Nyakurukwa and Seetharam (2023) propose enhancing the Efficient Market Hypothesis (EMH) by incorporating emerging alternative perspectives, while Sun and Zeng (2022) suggest the inclusion of sentiment-based models to better capture the influence of emotions on market behavior.

Investor sentiment remains difficult to define and measure, with no consensus in academia regarding the most accurate proxies. De Sousa-Gabriel et al. (2024) advocate for the identification of alternative indicators that more precisely reflect true market sentiment. Sun et al. (2021) highlight real-time sentiment-based asset pricing as a promising area for future research, and Ahmed (2020) emphasizes the need to build on existing findings using recent news and events, especially during crises, to minimize limitations and potential model errors.

The impact of geopolitical events on macroeconomic variables and financial markets is an increasingly important research area, especially as such events intensify investor sentiment. Ahmed et al. (2023) recommend studying the repercussions of the Russia-Ukraine war on global stock markets. Piserà et al. (2024) emphasize the need for sector-specific analyses, as industries respond differently to geopolitical pressures. Martins et al. (2023) specifically highlight the importance of investigating the effects of the Russia-Ukraine war on the European banking industry, given its critical role in economic stability.

3. Research Question

This study aims to determine whether investor sentiment significantly impacts banks belonging to the STOXX Europe 600 Banks Index during the Russia-Ukraine war, specifically between 1 January 2022 and 20 April 2023. It responds to the growing interest in the relationship between geopolitical events, investor sentiment and their impact on the financial market. This research question tries to answer Martins et al. (2023) since it is focused on the European banking sector, Piserà et al. (2024) by research into sector-specific reactions under geopolitical pressures, and to Ahmed et al. (2023) by further exploring the repercussions of the Russia-Ukraine war.

Secondary goals include assessing whether the impact of sentiment, measured by RUWESsent and its components (RUWESsent_Sanction, RUWESsent_War, RUWESsent_GT_WIKI), varies by banks' country of origin, and how these components individually influence bank returns.

4. Originality

The originality of this study lies in its use of a unique investor sentiment measure (RUWESsent), its focused analysis on banks within the STOXX Europe 600 Banks Index, and its reliance on updated, crisis-period data. To the best of my knowledge, no prior study has examined the relationship between the Russia-Ukraine War Economic Sanctions News Sentiment Index (RUWESsent) and the stock performance of banks included in the STOXX Europe 600 Banks Index. RUWESsent captures investor reactions specifically related to the conflict, providing a targeted approach to analyzing sentiment during this geopolitical crisis. Additionally, this research focuses on the European banking sector. While previous studies have examined the broader market implications of the war (Boungou and Yatié, 2022; Ahmed et al., 2023) or analyzed links between geopolitical risk, sentiment, and returns more generally (Bossman et al., 2023), the present study focuses on banks as a financially sensitive sector with systemic importance. Although Martins et al. (2023) explored the war's impact on bank returns, they did not incorporate any sentiment-based variables. Finally, by relying on up-to-date data, this study aims to provide new insights into the relationship between investor sentiment and bank stock performance during an ongoing geopolitical crisis.

5. Contribution to Knowledge

This study will represent another piece of empirical evidence on market behavior during geopolitical crises, focusing on the banking sector, especially sensitive to macroeconomic and geopolitical shifts. By using updated data and sentiment analysis in a European context, the research will complement the existing studies that usually focus on U.S. markets.

The findings will be relevant to investors, fund managers, and market regulators. For investors, a deeper understanding of how sentiment influences stock returns in the banking sector during periods of geopolitical tension will support more informed decision-making, helping to mitigate risks associated with sentiment-driven market fluctuations. Fund managers will benefit from insights into sentiment dynamics, allowing them to adjust portfolio strategies and manage exposures more effectively during crisis. Market regulators, like the European Securities and Market Authority (ESMA), and Securities and Exchange Commission (SEC), can utilize these insights to better understand the connection between geopolitical events and market sentiment. Recognizing this link will support the development of policies that enhance market efficiency and inform more effective regulatory responses.

6. Chapter Overview

The literature review is presented in chapter 2. Chapter 3 explains data and methodology. Chapter 4 presents the results. Chapter 5 presents the conclusions of this study.

Chapter 2

Literature Review

1. Key Concepts

1.1 Investor Sentiment

The concept of investor sentiment has evolved through a variety of theoretical lenses, demonstrating increasing recognition of how psychological and emotional factors influence financial markets. Black (1986) introduced the concept of "noise traders", describing investors whose decisions are guided more by sentiment or irrational beliefs than by fundamental information. Building on this, Shleifer and Summers (1990) defined investor sentiment as deviations from rational expectations, highlighting how emotional reactions or misinformation can produce persistent mispricings in financial markets.

This behavioral perspective was further developed by Barberis et al. (1998), who modeled how cognitive biases, such as representativeness and conservatism, contribute to anomalies like market underreaction and overreaction. Later, Shefrin (2001) and Hirshleifer (2001) deepened the psychological foundation of the concept, framing sentiment as a product of biases like overconfidence, herding, and emotional responses.

Brown and Cliff (2004) described investor sentiment as investors' general expectations about future market returns. They distinguish between individual and institutional sentiment, with the latter playing a more influential role in shaping market dynamics. Their approach frames sentiment less as a predictor and more as a reflection of prevailing market conditions.

In contrast, Baker and Wurgler (2006) emphasize the speculative nature of sentiment, describing it as investors' propensity to engage in speculative trading, particularly in assets that are difficult to value or arbitrage. Their framework underscores how sentiment-driven mispricing persists when rational traders face limits in correcting it.

Despite these varied perspectives, a shared understanding emerges investor sentiment reflects deviations from rationality driven by cognitive or emotional biases, leading to market inefficiencies. Where they differ is in emphasis, some view sentiment as primarily speculative (Baker and Wurgler, 2006), others as psychologically reactive (Black, 1986; Hirshleifer, 2001; Shefrin, 2001), and some as a broader indicator of current market expectations (Brown and Cliff, 2004).

For this study, the definition proposed by Brown and Cliff (2004) is the most suitable. Their emphasis on institutional sentiment and its reactive nature aligns with the characteristics of the banking sector, which is highly regulated and typically more tied to fundamentals than to speculative narratives. In times of geopolitical uncertainty, such as the Russia-Ukraine war, changes in investor expectations and perceived market risk become particularly relevant to bank stock performance.

2. Key Theories

2.1 The Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) is one of the foundational theories in finance and states that financial markets are informationally efficient, meaning stock prices fully reflect all available information at any given time. As a result, consistently achieving returns above the market average through stock picking or market timing is considered nearly impossible. The origins of EMH can be traced back to Samuelson (1965), who introduced the notion that price movements are random and unpredictable, laying the foundation for the random walk theory.

Fama (1965) expanded on this, emphasizing that prices incorporate all known information, changes are independent and cannot be predicted using historical data. This challenges the usefulness of technical trading and supports passive investment strategies like buy-and-hold. While Fama (1965) acknowledged that intrinsic value exists, he argued that any discrepancy between intrinsic and real prices is quickly corrected by the market.

Fama et al. (1969) further concluded that markets process new information effectively and prices adjust almost instantly. Fama (1970) defined three forms of market efficiency: the weak form (reflects past trading data), the semi-strong form (includes all public information), and the strong form (includes even insider information), each implying increasing levels of efficiency.

EMH supports the idea that markets allocate resources efficiently, minimize arbitrage opportunities, and promote transparency and stability. When prices reflect all relevant data, capital flows more efficiently to firms with strong fundamentals (Jensen, 1978), and arbitrage opportunities are reduced (Grossman and Stiglitz, 1980). Transparent pricing boosts investor confidence and contributes to a more stable financial system (Fama, 1970; Lo, 2004).

However, EMH has faced criticism during periods of financial instability. Malkiel (2003) and Shiller (2002) point to anomalies and speculative bubbles as evidence of irrational behavior that EMH does not fully address. The inconsistencies have paved the way for alternative frameworks such as behavioral finance, which incorporates psychological and cognitive biases into financial decision-making.

2.2. Behavioral Finance

Behavioral finance integrates insights from psychology and cognitive sciences into financial economics to explain anomalies that traditional theories like the Efficient

Market Hypothesis (EMH) cannot. While EMH assumes rational agents who process information efficiently (Fama, 1970), behavioral finance contends that real-world decision-making is often shaped by cognitive biases, emotions, and psychological errors, leading to persistent price distortions (Ritter, 2003). Its emergence was largely driven by EMH's inability to account for speculative bubbles, crashes, and other irrational market dynamics (Shiller, 2002).

One of the central arguments of behavioral finance is that markets are not always efficient because investor decisions are shaped by heuristics, sentiment, emotions and bounded rationality (Barberis et al., 1998). These biases lead to systematic mispricing, particularly during periods of financial instability, such as bubbles and crashes, where irrational behavior becomes more pronounced, further challenging the assumptions of efficient markets (Malkiel, 2003).

Neurofinance deepens this understanding by examining how the brain processes financial decisions. Several brain regions play a crucial role in shaping investor behavior. The ventral striatum, often referred to as the reward center, is activated in response to the anticipation of financial gains, which encourages risk-seeking behavior. When investors prioritize immediate gains, this area promotes impulsive decisions that may overlook long-term consequences (Knutson and Greer, 2008). The prefrontal cortex controls rational thinking, planning, and impulse control. However, intense emotional responses, such as fear or excitement, can override this brain region's activity, leading investors to make decisions driven by immediate emotions rather than careful rational analysis (Bechara et al., 2000; Kuhnen and Knutson, 2005). The amygdala, known as the brain's fear center, processes emotional responses to threats, particularly financial losses. Heightened activity in the amygdala triggers panic selling during market downturns (Kuhnen and Knutson, 2005). The hippocampus, responsible for memory recall, influences investment decisions by retrieving past financial experiences. However, reliance on outdated or irrelevant memories can lead to poor decision-making (Vieito et al., 2015). These neural mechanisms help explain why investors often rely on biased or emotionally charged heuristics instead of purely rational analysis.

