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Risk and Fear Indices as Predictors of Market Crash

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TIIVISTELMÄ:

Tutkielman tarkoituksena on muodostaa käsitys osakemarkkinoiden eri riski- ja pelkoindikaattoreiden markkinaromahduksen ennustekyvystä. Tutkielmassa tarkastellaan tarkemmin Chicago Board Options Exchange Volatility-, Economic Policy Uncertainty-, Geopolitical Risk- ja Global Financial Stress Indeksejä.

Tutkielmassa tarkastellaan aiheeseen liittyvää rahoituksen teoriaa ja kirjallisuutta eri indeksien ennustekyvyn näkökulmasta. Lisäksi tutkitaan indeksien keskinäisiä riippuvuuksia ja niiden mahdollista yhdistämistä ennustusmallien tarkkuuden parantamiseksi.

Tutkielman tulosten perusteella voidaan todeta, että indikaattorit omaavat kyvyn ennustaa markkinaromahduksia. Kriisien erialaisuuden johdosta myös indikaattoreiden ennustekyvyssä on eroa kriisikohtaisesti. Indikaattoreiden yhdistäminen näyttää parantavan ennustekykyä. Tämä löydös tarjoaa lähtökohdan tehokkaamman ja paremman ennustekyvyn omaavan mallin kehittämiselle.

Tutkielma tarjoaa poliittisille päättäjille, tutkijoille ja sijoittajille uusia oivalluksia VIX-, EPU-, GPR- ja GSFI-indeksien ennustuskyvyn hyödyntämiseen kansainvälisillä osakemarkkinoilla ennen markkinoiden romahdusta ja sen aikana.

AVAINSANAT: Osakemarkkinat, Ennustettavuus, Markkinaromahdus, Volatiliteetti, Taloudellinen epävarmuus

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ABSTRACT:
The purpose of the thesis is to gain an understanding of the predictability of various risk and fear indicators in the stock market. The study examines the Chicago Board Options Exchange Volatility-, Economic Policy Uncertainty-, Geopolitical Risk- and Global Financial Stress Indices in more detail.

The thesis examines the related financial theory and literature from the perspective of the predictive ability of different indices. It also examines the interdependencies of indices and their possible combination to improve the accuracy of forecasting models.

Based on the results of the study, it can be stated that indicators have the ability to predict market crashes. Due to the specialization of crises, the predictive ability of indicators also differs from crisis to crisis. Combining indicators seems to improve predictive ability. This finding provides a starting point for the development of a more efficient and better predictive model.

The study provides policymakers, researchers, and investors with new insights into utilizing the predictive power of the VIX, EPU, GPR, and GSFI indices in international stock markets before and during market crashes.

KEYWORDS: Security markets, Predictability, Market crash, Volatility, Economic uncertainty

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1 Introduction

Stock market crashes have historically caused significant financial losses. The losers include private and institutional investors, as well as governments. The most recent crash led to a decline of over 3,1 trillion US dollars shed in market capitalization in a single day, following the announcement of president of United States Donald Trump to set tariffs on April 2, 2025 (Wiltermuth, 2025). This was the biggest market capitalization loss in a single day since the COVID crisis. Such dramatic reactions in the market raise questions about the underlying mechanisms that drive stock price movements.

When studying price movements, there are two main conflicting approaches in financial economics: the Efficient Market Hypothesis and behavioral finance. While the Efficient Market Hypothesis assumes that investors are rational and that market prices fully reflect all available information, behavioral finance offers an alternative view. It accepts people are normal and they can be irrational. It argues that psychological and emotional factors can influence stock prices. Both approaches aim to address solutions for economic and financial problems. Accordingly, the theoretical assumptions and empirical research associated with these two distinct models are essential for comprehending market dynamics.

The dynamics of financial markets and investor behavior have long been central research topics in economics and finance. One particularly significant area of study is the measurement of market stress and uncertainty, as well as the predictive capacity of these factors in predicting market crashes. Various risk and fear indices, such as the VIX (Volatility Index), EPU (Economic Policy Uncertainty Index), GPR (Geopolitical Risk Index) and GSFI (Global Financial Stress Index) have emerged as essential tools for assessing the future direction of financial markets. These indices help investors and researchers understand how financial markets respond to uncertainty and which factors may serve as early warning signals in times of crisis.