Cognitive biases arising from these mechanisms significantly shape market outcomes. Availability bias and representativeness heuristic cause investors to overweight recent or salient events, contributing to momentum trading and short-term trend reinforcement (Barberis and Thaler, 2003). Overconfidence and self-attribution bias lead to excessive trading and increased volatility, as individuals misjudge their predictive abilities (Gervais and Odean, 2001). Hindsight bias fosters an illusion of predictability, causing investors to underestimate uncertainty and overstate the accuracy of past forecasts (Barberis and Thaler, 2003).

Social and psychological influences also impact decisions. Conformity bias encourages herding, fueling speculative bubbles, while home-bias reduces diversification, increasing domestic risk exposure (Hirshleifer, 2001; Huberman, 2001). Conservatism bias and cognitive dissonance explain resistance to updating beliefs despite new data, delaying necessary market corrections (Shiller, 1999). Anchoring bias causes fixation on past price levels or initial valuations, making investors resistant to adjustments even when market conditions change (Kahneman and Tversky, 1979).

Together, these biases help explain the dynamics of market cycles. Behavioral finance provides insight into boom-and-bust cycles, where irrational exuberance inflates prices until sentiment shifts and sharp corrections follow (Shiller, 2002). During crises, fear and panic trigger herd-like behavior and broad market sell-offs (Kallinterakis and Gregorious, 2017). Conversely, bubbles can form when sentiment detaches from fundamentals (Brunnermeier and Nagel, 2004). As De Bondt and Thaler (1985) argue, prices often overreact to news, deviating from intrinsic values before reverting.

One of the main advantages of behavioral finance is its ability to explain real-world phenomena that traditional models cannot, especially under stress or uncertainty (Ritter, 2003; Shiller, 2002). It provides a more nuanced understanding of volatility and mispricing by emphasizing the role of sentiment and biases in asset valuation (Hirshleifer, 2001). However, it remains limited by the absence of a unified theory and the difficulty of integrating psychological variables into predictive, quantitative frameworks (Barberis and Thaler, 2003; De Bondt and Thaler, 1985).

Cognitive Bias	Description
Availability Bias	Tendency to overestimate the probability of events based on how easily similar examples come to mind (Barberis and Thaler, 2003).
Conservatism Bias	Aversion to change their beliefs when new information contradicts prior expectations (Shiller, 1999).
Cognitive dissonance	Struggle to reconcile new information that contradicts existing beliefs, often ignoring or misinterpreting new information (Shiller, 1999).
Familiarity Bias	Preference for familiar investments over unfamiliar ones, regardless of objective value (Huberman, 2001).
Home-Bias	The strong tendency to disproportionately allocate capital to domestic markets rather than international opportunities (Huberman, 2001).
Overconfidence Bias	Overestimation of self knowledge or predictive skill (Gervais and Odean, 2001).
Self-attribution Bias	Attributing successes to self own skill and failures to external factors (Gervais and Odean, 2001).
Hindsight Bias	Tendency to see past events as having been predictable (Barberis and Thaler, 2003).

Anchoring Bias	Relying to heavily on an initial information, even when more relevant data becomes available (Kahneman and Tversky, 1979).
Representativeness heuristic	Assume past patterns will continue, leading to misjudgments (Barberis and Thaler, 2003).
Conformity (Herding)	Tendency to follow the crows or group consensus, assuming the group is better informed (Hirshleifer, 2001).

Table 1: Cognitive Biases and Their Implications.

2.3 Investor Sentiment

Investor sentiment refers to the collective emotional and psychological disposition of market participants that shapes investment decisions, market expectations, and risk perceptions (Baker and Wurgler, 2007). Contrary to traditional financial theories that assume rational agents, behavioral finance recognizes that sentiment is influenced by cognitive biases, emotional responses, and psychological mechanisms, often interacting with external conditions to produce market inefficiencies (Ritter, 2003; Shiller, 1999).

The formation of investor sentiment arises from the interaction between internal psychological mechanisms and external contextual factors (Shiller, 1999). Cognitive biases such as overconfidence, anchoring, and availability heuristics affect how investors process information and evaluate risk. These internal processes are further shaped by macroeconomic trends, media narratives, and geopolitical events, creating cyclical market behavior. These internal and external dynamics create self-reinforcing cycles, where rising optimism drives prices upwards, and fear during downturns fuels selling pressure (Shleifer and Vishny, 1997).

Neuroscientific evidence shows that investor sentiment is also neurologically grounded. Bechara et al. (2000) demonstrate that emotional responses processed in the ventromedial prefrontal cortex and amygdala guide decision-making, especially under uncertainty. These somatic markers influence behavior at a subconscious level, helping form investor sentiment and influencing expectations before rational analysis takes place. Wang et al. (2015) add that the brain generates error-related negativity and feedback signals that help reinforce caution or confidence based on prediction errors.

As Maharani (2016) discussed, investor sentiment is shaped through the interaction between an intuitive, emotional, and fast system and a rational, analytical, and slow system. During high volatility or ambiguous information, emotional processing overrules analytical reasoning, driving sentiment shifts that are not rooted in fundamentals.

Bank and Brustbauer (2014) emphasize that sentiment is further influenced by emotional predispositions and personality traits, with investors responding differently to risk depending on their past experiences and psychological resilience. These subjective reactions make sentiment difficult to capture using quantitative models alone, as these responses are shaped by personal experiences and reinforced by collective interpretations of risk and opportunity.

Fisher and Statman (2000) highlighted differences in sentiment across investor groups. While individual investors often respond emotionally to fear and recent market trends, institutional investors display more stable sentiment patterns yet still exploit retail sentiment tactically. This underscores the idea that sentiment affects all market participants, but in distinct ways.

Da et al. (2011) showed that investor attention, as proxied by Google search volume, predicts trading behavior and price fluctuations. Heightened attention often precedes sentiment shifts, especially among retail investors, and leads to market imbalances even before fundamental justification emerges.

Media and information dissemination play a central role in directing attention and shaping sentiment. Tetlock (2007) finds that negative news correlates with pessimistic sentiment and heightened volatility. In the digital age, social media accelerates sentiment shifts. Platforms like Twitter and financial forums facilitate rapid narrative formation, often spreading emotional reactions that influence short-term trading (Ji and Han, 2022).

Shiller (2017) expands this by introducing the concept of narrative economics, emotionally resonant stories such as fears of recession or optimism around policy reform, spread virally, shaping collective behavior. These narratives, especially in times of uncertainty, become powerful tools for shaping investor sentiment independently of objective economic indicators.

While internally formed, investor sentiment is also highly responsive to external forces. According to Tetlock (2007), past market performance is a key driver of sentiment, with periods of low returns triggering negative sentiment and increasing fear and risk aversion. Conversely, positive performance promotes optimism, fueling momentum-based behavior even in the absence of fundamental support.

Macroeconomic conditions also influence sentiment. Lutz (2015) demonstrates that expansionary monetary policy improves confidence by enhancing liquidity and encouraging investment in riskier assets. Gu et al. (2021) showed that sentiment can mediate the impact of policy announcements on asset prices, amplifying or muting reactions to central bank signals. Similarly, Guenich et al. (2022) found that investor sentiment is highly sensitive to changes in economic uncertainty, particularly in periods of financial stress.

Geopolitical risk plays an especially disruptive role in shaping investor sentiment. Wars, terrorism, and political instability introduce uncertainty that shifts investor behavior toward safe-haven assets (He, 2023). Bossman et al. (2023) show that such periods are associated with heightened volatility and capital flight from equities. Hudson and Urquhart (2015) demonstrate that geopolitical risks heighten volatility and produce stronger reactions to negative events, while Sulong et al. (2023) highlight how the Russia-Ukraine conflict induced pessimism and a shift toward fixed-income instruments. Trade sanctions, inflationary pressures, and international policy responses further intensify these effects, with sentiment becoming a transmission channel through which global instability affects market dynamics (Bossman et al., 2023; Sulong et al., 2023).

In the financial sector, sentiment plays a particularly sensitive role. Due to the complexity and opacity of financial firms, it is difficult for investors to accurately assess risk exposures or asset quality (Bank and Brustbauer, 2014). As a result, investors tend to rely on trust, perceived stability, and institutional reputation, and in times of uncertainty, rely on heuristic judgments shaped by sentiment.

Investor sentiment significantly influences liquidity, volatility, and asset pricing. Periods of heightened sentiment, whether optimistic or pessimistic, often lead to fluctuations that extend beyond what traditional valuation models predict (De Long et al., 1990; Tetlock, 2007). These conditions may generate short-term momentum, increased trading volume, and capital inflows (Baker and Stein, 2004; Baker and Wurgler, 2007). Sentiment also serves as a benchmark of market risk tolerance. During bullish periods, high sentiment signals a greater willingness to take on risk, while in pessimistic phases, sentiment can drive investors towards safer assets. This cyclical shift in risk perception influences portfolio allocation and can provide insights into potential market turning points (Baker and Wurgler, 2006).

Despite its positive effects on market activity, sentiment introduces systematic inefficiencies. Shiller (2002) argues that excessive optimism can inflate speculative bubbles, eventually leading to sharp declines. Baker and Wurgler (2007) find that sentiment-driven stocks often yield lower future returns as mispricing is corrected. Moreover, De Bondt and Thaler (1985) show that sentiment-driven markets tend to overreact to both positive and negative news, exacerbating volatility.

Finally, the limits to arbitrage mean that sentiment-induced mispricings tend to persist. Rational investors may recognize these distortions but face barriers that prevent them from exploiting these inefficiencies (Baker and Wurgler, 2006; Baker and

Wurgler, 2007). This persistence increases the potential for systemic shocks, especially when sentiment contagion spreads across asset classes (Kallinterakis and Gregorious, 2017).

3. Empirical Evidence

3.1 Significant Studies: Evidence of Investor Sentiment Impact

Empirical research has consistently demonstrated that investor sentiment significantly influences stock returns, asset pricing, and market volatility. Baker and Wurgler (2006) argue that investor sentiment particularly affects stocks whose valuations are highly subjective and difficult to arbitrage. Their study found that when sentiment was high, small, young, and high-volatility stocks exhibited lower subsequent returns. This suggests that speculative demand and arbitrage constraints drive the impact of sentiment on asset prices. Brown and Cliff (2005) confirmed this by showing that excessive optimism leads to overvaluation, with high sentiment levels followed by lower returns in the following years.

Barber and Odean (1999) provided strong evidence that sentiment-induced overconfidence leads to excessive trading and systematic mispricing, particularly among retail investors. Fernandes et al. (2013) also found that sentiment negatively predicts returns in Portugal, especially for small and illiquid stocks. These results highlight that the effect of sentiment is magnified where arbitrage is constrained and information asymmetry is high.

The strength of sentiment effects also appears to be dependent on market structure and cultural context. Chui et al. (2010) and Schmeling (2009) demonstrated that sentiment-driven price fluctuations are stronger in culturally individualistic and emerging markets, where speculative trading is more prevalent. Andleeb and Hassan (2023) and Kamath et al. (2024) confirmed that sentiment significantly drives asset prices in emerging markets, particularly under conditions of low liquidity and heightened speculative activity. This highlights how behavioral biases vary across regions and how cultural characteristics can amplify or mitigate the effects of sentiment on financial markets.

Focusing on the banking sector, Cubillas et al. (2021) show that investor sentiment affects not only stock returns but also bank behavior. Their findings indicate that optimistic sentiment leads to rapid credit growth and less strict lending standards, which increase systemic risk and reduce financial stability, especially in countries with weaker regulatory environments. Di et al. (2021) extended this finding by showing that Islamic banks, due to their greater opacity and differing governance frameworks, are even more sensitive to sentiment shifts than conventional banks.

Shah and Albaity (2022a) demonstrate that in the MENA banking sector, investor sentiment positively affects bank stock returns, especially when moderated by trust in financial institutions. Shah and Albaity (2022b) emphasize that governance quality plays a critical role, when governance is strong, the negative effects of sentiment and uncertainty are moderated. Oyetade et al. (2024) add that regulatory compliance and bank-specific characteristics shape how sentiment translates into performance. Collectively, these studies suggest that bank-specific features, such as transparency, complexity, and governance, moderate the intensity of sentiment effects.

Investor sentiment also significantly influences price dynamics and digital assets. P H and Rishad (2020) find that sentiment-driven behavior increases volatility in gold markets, especially during periods of economic or geopolitical uncertainty. Similarly, Abakah et al. (2024) show that digital asset markets, such as cryptocurrencies, are highly reactive to war-related sentiment shocks, with investor panic and uncertainty substantially amplifying volatility.

Geopolitical disruptions also contribute to sentiment-driven market fluctuations. Arfaoui and Naoui (2022) and Drakos (2010) show that terrorism leads to significant short-term declines in stock markets due to sudden drops in investor confidence and heightened risk aversion. These findings reinforce that sudden, high-impact events provoke stronger sentiment reactions, especially in politically unstable environments.

These studies reveal recurring patterns. Market structure and institutional strength are critical determinants of sentiment-driven price fluctuations, with sentiment being particularly pronounced in emerging markets characterized by limited liquidity and higher speculative activity (Chui et al., 2010; Schmeling, 2009). Investor composition also plays a crucial role, as retail-dominated markets tend to exhibit stronger sentiment-driven mispricing due to the increased reliance on heuristics and psychological biases among non-institutional investors. Moreover, geopolitical events consistently amplify sentiment effects, particularly in regions experiencing heightened political instability, where investor fear and risk aversion intensify market downturns (Drakos, 2010).

3.2 Non-Significant Studies: Limited Impact of Investor Sentiment

Contrary to the findings above, some studies suggest that investor sentiment's impact is limited or inconsistent, depending on market efficiency, asset class, and crisis type. Wang et al. (2006) found that investor sentiment does not reliably predict stock volatility, suggesting that sentiment indicators are often reactionary, driven by existing market movements and volatility rather than driving them. Similarly, Finter et al. (2010) observed that while sentiment can explain short-term market fluctuations, it lacks predictive power for future returns in Germany, a market largely dominated by institutional investors who are less susceptible to sentiment-driven trading. Banchit et al. (2020) found that while sentiment can explain short-term price movements, its long-term effects are largely diluted, aligning with the efficient market hypothesis.

Moutinho et al. (2024) found mixed effects of sentiment during crises, while COVID-related sentiment strongly influenced asset spreads, Russia-Ukraine war-related sentiment had minimal impact. This implies that crisis type and context play a significant role. Global and health-related shocks like pandemics may provoke stronger emotional responses than geopolitical conflicts. Halousková et al. (2022)

show that investor attention, proxied by Google Trends, only significantly predicts stock market volatility in countries with strong economic trade ties to Russia during the Russia-Ukraine war. These results suggest that geographic proximity and economic interdependence moderate the effect of sentiment shocks.

Abakah et al. (2023) further explored geopolitical sentiment effects on digital assets, finding that while sentiment significantly impacted returns in bearish conditions, its effects were inconsistent across asset classes. Their findings suggest that digital asset markets may exhibit a different sensitivity to geopolitical sentiment than traditional markets, reinforcing that sentiment-driven mispricing may be context-dependent.

Studies reporting limited effects suggest that market efficiency plays a crucial role in limiting sentiment-driven effects. In highly developed markets, where institutional investors dominate and arbitrage mechanisms function efficiently, sentiment-induced mispricing is often corrected, leading to a weaker influence of sentiment over time (Chui et al., 2010; Finter et al., 2010; Schmeling, 2009). Furthermore, the impact of investor sentiment varies across asset classes and crisis types. While sentiment can have strong short-term effects, its long-term influence is often diluted, particularly in stable financial environments (Banchit et al., 2020). Finally, geopolitical events do not uniformly trigger sentiment-driven responses. While certain geopolitical crises, such as terrorism, have immediate market impacts (Arfaoui and Naoui, 2022; Drakos, 2010), broader conflicts like the Russia-Ukraine war exhibit mixed sentiment effects depending on the region and sector.

4. Research Context

4.1 Macroeconomic Environment

Between January 2022 and April 2023, the global economy faced significant challenges, including high inflation, slowing growth, and financial market volatility. The lingering effects of the COVID-19 pandemic were aggravated by the Russia-Ukraine conflict, which began in February 2022, generating further economic disruptions.

Global GDP growth slowed from 6.1% in 2021 to 3.1% in 2022, according to IMF estimates. This unusually high growth in 2021 reflected a post-pandemic rebound from the sharp contraction of 2020, rather than a sustainable expansion trend. Meanwhile, inflation peaked near 10% in OECD countries, fueled by soaring food and energy prices. Central banks, such as the U.S. Federal Reserve and the European Central Bank (ECB) implemented aggressive monetary tightening, raising interest rates and dampening growth.

Financial markets turned volatile, with investor caution prompting shifts towards safer assets like bonds and gold. In Europe, dependency on Russian energy intensified inflationary pressures, with eurozone inflation reaching 10.6% in October 2022. Although unemployment remained low (~6%), real incomes fell, reducing consumer demand. The ECB's tightening and the energy crisis placed downward pressure on European equities, heightening investor sensitivity to geopolitical and policy developments.

4.2 The Russia-Ukraine War and Its Impact

The escalation of the Russia-Ukraine conflict in February 2022, triggered global economic and financial disruptions. Sanctions against Russia, such as SWIFT restrictions, frozen central bank assets, and energy export bans, fueled market volatility and currency depreciation (Sio-Chong U et al., 2024; Tong, 2024; Umar et al., 2022). Natural gas prices spiked by approximately 7.5% (Aizenman et al., 2024), intensifying the energy crisis (Chishti et al., 2023).

Investor sentiment played a key role in shaping market reactions to geopolitical uncertainty (Bossman et al., 2023), fueling risk aversion and capital flows into safe-haven assets (Feng et al., 2023). Volatility increased, with the VIX reaching elevated levels and markets responding more strongly to negative news (Bossman et al., 2023).

European banks were particularly exposed due to ties to energy-dependent industries and to Russia. Sentiment-driven overreactions further amplified stock market instability, underscoring the vulnerability of the financial sector to geopolitical shocks and the amplifying role of investor sentiment.

4.3 European Banking Sector

The European banking sector is vital to financial stability and economic activity. Beyond traditional functions, such as deposits and lending, banks also engage in investment banking, trading, asset management, and financial advisory, making them integrated into the global financial system and exposed to macroeconomic and geopolitical shocks (Adrian and Shin, 2010).

Bank equities are widely held by institutional investors such as pension funds, mutual funds, insurance companies, and sovereign wealth funds, who often maintain significant stakes just below regulatory thresholds (Frazzani et al., 2020). The inclusion of banks in broad financial indices and ETFs makes them more susceptible to sentiment-driven flows and market-wide adjustments.

The STOXX Europe 600 Banks Index, tracking major European banks across 17 countries, experienced sharp fluctuations during the Russia-Ukraine conflict. This index is highly sensitive to both economic cycles and geopolitical events. Some of the banks included in this index, such as Société Générale and Crédit Agricole (France), Unicredit and Intesa Sanpaolo (Italy), and ING (Netherlands) were among the most affected due to their exposure to Russia (Martins et al., 2023). In contrast, banks with minimal Russian ties and stronger efficiency metrics showed greater resilience.

Sanctions, transaction disruptions, and energy price shocks deepened uncertainty, especially for banks linked to Eastern European markets or foreign exchange exposure. Investor sentiment amplified these effects, investors engaged in flight-to-safety behavior, shifting capital away from riskier stocks toward safer assets (Feng et al., 2023), while media-driven risk perception led to sharper declines for banks perceived as vulnerable. The availability heuristic (Tversky and Kahneman, 1973) explains how repeated exposure to negative news heightens investor fear and overreaction.

Despite strong regulatory oversight, banks could not escape the market impact of geopolitical tension. This reaction highlights the interaction between ownership structure, sentiment, and external exposure to drive volatility under crisis conditions.