The world has faced multiple crises in recent years, including the Global Financial Crisis, the COVID-19 pandemic, and the ongoing Russia-Ukraine war. Recently, the world has also faced the newest market crash after Donald Trump, the president of United States, imposed tariffs. These events have exerted a significant influence on the global economy, stock market returns, and overall market structures. It is crucial to understand how different asset classes and market sectors respond during such periods. This study focuses specifically on the market crashes resulting from the 2008 financial crisis and the COVID-19 crisis, which have been the subject of considerable recent research, particularly from the perspective of prediction (Wang et al., 2020; Tutuncu et al., 2024) There is evidence supporting the predictability of market crashes. As demonstrated by the 2007 financial crisis, structural weaknesses in the markets were observable well before the collapse; however, they were largely either overlooked or not adequately addressed in a timely manner (McKelvey & Yalamova, 2011). Kusumasari et al. (2023) find that countries which have good governance indicators, were able to react faster and managed the Covid-19 crisis better. Crisis and market crashes are recurring phenomenon. This underscores the motivation for examining the topic, as it enables private and institutional investors, as well as regulatory authorities, to take preemptive action before a potential market crash.

This study contributes to the existing literature in the following ways. Previous research demonstrates that volatility and uncertainty indices can provide valuable insights into market movements. For instance, Bollerslev et al. (2018) and Ma et al. (2019) demonstrate that accurate volatility forecasting provides essential insights for market participants, policymakers, and economic agents and is fundamentally linked to the mitigation of extreme financial risks, such as tail risk and risk spillovers. Latif et al. (2025) identify the volatility index, the financial stress index, and economic policy uncertainty as the most significant factors in predicting returns of the S&P 500, reinforcing the effectiveness and the relevance of the study. However, it is appropriate to notice limitations in the predictive power of individual indicators, suggesting that combining multiple indicators could provide a more accurate prediction ability.

This study is highly motivated by the study by Wang et al. (2020). They study VIX and EPU to identify which is more useful to forecast international stock markets during the coronavirus pandemic. The study focus on up to 19 international stock markets including AEX (The Netherlands), All Ordinaries (Australia), BOVESPA (Brazil), CAC 40 (France), FTSE MIB (Italy), FTSE 100 (United Kingdom), DAX 30 (Germany), S&P TSX (Canada), Hang Seng (China Hong Kong), IBEX 35 (Spain), KOSPI (South Korea), IPC Mexico (Mexico), Nikkei 225 (Japan), S&P CNX Nifty (India), S&P 500 (United States), SSEC (China), Swiss Market Index (Switzerland), FT Straits Times (Singapore) and Euro STOXX 50 (Euro Area), making it more advanced compared to other existing studies which mostly focus to only one market area. However, there are still possibilities to expand the study to cover more indices and/or more market areas to improve the quality of study.

This thesis is a literature review that combines and discusses the findings of previous studies on the topic of the dynamics and predictability of stock market during the market crashes. The findings of this thesis may provide valuable insights for private and institutional investors, regulatory authorities, and other market participants seeking to understand market sensitivity to uncertainty factors. A more profound understanding of the functioning of various uncertainty indices could facilitate the development of strategies aimed at anticipating market crashes and managing associated risks more effectively. By doing so, they can safeguard portfolio returns or, in extreme cases, even prevent the market crash and mitigate the risk of a broader global financial crisis.

1.1 Purpose of the study

The purpose of this thesis is to compare different risk and fear indices in terms of their predictive ability regarding market crashes. The study examines how well these indices can anticipate financial market crises and over what time horizon they provide useful information for investors and policymakers. Additionally, it analyzes how different indices react to changes in one another and whether their combination could potentially enhance predictive accuracy.

In contrast to the Efficient Market Hypothesis, which states it should be impossible to predict returns, the existing literature seems to suggest that the indices selected for study have the ability to predict stock market returns during market crashes (Liang et al. 2020; Dai et al. 2021; Salisu et al. 2022; Hoque et al. 2024). An explanation for this might be found in behavioral finance. Behavioral biases might lead to predictable market movements. Based on the preceding discussion, the first hypothesis can be formulated as follows:

H1: Different risk and fear indicators can predict market crashes.

While individual indicators can offer valuable insights, relying solely on a single measure may fail to capture the full complexity and multidimensional nature of financial markets. Market crashes are often driven by multiple interconnected factors, suggesting that a combination of indicators could enhance predictive accuracy (Wang et al. 2020). Similarly, Li et al. (2024) find that by combining EPU and GPR, predictability is improved. By integrating various indicators, it may provide a more comprehensive assessment of financial instability and possible market crash. There is evidence from oil market that combination method improves accuracy of predicting (Baumeister & Kilian, 2013; Zhang et al., 2018). These considerations lead to the formulation of the second hypothesis:

H2: A combination of indicators enhances the accuracy of market crash predictions.