5. Hypothesis

H1: Investor sentiment significantly impacted the returns of banks within the STOXX Europe 600 Banks Index during the Russia-Ukraine war, specifically between January 1, 2022 and April 20, 2023.

This hypothesis builds on the behavioral finance literature, which challenges the assumptions of traditional models such as the Efficient Market Hypothesis (Fama, 1970). While EMH suggests that prices reflect all available information and investors act rationally, behavioral finance highlights the influence of psychological and cognitive biases on decision-making, often resulting in asset mispricing (Barberis and Thaler, 2003; Kahneman and Tversky, 1979; Shiller, 2002).

Investor sentiment, the collective emotional and psychological disposition of market participants, becomes especially influential during periods of heightened uncertainty. In crises such as geopolitical conflicts, investors often rely on heuristics like the availability bias, which amplifies attention to negative news (Tversky and Kahneman, 1973). As shown by Black (1986) and De Long et al. (1990), sentiment-driven noise traders can dominate markets, creating price distortions that deviate from fundamentals.

Geopolitical shocks, particularly those that are sudden and severe, tend to trigger market downturns and volatility (Caldara and Iacoviello, 2022; Schneider and Troeger, 2006). The RUWESsent index, developed by Abakah et al. (2023), captures sentiment related to the Russia-Ukraine war, and its spikes have been linked to increased risk aversion and market instability.

Although banks are typically seen as stable and well-regulated, they are particularly vulnerable during geopolitical crises due to their systemic importance, complex exposures, and reliance on investor confidence. Martins et al. (2023) find that

European banks with greater exposure to Russia and energy-dependent industries experienced sharper losses. Oyetade et al. (2024) further emphasize that governance and transparency influence how sentiment translates into bank performance.

Grounded in these theoretical and empirical insights, this study hypothesizes that investor sentiment related to the Russia-Ukraine war, as measured by RUWESsent and its components, had a statistically significant influence on bank stock returns within the STOXX Europe 600 Banks Index.

Chapter 3

Methodology

1. Method

This study adopts a quantitative methodology. Given the quantifiable nature of financial variables, such as stock prices, returns, and sentiment indices, and the objective of testing a specific hypothesis, a statistical approach is more appropriate. It allows for the identification of patterns within large datasets while ensuring replicability, generalizability, and reduced researcher bias (Bryman, 2012). Although qualitative methods offer valuable insights into the psychological and social aspects of investor behavior, they often lack external validity and are more susceptible to subjectivity (Bryman, 2012). Therefore, a quantitative strategy provides a more robust and credible foundation for analyzing sentiment-driven market dynamics during geopolitical crises.

2. Data

This study uses secondary data with a panel structure, combining daily observations across 44 banks in the STOXX Europe 600 Banks Index from January 1, 2022 to April 20, 2023. These banks were selected because they were part of the index throughout the studied period. The dataset initially contained 13420 observations. After removing missing values and extreme outliers to improve accuracy and reliability (Obikee et al., 2014), the final sample included 10516 observations, with 239 trading days per bank.

Variable	**Source**
Bank Returns	Refinitiv Eikon
RUWESsent	Abakah et al. (2023)
US Daily News Index	Economic Policy Uncertainty website
10-Year Bond Spot Rate	European Central Bank (ECB)
VIX	Chicago Board Options Exchange (CBOE)
Brent Crude Oil Price	Archival Federal Reserve Economic Data (FRED)

Table 2: Variables and Its Sources.

The credibility of these sources is strongly supported in literature. Refinitiv Eikon is a widely recognized and credible financial data provider used in empirical finance research (Ferreira and Malanski, 2023; Kling et al., 2021; Martins, 2024). The Russia-Ukraine War Economic Sanctions News Sentiment Index (RUWESsent) was formulated and provided by Abakah et al. (2023), and offers an event-specific measure of sentiment related to the Russia-Ukraine war. The Economic Policy Uncertainty Index is a recognized uncertainty measure and was developed by Baker et al. (2016). Data from ECB, CBOE, and FRED is considered independent, robust, and widely used in academic studies (Barut-Etherington and Golfier-Chataignault, 2024; Hirsa et al., 2021; Jeon et al., 2019; Mendez-Carbajo and Podleski, 2021).

3. Variables

3.1 Dependent Variable: Stock Returns

Daily stock returns were computed using logarithmic returns, $R_t = \ln(P_t/P_{t-1})$, where R_t represents the return at time t, P_t is the stock price at time t, and P_{-1t} is the stock price from the previous trading day. The logarithmic transformation ensures a more consistent statistical distribution for empirical analysis and stabilizes return variability across different price levels, as supported by Fama (1965). However, arithmetic returns better reflect actual gains and are more intuitive for investors. Hudson and Gregoriou (2010) highlight that return choice can affect risk estimates and test outcomes, especially in volatile periods. Given this study's focus on volatility and sentiment, log returns are more appropriate.

3.2 Independent Variables

3.2.1 Investor Sentiment

This study employs the Russia-Ukraine War Economic Sanctions Sentiment Index (RUWESsent) as a proxy for investor sentiment. Developed by Abakah et al. (2023), RUWESsent captures war- and sanction-related sentiment by aggregating data from Twitter, Google Trends, Wikipedia, and news sources. Grounded in behavioral finance theory, which emphasizes the role of emotions, heuristics, and attention in shaping market behavior (Da et al., 2011; Kahneman and Tversky, 1979; Tetlock, 2007), RUWESsent reflects the psychological response of investors during periods of geopolitical instability. Its subcomponents, RUWESsent_Sanction, RUWESsent_War, and RUWESsent_GT_WIKI, allow for an understanding of how specific aspects of the war shaped investor sentiment. Moreover, RUWESsent has been empirically validated as a transmitter of price shocks in periods of uncertainty (Abakah et al., 2024), reinforcing its applicability in the context of this study.

Alternative proxies for investor sentiment have been widely used in the literature. Baker and Wurgler (2006) introduced a composite sentiment index that relies on financial market indicators such as trading volume, IPO activity, and the equity share in new issues, reflecting speculative behavior and investor optimism within financial markets. While widely adopted, this type of index may underrepresent sentiment changes driven by exogenous events like geopolitical shocks. More recently, Huang et al. (2015) proposed a sentiment index based on social media and textual analysis, emphasizing the growing role of online discussions in shaping investor sentiment.

Although these proxies are valuable in broad-market contexts, they are limited in their ability to capture geopolitical sentiment shifts. RUWESsent's targeted construction around the Russia-Ukraine war makes it more suitable for capturing sentiment fluctuations tied specifically to this event, offering a more accurate measure for this study.

3.2.2 Market Volatility (VIX)

Market volatility is a key measure of risk in financial markets, with the CBOE Volatility Index (VIX) being one of the most widely used indicators. Also known as the investor fear gauge, it reflects market expectations for near-term volatility based on S&P 500 options. The importance of the VIX in financial research has been highlighted by Whaley (2009), who demonstrated its predictive power in periods of market stress.

Other alternative volatility measures exist, Engle et al. (2008) introduced a dynamic conditional correlation model to assess time-varying volatility spillovers across global markets. While such models provide a more detailed view of volatility interactions, the VIX offers real-time availability and is widely used in empirical finance. Given its extensive use and reliability, it is chosen as the proxy for market volatility in this study.

3.2.3 Oil Prices

Oil prices play a fundamental role in shaping macroeconomic conditions and financial markets. Given its status as a global benchmark, this study uses the daily closing price of Brent Crude Oil to measure oil price movements. Smales (2021) and Caldara and Iacoviello (2022) demonstrate that Brent crude prices are highly sensitive to geopolitical tensions and can significantly impact financial stability.

Several alternative oil price measures exist. For instance, West Texas Intermediate (WTI) is the main oil benchmark for North American markets, while Brent Crude Oil is preferred for global markets, particularly in Europe. Given its higher relevance to

European economies and its sensitivity to geopolitical events, this study selects the daily closing price of Brent Crude Oil as the proxy for oil price movements.

3.2.4 10-Year Government Bond Spot Rate

This study employs the 10-year government bond spot rate as a key measure of long-term interest rate expectations. The 10-year rate is widely regarded as a benchmark for long-term borrowing costs and the risk-free interest rate. It captures market expectations regarding future economic conditions, inflation trends, and central bank policies (Campbell and Shiller, 1991).

Alternative bond market indicators include yield curve spreads, such as the difference between 10-year and 2-year bond yields, which can signal recession risk (Estrella and Mishkin, 1998). However, given the central role of the 10-year bond spot rate in economic forecasting and financial stability, it is chosen as the measure for this study.

3.2.5 US Daily News Index

This study adopts the US Daily News Index as the measure of economic policy uncertainty. This index captures real-time uncertainty by analyzing daily news coverage, offering more frequent updates than the traditional Economic Policy Uncertainty (EPU) Index introduced by Baker et al. (2016). While the EPU Index aggregates news articles discussing economic uncertainty-related terms, its lower frequency may result in delayed reflections of real-time economic conditions.

An alternative measure is the Macroeconomic Uncertainty Index, as proposed by Jurado et al. (2015), which uses econometric models to estimate macroeconomic uncertainty but lacks real-time responsiveness. Given its higher frequency and real-time tracking capability, the US Daily News Index is selected as the most suitable measure for this study.

4. Main Methodology

Given the panel structure, 44 banks observed daily over time, panel data regression was selected as the main methodology. This approach enables the analysis of both cross-sectional and time-series variations, improving estimation precision and controlling for unobserved heterogeneity (Baltagi, 2008). Several econometric approaches were considered, with the Random Effects model selected based on theoretical relevance and statistical validation.

A key decision was between Fixed Effects (FE) and Random Effects (RE). FE controls for time-invariant characteristics by assigning bank-specific intercepts, while RE assumes these characteristics are uncorrelated with explanatory variables, enabling estimation of both within- and between-group variation (Borenstein et al., 2009). Since bank-level differences such as size, regulatory environments, and market exposure influence returns are unlikely to correlate with sentiment proxies, RE was preferred. The Hausman test confirmed its suitability, indicating higher efficiency and consistency (Hausman, 1978).

Pooled OLS was excluded due to its inability to control for bank-level heterogeneity, raising the risk of omitted variable bias (Baltagi, 2008). The Generalized Method of Moments (GMM), while robust for dynamic panels and endogeneity (Arellano and Bond, 1991), was not applicable given the static structure of this study.

RE also enhances generalizability across banks with heterogeneous characteristics and its lower computational complexity makes it well-suited for large panel datasets. Prior research (Prakash and Savitha, 2017) has successfully used RE to analyze banking sector performance.

To assess sentiment effects more precisely, two RE models were estimated:

Model 1-General Sentiment:

$$Return_{it} = \beta_0 + \beta_1 RUWESsent_{it} + \beta_2 US\ Daily\ News\ Index_{it} + \beta_3 10y\ Spot\ Rate_{it} + \beta_4 VIX_{it} + \beta_5 BRENT_{it} + u_{it}$$

Model 2-Sentiment Subcomponents:

$$\begin{aligned} Return_{it} = \beta_0 &+ \beta_1 RUWESsent\_Sanctions_{it} + \beta_2 RUWESsent\_War_{it} \\ &+ \beta_3 RUWESsent\_GT\_WIKI_{it} + \beta_4 US\ Daily\ News\ Index_{it} + \beta_5 10y\ Spot\ Rate_{it} \\ &+ \beta_6 VIX_{it} + \beta_7 BRENT_{it} + u_{it} \end{aligned}$$

Where $Return_{it}$ represents stock returns of bank i on day t. $RUWESsent_{it}$ captures overall investor sentiment related to the Russia-Ukraine war, while

$RUWESsent\_Sanctions_{it}$, $RUWESsent\_War_{it}$, $RUWESsent\_GT\_WIKI_{it}$ measure sentiment specific to sanctions, war events, and media attention, respectively. $US\ Daily\ News\ Index_{it}$ accounts for economic policy uncertainty, $10y\ Spot\ Rate_{it}$ represents long-term interest rate expectations, VIX_{it} captures market volatility, $BRENT_{it}$ represents daily Brent Crude oil prices. The coefficients β measure the effect of each explanatory variable, and u_{it} is the error term.

Model 1 evaluates the general impact of sentiment and Model 2 explores whether sanctions, war, or media-driven attention had distinct effects on market behavior. This approach enables a more nuanced understanding of how investor psychology influenced banking sector performance during the Russia-Ukraine war.

5. Software

Python was selected for its efficiency in processing large financial datasets and implementing econometric models. Its flexibility and increasing adoption in financial research, including sentiment analysis, make it a suitable tool (Bivand and Piras, 2015; Pan et al., 2022).

Chapter 4

Results

1. Descriptive Statistics General Framework

1.1 Summary Statistics and Distribution Analysis

Table X and Appendix 1 present summary statistics for the full dataset (305 observations), while Table Y and Appendix 2 show statistics after outlier removal (239 observations). Metrics include mean, standard deviation, skewness, and kurtosis.

The dataset exhibits signs of distortion in the distribution of several variables. Sentiment-related measures like RUWESsent and its subcomponents show extreme skewness and high kurtosis, indicating long-tailed distributions and the presence of extreme values. Histograms confirm strong right-skewness, suggesting that investor sentiment occasionally spikes in response to events related to the Russia-Ukraine war.

After removing outliers, based on extreme return values, return volatility decreased, reflected in lower standard deviation and kurtosis. However, some sentiment proxies became more asymmetric. For instance, RUWESsent_GT_WIKI shows a kurtosis above 50. This suggests that removing extreme return days concentrated the sample around sentiment-heavy days.

Control variables such as VIX, the 10-year Spot Rate, US Daily News Index, and the Oil Prices remained statistically stable. Histograms show that the VIX clusters at lower values with occasional spikes; Brent Crude Prices are slightly right-skewed, reflecting oil shocks; and the Spot Rate histogram is multi-peaked, hinting at shifting monetary regimes. Interestingly, the US Daily News Index displays a bimodal distribution, likely capturing alternating periods of high and low uncertainty.

Overall, the dataset maintains strong analytical quality and a balanced panel structure after preprocessing. Elevated means and variability in sentiment indices reflect heightened concern during the Russia-Ukraine conflict, while distributional asymmetries are consistent with crisis-period financial data.

1.2 Correlation Analysis

The correlation analysis reveals statistically significant relationships among most variables, with many coefficients reaching the 1% significance level (***). As expected, the RUWESsent subcomponents, *Sanction, War*, and *GT_WIKI*, are highly correlated due to their shared construction, introducing potential multicollinearity risks when included together.

Returns exhibit weak, yet statistically significant, negative correlations with all sentiment proxies and the VIX, aligning with literature linking geopolitical tension and volatility to declining market performance. RUWESsent (-0.20***) demonstrates a modest inverse relationship with returns, suggesting that rising geopolitical sentiment reduces investor confidence.

Among controls, the 10Y Spot Rate and the Brent Crude prices are significantly correlated (-0.48***), raising potential collinearity concerns, though both remain essential for capturing broader market influences. Overall, the correlation structure indicates data coherence, but clustering among sentiment variables warrants careful modeling.

1.3 Stationarity Tests

The Augmented Dickey-Fuller (ADF) test was conducted to assess stationarity. As shown in Table X, all variables are stationary at the 1% significance level, indicating that their statistical properties remain constant over time. This confirms that differencing is not required, and the dataset is appropriate for panel regression analysis without further transformation.

Variable	**ADF Statistic**	**Stationarity**
Returns	-16.76***	Stationary at 1% level
RUWESsent	-13.89***	Stationary at 1% level
RUWESsent_Sanction	-14.95***	Stationary at 1% level
RUWESsent_War	-14.52***	Stationary at 1% level
RUWESsent_GT_WIKI	-16.14***	Stationary at 1% level
US Daily News Index	-21.24***	Stationary at 1% level
Spot Rate 10Y	-13.21***	Stationary at 1% level
VIX	-12.03***	Stationary at 1% level
Brent Crude	-10.88***	Stationary at 1% level

Table 3: ADF Test Results.

2. Main Results

2.1 Model Performance and Quality Assessment

This study estimated two Random Effects (RE) panel data models to assess the impact of investor sentiment on European bank stock returns during the Russia-

Ukraine war. Model 1 evaluates the general RUWESsent index, while Model 2 decomposes it into sentiment subcomponents related to sanctions, war events, and media/public interest.

Both models demonstrate statistically robust results. The F-statistics are highly significant, 97.706*** for Model 1 and 85.398*** for Model 2, indicating that the set of independent variables significantly explains variations in stock returns. Adjusted R-squared values are low, yet consistent with expectations for return-based models, 4.44% in Model 1 and 5.38% in Model 2. The slight improvement in Model 2 suggests that disaggregating sentiment may offer a marginal gain in explanatory power. The Durbin-Watson statistics, 1.98 for Model 1 and 2.00 for Model 2, indicate no evidence of autocorrelation in the residuals, supporting the reliability of the estimations.

These outcomes suggest the models are well-specified and suitable for capturing sentiment-driven effects in the data. However, the low R-squared values reflect the complexity and regulatory resilience of the banking sector. Banks operate under strict supervision, which can diminish the impact of behavioral variables like sentiment. Therefore, even in times of heightened uncertainty, investor sentiment may only partially explain stock performance in this sector.

2.2 Analysis of Individual Variables

In Model 1, the RUWESsent index shows a negative and statistically significant effect on returns (-0.0004***), indicating that higher geopolitical sentiment is associated with slightly lower daily bank stock performance. While the absolute effect is modest, it is consistent with expectations for high-frequency financial data. This suggests that investor sentiment related to the war tends to depress returns, possibly reflecting increased perceived risk or uncertainty.

The VIX is also negative and statistically significant (-0.0003***), reinforcing the idea that heightened market volatility corresponds to declining bank returns. Brent crude oil prices exhibit a small and marginally significant negative influence (-0.00003*), indicating that short-term oil fluctuations may have limited spillover to the banking sector. The US Daily News Index and the 10-year Spot Rate do not display statistically significant effects, underscoring their limited short-term influence on European bank stocks. This may reflect the European focus of the sample, as well as the highly regulated and resilient nature of the banking sector, which often absorb short-run macroeconomic noise.

In Model 2, *RUWESsent_Sanction* presents a positive and statistically significant effect (0.0021***), this may reflect investor interpretations of sanctions as strengthening the competitive or regulatory positioning of European banks. Sanctions may also signal supportive monetary or fiscal policy within the EU, increasing investor confidence in the sector's stability. Similarly, *RUWESsent_War* shows a positive and significant effect (0.0003***), possibly reflecting a partial flight-to-safety mechanism, where large, important banks are viewed as relatively secure investments during periods of uncertainty. This could be especially relevant in a European context, where strong regulatory framework and coordinated policy responses are expected during crises.

On the other hand, *RUWESsent_GT_WIKI,* which captures sentiment driven by media and public attention, has a negative and significant effect (-0.0028***). This suggests that increased public visibility and media focus around the conflict may amplify investor fear, leading to reduced bank valuations.

The VIX remains negative and significant (-0.0003***), while Brent crude oil prices continue to display a small and marginally significant negative influence (-0.00007***). The US Daily News Index and 10-year Spot Rate remain statistically insignificant.

Variable	Coefficient	Std. Error	t-stat
Constant	0.0168***	0.0019	8.95
RUWESsent	-0.0004***	0.000025	-15.85
US Daily News Index	-0.0000027	0.0000036	0.76
Spot Rate 10Y	-0.0001	0.0003	-0.50
VIX	-0.0003***	0.000052	-6.51
Brent Crude	-0.00003*	0.000017	-1.72

Table 4: Model 1 Results.

Observation	10516
Entities (Banks)	44
R-squared	0.0444
F-statistic	97.706***
Durbin-Watson statistic	1.98

Table 5: Model 1 Specifications.

Variable	Coefficient	Std. Error	t-stat
Constant	0.0136***	0.0022	6.27
RUWESsent_Sanction	0.0021***	0.0002	10.60
RUWESsent_War	0.0003***	0.00009	3.55
RUWESsent_GT_WIKI	-0.0028***	0.0002	-11.32
US Daily News Index	-0.0000006	0.0000036	-0.18
Spot Rate 10Y	0.000035	0.0003	0.13
VIX	-0.0003***	0.00005	-5.93
Brent Crude	-0.00007***	0.00002	-3.54

Table 6: Model 2 Results.

Observation	10516
Entities (Banks)	44
R-squared	0.0538
F-statistic	85.398***
Durbin-Watson statistic	2.00

Table 7: Model 2 Specifications.

2.3 Country-Specific Analysis

To further explore the impact of investor sentiment, country-level random effects models were estimated. The results reveal considerable variation across regions, suggesting that country-specific factors may play a crucial role in shaping investor reactions.

In Model 2 (Sentiment Subcomponents), France (R^2=0.1478) and the Netherlands (R^2=0.1136) exhibit the highest explanatory power. Both countries were deeply involved in EU sanctions and policymaking, with France providing military and diplomatic support, and the Netherlands fully aligned with EU sanctions, regarding its significant exposure to Russian commodities. In contrast, Norway (R^2=0.0201) and Finland (R^2=0.0323) display weak explanatory power and insignificant F-statistics. Each country is represented by only one bank in the sample, which limits statistical power. Additionally, their reputations for financial stability and lower international banking exposure may have mitigated sentiment effects or facilitated faster information absorption by markets.

Model 1 (General Sentiment) shows a negative and statistically significant impact on bank returns in countries like Italy (-0.0006***), Spain (-0.0004***), France (-0.0007***), and the UK (-0.0003***). These countries were among the most represented in the dataset (UK:8 banks; Italy and Spain:5 banks each; France:3 banks) and were also key players in EU-wide policy responses. Their larger, globally integrated banking systems are likely more sensitive to sentiment shifts related to the Russia-Ukraine war.

Conversely, in Sweden and Norway, none of the sentiment variables reach statistically significant, and the F-statistic is also insignificant. This may reflect a combination of smaller sample sizes, strong investor confidence in institutional stability, and lower speculative behavior, which may limit the transmission and detectability of sentiment effects.

Overall, the findings underscore that sentiment impacts are not uniform across Europe. They appear stronger in countries with larger, more interconnected banking sectors and greater political engagement in the conflict, and weaker where stability, confidence, or limited sample size constrain observable effects.

3. Discussion of Results

This study hypothesized that investor sentiment significantly impacted bank stock returns within the STOXX Europe 600 Banks Index during the Russia-Ukraine war. Results show that RUWESsent had a statistically significant negative effect (-0.0004***), suggesting that heightened geopolitical sentiment modestly lowered bank valuations. This supports behavioral finance theory, which suggests that investor overreaction (Barberis et al., 1998; De Bondt and Thaler, 1985) and noise trading (Black,1986; De Long et al., 1990) contribute to short-term mispricing.

Although significant, model explanatory power remained low (R^2 ≈4-5%), suggesting that sentiment operates alongside other institutional and structural factors. The European banking sector is highly regulated, capital-intensive, and dominated by institutional investors, factors which reduce susceptibility to behavioral effects (Fernandes et al., 2013; Finter et al., 2010). Furthermore, macroeconomic pressures during the war, such as rising interest rates, and inflationary shocks, may have interacted with sentiment-driven reactions, especially in a sector whose profitability is tightly linked to monetary policy and credit risk conditions.

Decomposing RUWESsent revealed divergent sentiment effects. While *RUWESsent_GT_WIKI* (-0.0028***) had a negative and significant impact, consistent with media-driven pessimism (He, 2023; Ji and Han, 2022; Tetlock, 2007), *RUWESsent_Sanction* (0.0021***) and *RUWESsent_War* (0.0003***) exhibited positive and significant effects. These may reflect confidence in EU regulatory responses, such as coordinated sanctions, which potentially reassured markets about the sector's resilience.

At the country level, sentiment effects were stronger in Italy, Spain, France, and the UK, countries with larger, globally integrated banks and active political engagement in the conflict. Martins et al. (2023) highlight sharp declines in banks like Société Générale (France), Unicredit and Intesa Sanpaolo (Italy), partly due to financial exposure to Russia. Chui et al. (2010) also link higher sensitivity to sentiment with individualistic cultures, supporting stronger reactions in countries like the UK and Italy. Conversely, Norway and Finland showed weaker or insignificant effects, consistent with Schmeling (2009), who found that countries with stronger institutions and lower behavioral bias exposure show reduced sentiment sensitivity.

A principal component analysis (PCA) confirmed these findings: the first component, accounting for over 97% of sentiment index variance, had a negative significant effect (-0.0020***). However, its low explanatory power mirrors other models, emphasizing that sentiment is one of many interacting forces affecting returns during crises.

Overall, while investor sentiment did shape bank stock performance during the Russia-Ukraine war, its effect was influenced by institutional resilience, macroeconomic context, and cultural predisposition.

Chapter 5

Conclusion

1. Conclusions

This study examines how investor sentiment, measured through the RUWESsent and its subcomponents, influenced European bank stock returns during the Russia-Ukraine war. The results confirm that sentiment had a statistically significant but moderate negative impact, shaped by institutional, regulatory, and macroeconomic conditions.

The use of a conflict-specific sentiment measure enabled a more detailed view of varied sentiment effects. While media-driven sentiment had a negative effect, likely reflecting pessimism and fear contagion, sentiment related to sanctions and institutional responses showed positive impacts. These contrasting outcomes suggest that geopolitical sentiment does not affect markets uniformly and that its influence is contingent on the nature and framing of the information.

The models' limited explanatory power aligns with Finter et al. (2010) and Banchit et al. (2020), who argue that sentiment effects are weaker in sectors dominated by institutional ownership, strong governance, and regulatory oversight. This was especially evident in countries such as Norway and Finland, where robust financial institutions and greater investor confidence appeared to dampen the influence of psychological factors.

Conversely, sentiment had a stronger influence in Italy, France, and the UK, countries with larger, globally exposed banks and greater involvement in the conflict. These cross-country differences highlight the role of cultural and structural factors, with stronger effects in markets marked by individualism and speculative behavior. This supports the findings of Chui et al. (2010), Schmeling (2009), and Shah and Albaity (2022b), who point to the moderating role of governance and investor behavior. The amplification of sentiment in countries with closer economic ties to Russia, as seen in Halousková et al. (2022), also supports this interpretation.

Finally, the results are consistent with recent work by He (2023) and Sulong et al. (2023), who emphasize that the effects of sentiment shocks are context-dependent, shaped by macroeconomic uncertainty, institutional credibility, and investor expectations. By focusing on the European banking sector during a major geopolitical crisis, this study contributes to a clearer understanding of how sentiment interacts with broader financial and institutional dynamics in times of stress.

2. Implications for Stakeholders

The findings of this research could be relevant for investors, fund managers, and market regulators. For investors and fund managers, the results support the integration of sentiment indicators like RUWESsent index into asset pricing models and portfolio risk assessments. Additionally, they should consider country-level sentiment dynamics. Stronger effects in countries like Italy or France suggest that localized behavioral patterns can inform portfolio adjustments, hedging, and stress testing.

For regulators such as the European Securities and Market Authority (ESMA), and Securities and Exchange Commission (SEC), the findings support incorporating sentiment metrics into market monitoring tools. Spikes in sentiment, especially media-driven, could act as early warnings of instability. While not calling for immediate reform, the results highlight the value of sentiment-aware analytical frameworks, especially when price movements diverge from fundamentals.

Given the role of media narratives, regulators could also explore sentiment tracking systems to anticipate volatility driven by fear or misinformation. Country-specific models may further improve supervisory responses by aligning with local market behavior.

3. Limitations

This study has several limitations. First, the sentiment index used, RUWESsent, may not fully capture the complexity of investor sentiment. Alternative sentiment measures could offer complementary perspectives. Second, the focus on banks within the STOXX Europe 600 Banks Index may limit the generalizability of the findings to other industries or broader markets. Lastly, the study centers on a specific geopolitical event, the Russia-Ukraine war, so the results may not be generalizable to other crises with distinct characteristics.

4. Future Research

Future research could build on this study by exploring alternative sentiment measures to deepen understanding of how sentiment influences bank stock performance. Investigating the long-term impact of sentiment could also reveal whether its impact extends beyond short-term market reactions. Moreover, expanding the analysis to other sectors or applying the framework to different geopolitical events could clarify whether sentiment-driven effects are industry- or event-specific, or more broadly generalizable across contexts.

AI Declaration

During the preparation of my written work/dissertation, Master's Final Assessment, the ChatGPT was used for tasks such as generating summaries, refining language, data manipulation, and manuscript manipulation, with the prompts listed at the end of the document in the Prompt List section. After using this tool/service, I reviewed and edited the content as necessary and take full responsibility for the publication's content. I also declare that I am aware of and respect the Artificial Intelligence Conduct Rules of the Católica Porto Business School.

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Appendices

A) Summary Statistics

Variables	Obs	Mean	St Dev	Min	Median	Max	Skewness	Kurtosis
RUWESsent	305	11,7258	9,5096	4,1733	9,2144	100	5,0917	34,8002
RUWESsent_Sanction	305	10,1516	9,7829	2,0532	7,7864	100	4,9317	32,2087
RUWESsent_War	305	14,1903	9,4181	3,5732	11,9718	100	4,8165	32,9811
RUWESsent_GT_WIKI	305	8,7716	9,5423	1,2549	6,0921	100	5,3752	38,1715
US Daily News Index	305	136,4818	54,4759	38,20	126,46	386,40	1,2326	2,5541
Spot Rate 10Y (%)	305	1,5342	0,8483	-0,1073	1,7102	2,8054	-0,4497	-1,0869
VIX	305	24,4136	4,4748	16,46	23,73	36,45	0,4462	-0,7935
BRENT CRUDE	305	96,1391	14,1857	71,03	93,09	133,18	0,5550	-0,6365

Table 8: Summary Statistics of the Independent Variables.

Variables	Obs	Mean	St Dev	Min	Median	Max	Skewness	Kurtosis
RUWESsent	239	0,0009	0,0194	-0,0833	0,0005	0,0578	-0,4310	2,7671
RUWESsent_Sanction	239	9,8935	9,3224	2,0532	7,7332	100	5,8582	45,6717
RUWESsent_War	239	13,8468	9,3443	3,5732	11,6906	100	5,5399	42,1795
RUWESsent_GT_WIKI	239	8,5395	9,3145	1,2549	6,0877	100	6,2917	50,9638
US Daily News Index	239	139,1030	57,2981	38,20	126,89	386,40	1,2371	2,3826
Spot Rate 10Y (%)	239	1,5122	0,8603	-0,1073	1,6917	2,8054	-0,4359	-1,1034
VIX	239	24,1804	4,4434	16,46	23,53	36,45	0,4846	-0,7030
BRENT CRUDE	239	96,2731	14,4006	71,03	92,61	133,18	0,5802	-0,6337

Table 9: Summary Statistics of the Independent Variables Without Outliers.

Identifier (RIC)	Obs	Mean	St Dev	Min	Median	Max	Skewness	Kurtosis
ABNd.AS	305	-0,000012	0,0253	-0,1265	0,0003	0,1081	-0,5718	5,6376
AIBG.I	305	0,0018	0,0272	-0,1099	0,0020	0,1037	-0,0579	1,5613
AVANZ.ST	305	-0,0016	0,0348	-0,1457	-0,0016	0,1173	-0,2385	1,5553
BAMI.MI	305	0,0013	0,0283	-0,1284	0,0019	0,0975	-0,3299	2,4776
BARC.L	305	-0,0017	0,0224	-0,0903	-0,0009	0,0624	-0,6549	1,8834
BAWG.VI	305	-0,0007	0,0228	-0,0979	0,0004	0,0804	-0,8830	3,8253
BBVA.MC	305	0,0004	0,0231	-0,1009	0,0019	0,0831	-0,7171	3,2377
BCVN.S	305	0,0009	0,0149	-0,0800	0,0023	0,0438	-1,2335	4,7601
BIRG.I	305	0,0015	0,0285	-0,1329	0,0031	0,0814	-0,4582	1,9193

BKT.MC	305	0,0003	0,0243	-0,0893	0,0010	0,0821	-0,3738	1,3058
BNPP.PA	305	-0,0008	0,0229	-0,1066	0,0008	0,0949	-0,5870	3,0012
CABK.MC	305	0,0010	0,0238	-0,0902	0,0015	0,0697	-0,3027	1,4162
CAGR.PA	305	-0,0010	0,0200	-0,0837	0,0012	0,0868	-0,6929	4,2165
CBKG.DE	305	0,0005	0,0344	-0,1405	0,0022	0,1097	-0,6092	2,7425
CBRO.L	305	-0,0022	0,0233	-0,1137	-0,0024	0,0815	-0,8013	4,8147
CMBN.S	305	0,0006	0,0164	-0,0761	0,0018	0,0594	-0,4177	2,2406
CRDI.MI	305	0,0009	0,0309	-0,1578	0,0010	0,1160	-0,6439	5,1803
DANSKE.CO	305	0,0011	0,0210	-0,0760	0,0018	0,1131	0,0012	3,4126
DBKGn.DE	305	-0,0012	0,0294	-0,1340	0,0004	0,0767	-0,7824	3,2763
DNB.OL	305	-0,0005	0,0176	-0,0700	0,0000	0,0435	-0,4315	1,0549
EMII.MI	305	0,0009	0,0288	-0,1383	0,0023	0,0952	-0,6269	3,4084
ERST.VI	305	-0,0012	0,0285	-0,1328	-0,0008	0,1257	-0,2595	4,6986
FBK.MI	305	-0,0005	0,0254	-0,0995	0,0014	0,1121	-0,2173	1,9608
HSBA.L	305	-0,0002	0,0185	-0,0662	0,0006	0,0561	-0,2203	1,3944
INGA.AS	305	-0,0007	0,0251	-0,1131	0,0000	0,1103	-0,5066	4,6154
INVP.L	305	0,0004	0,0211	-0,0985	0,0018	0,1028	-0,6077	4,0312
ISP.MI	305	-0,0002	0,0237	-0,0944	0,0014	0,1052	-0,4930	3,1900
JYSK.CO	305	0,0017	0,0267	-0,1059	0,0003	0,1645	0,8041	6,2131
KBC.BR	305	-0,0010	0,0236	-0,1353	0,0003	0,1053	-0,6370	4,8586
LLOY.L	305	-0,0006	0,0209	-0,1166	0,0005	0,0794	-0,4971	3,6707
NDAFI.HE	305	-0,0001	0,0198	-0,1027	0,0009	0,0676	-0,9393	3,8687
NWG.L	305	-0,0004	0,0215	-0,0927	0,0006	0,0870	-0,4724	2,8985
PEO.WA	305	-0,0010	0,0310	-0,1655	0,0001	0,1570	-0,2495	6,2625
PKO.WA	305	-0,0016	0,0295	-0,1927	-0,0012	0,1234	-0,3954	6,8771
RILBA.CO	305	0,0009	0,0193	-0,0791	0,0009	0,0757	0,1416	2,1061
SABE.MC	305	0,0013	0,0309	-0,1257	0,0027	0,1042	-0,3970	1,6766
SAN.MC	305	0,0002	0,0229	-0,0800	0,0000	0,0700	-0,2892	1,2250
SEBa.ST	305	-0,0003	0,0208	-0,0918	0,0020	0,0805	-0,4451	2,3356
SHBa.ST	305	-0,0001	0,0193	-0,1171	0,0008	0,0567	-0,9150	5,9542
SOGN.PA	305	-0,0015	0,0276	-0,1298	-0,0008	0,1092	-0,8740	4,7727
STAN.L	305	0,0007	0,0253	-0,1125	0,0007	0,1308	0,1925	4,3923
SWEDa.ST	305	0,0002	0,0201	-0,1325	0,0017	0,0776	-1,0310	6,4461
SYDB.CO	305	0,0015	0,0235	-0,1155	0,0016	0,0748	-0,2871	2,4949
VMUK.L	305	-0,0010	0,0256	-0,1057	-0,0005	0,1392	0,1632	4,2350

Table 10: Summary Statistics of the Stock Returns.

Identifier (RIC)	Obs	Mean	St Dev	Min	Median	Max	Skewness	Kurtosis
ABNd.AS	239	-0,0008	0,0192	-0,0684	-0,0023	0,0785	-0,0105	1,9419
AIBG.I	239	0,0007	0,0186	-0,0848	0,0008	0,0595	-0,4966	2,7481
AVANZ.ST	239	-0,0006	0,0256	-0,0773	-0,0006	0,0918	0,1023	0,4515
BAMI.MI	239	-0,0012	0,0324	-0,0841	-0,0016	0,1173	0,2367	0,6109
BARC.L	239	0,0012	0,0183	-0,0554	0,0013	0,0794	-0,0570	1,6563
BAWG.VI	239	0,0025	0,0229	-0,0787	0,0010	0,0767	0,3889	1,3579
BBVA.MC	239	0,0023	0,0242	-0,0995	0,0020	0,0829	-0,1962	2,2514
BCVN.S	239	0,0021	0,0196	-0,0602	0,0017	0,0608	-0,1770	1,0777
BIRG.I	239	-0,0003	0,0243	-0,1099	-0,0004	0,0918	-0,4254	4,4410
BKT.MC	239	0,0023	0,0164	-0,0645	0,0021	0,0453	-0,2496	0,6690
BNPP.PA	239	0,0042	0,0253	-0,0702	0,0043	0,0814	-0,0527	0,6487
CABK.MC	239	0,0004	0,0189	-0,0918	0,0023	0,0554	-0,7625	3,0433
CAGR.PA	239	0,0005	0,0197	-0,0735	0,0006	0,0676	-0,1526	1,4910
CBKG.DE	239	0,0030	0,0245	-0,0763	0,0026	0,0975	0,1923	1,8718
CBRO.L	239	0,0028	0,0199	-0,0544	0,0019	0,0668	0,3392	0,9537
CMBN.S	239	0,0007	0,0194	-0,0777	0,0013	0,0621	-0,4174	1,6883
CRDI.MI	239	0,0019	0,0216	-0,0816	0,0023	0,0656	-0,3302	1,1704
DANSKE.CO	239	0,0004	0,0171	-0,0808	0,0018	0,0652	-0,7515	4,6721
DBKGn.DE	239	-0,0001	0,0264	-0,1087	0,0010	0,0957	-0,1348	1,2113
DNB.OL	239	0,0005	0,0191	-0,0533	0,0003	0,0624	-0,0850	0,4254
EMII.MI	239	0,0009	0,0163	-0,0645	0,0016	0,0563	0,0911	1,5206
ERST.VI	239	0,0034	0,0273	-0,1188	0,0027	0,0846	-0,1735	1,5378
FBK.MI	239	0,0019	0,0163	-0,0579	0,0012	0,0587	-0,0862	0,8134
HSBA.L	239	0,0009	0,0194	-0,0833	0,0005	0,0578	-0,4310	2,7675
INGA.AS	239	0,0009	0,0145	-0,0439	0,0018	0,0420	-0,1380	0,3581
INVP.L	239	0,0033	0,0214	-0,0902	0,0029	0,0697	-0,1102	1,6764
ISP.MI	239	0,0009	0,0219	-0,0669	0,0012	0,0795	0,0826	1,3644
JYSK.CO	239	0,0023	0,0195	-0,0779	0,0031	0,0650	-0,2982	2,0955
KBC.BR	239	0,0010	0,0219	-0,0608	0,0018	0,0651	-0,0318	0,5334
LLOY.L	239	0,0011	0,0156	-0,0629	0,0011	0,0440	-0,1532	1,2666
NDAFI.HE	239	0,0032	0,0241	-0,0680	0,0028	0,0874	0,1895	0,7984
NWG.L	239	0,0038	0,0268	-0,0773	0,0038	0,0720	-0,0600	0,6031
PEO.WA	239	0,0015	0,0160	-0,0451	0,0014	0,0423	-0,2034	0,3099
PKO.WA	239	0,0007	0,0212	-0,1131	0,0005	0,0780	-0,5620	4,8476
RILBA.CO	239	0,0016	0,0175	-0,0791	0,0011	0,0757	0,1510	3,5278
SABE.MC	239	0,0019	0,0182	-0,0582	0,0025	0,0870	0,1255	2,0890
SAN.MC	239	0,0021	0,0170	-0,0556	0,0023	0,0485	-0,3424	0,5938
SEBa.ST	239	0,0027	0,0214	-0,0650	0,0003	0,0767	0,1126	0,8276
SHBa.ST	239	0,0013	0,0165	-0,0505	0,0017	0,0548	-0,0944	0,3708
SOGN.PA	239	0,0010	0,0204	-0,0803	0,0018	0,0674	-0,5431	2,7869
STAN.L	239	0,0008	0,0232	-0,1042	0,0002	0,0874	-0,5300	3,8819

SWEDa.ST	239	0,0029	0,0233	-0,0779	0,0035	0,0926	-0,1012	1,8716
SYDB.CO	239	0,0020	0,0134	-0,0521	0,0030	0,0438	-0,4759	1,3448
VMUK.L	239	0,0020	0,0197	-0,0533	0,0011	0,0675	0,1584	0,4194

Table 11: Summary Statistics of the Stock Returns Without Outliers.

B) Correlation Matrix

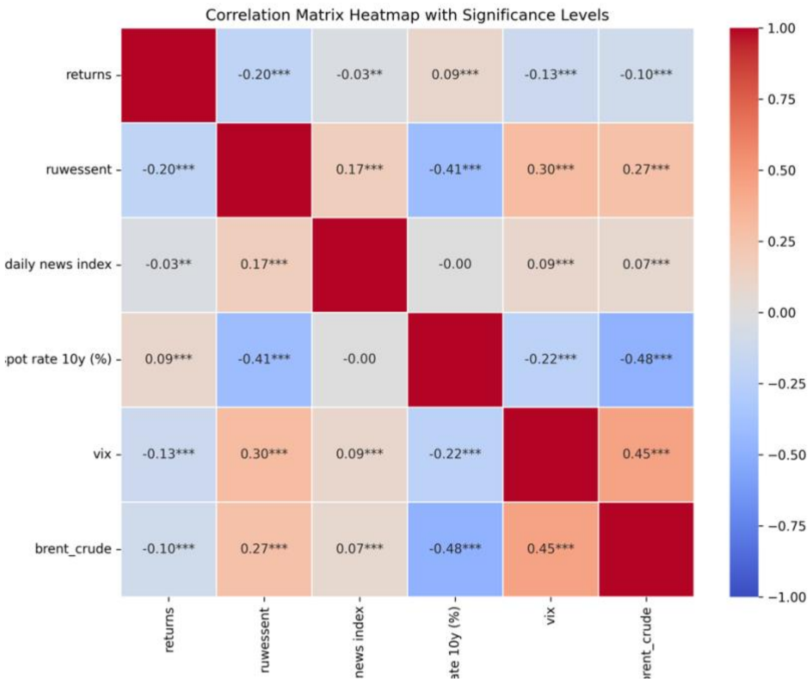

Figure 1: Correlation Matrix with RUWESsent index.

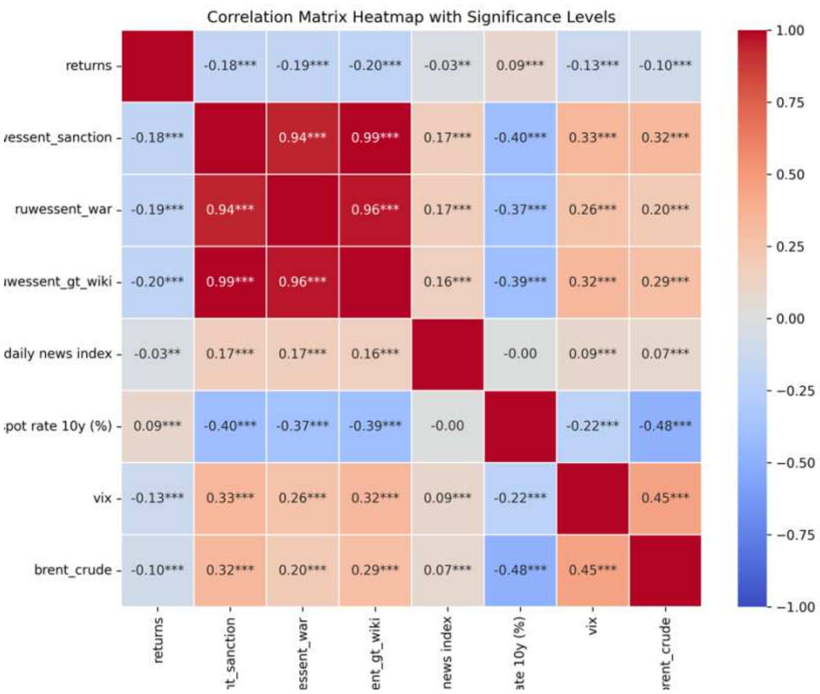

Figure 2: Correlation Matrix with RUWESsent subcomponents.

C)Histograms

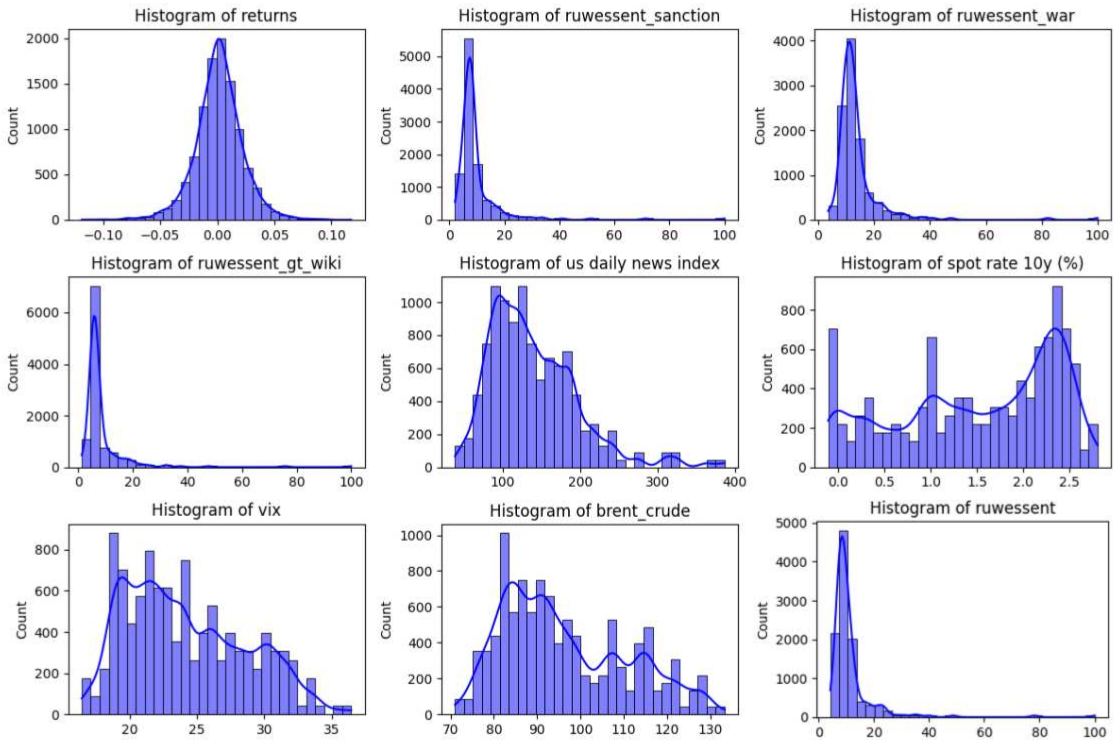

Figure 3: Variables' Histograms.

Prompt List

1. How to remove entire dates from the dataset if any identity has an outlier on that day?
2. I have a panel dataset with 44 identities and 305 dates for each. How to clean it by removing rows (dates) where any identity has missing values?
3. Python script to add country-level identifiers to each bank in the panel.
4. Python script to clean panel data and remove days with missing or outlier values.
5. Python script to detect outliers.
6. Python script to validate whether the panel is balanced, ensuring all banks have data for every date.
7. Python script to handle formatting errors, like inconsistent column types.
8. Python script to generate descriptive statistics for the dataset, including: Mean, Standard deviation, Median, P25, P75, Kurtosis, Skewness, Min, and Max.
9. Python script to compute a correlation matrix for all variables.
10. Python script to generate Histograms for all variables.
11. Python script for Hausman Test.
12. Python script for ADF test for stationarity.
13. Python script for Random Effects Model.
14. Python script for Fixed Effects Model.
15. Python script for Random Effects Model including country-level effects (bank groups by country).
16. How to check and fix multicollinearity?
17. Python script to perform PCA on the sentiment subcomponents.
18. How to spot abnormalities in histograms?
19. How to save model results?
20. How to interpret t-statistics and p-values?
21. Write bullet points summarizing the findings for each estimated model.
22. Compare the results of the models with the general RUWESsent and the subcomponents.
23. Having into account the document I attached where it is the Literature Review, compute a table linking the model findings with existing literature.
24. Summarize these papers, please focus on the methodology section.
25. Compare these papers that use investor sentiment, focus on the differences in sentiment measure, in sample/region studied, and the model specification.
26. Help with the data description chapter in an academic but clear way.
27. Improve the transitions between sections to improve cohesion.

28. Summarize this section, the goal to cut the word count by 50%.
29. How to present limitations and critically evaluate this study in an honest but academic way?
30. Check for grammar errors and improve academic tone.
31. My word count is above the limit, how can I trim it down?