These hypotheses will be examined by evaluating the evidence from prior literature on the predictive power of different indicators individually and in combination, assessing their effectiveness in forecasting market crashes.

1.2 Structure of the study

The first chapter as an introduction defines the background, significance, and objectives of the study. It presents the research questions and hypotheses that guide the literature review. The second chapter discusses the theoretical background of the study. The third chapter presents previous market crashes that are important for the study. The fourth chapter explores and analyzes various indicators and their ability to predict market returns, particularly during market crashes. The fifth chapter evaluates and compares the indicators presented in the previous chapter and justifies the potential benefits of combining multiple indicators in future research. The final section offers a synthesis of the study’s central results and conclusions.

2 Theoretical background

The purpose of this chapter is to provide an understanding of the financial theory relevant to the topic of the thesis. The process of the determination of stock prices is quite simple. It is all about supply and demand. But the factors behind the decision process make it more complicated. The Efficient Market hypothesis and the behavioral finance propose a slightly different perspective on the determination of stock prices.

2.1 The Efficient Market Hypothesis

The efficient market hypothesis (EMH) is a foundational concept in financial economics, asserting that asset prices fully reflect all available information. Fama (1970) identifies three levels of efficiency. The weak form of the efficient market hypothesis suggests that stock prices fully reflect all historical price information, implying that technical analysis cannot be effectively used to generate consistent trading profits. According to the semi-strong form of the efficient market hypothesis, stock prices adjust rapidly to all publicly available information, rendering both technical and fundamental analysis ineffective for achieving excess returns. The strong form of the efficient market hypothesis asserts that all information, both publicly available and private, is fully reflected in current stock prices. That means no investor can consistently achieve superior returns by possessing any type of information. This leads to the conclusion that investors cannot consistently beat the market on a risk-adjusted basis, given that prices reflect all available information and only adjust when new data emerges (Fama, 1970). According to this perspective, forecasting investment returns should be impossible.

Although the hypothesis is a relatively widely accepted concept in economics, it has also been criticized for its simplistic nature. It is not able to fully reflect real-world conditions and has its own limitations. Loredana (2019), in comparing theoretical and empirical research, finds that most empirical studies have rejected the three forms of the Efficient Market Hypothesis, particularly the semi-strong and strong forms of efficiency. Crotty (2009) states that the Efficient Market Hypothesis is dangerous and the theory should be abandoned. It is evident that this theoretical approach overlooks both investor overreaction and underreaction (Loredana, 2019). This phenomenon is particularly present during market crashes when fear and uncertainty have a bigger role in the market movements.

Öztürk et al. (2024) compared normal and abnormal returns and find that all stock markets in BRICS-T countries (Brazil, Russia, India, China, South Africa, and Turkey), except China, were not semi-strongly efficient during Covid-19. They also examine previous literature, finding the conclusion about the weakness of the Efficient Market Hypothesis during the stressful and unstable market conditions. This suggests that, especially in a market situation such as a market crash, pricing mechanisms will not function efficiently. If the prices do not reflect all the available information, that might give a chance to make a profit.

Especially, while focusing the subject of this thesis, it is vital to recognize the limitations of Efficient Market Hypothesis. Higher continuous volatility and under- and overreacting have changed market dynamics. These phenomes have a vital role in the formation of crises.

The previously dominant theory of market efficiency faced a new competitor when behavioral finance became the focus of academic interest. According to López-Cabarcos, et al. (2020) recently, there is an increase in the number of published papers in behavioral finance, indicating its growing significance. Shiller (2003) strengthens the position of behavioral finance as a viable research direction that helps understand the true, often unsystematic nature of financial markets.

2.2 Behavioral Finance

Traditional finance theories expect investors to be rational and the pricing to be efficient. However, from the past to the present, the financial environment has changed. Investors might not be that rational, while making investment decisions. Several theoretical discussions began to shift away from traditional econometric time series analyses, such as examining prices, dividends and earnings towards examining the relationship between the human mind and financial markets from the 1990s onwards, as Shiller (2003) notes. This gave rise to the development of behavioral finance as a response to the limitations of traditional financial theories. According to Kahneman and Tversky (1979), investors often rely on subjective reference points when making decisions, rather than objectively evaluating the best possible outcome.

Behavioral finance helps to understand especially how the stock market and the people behave during periods of positive and negative growth, such as stock market crashes. According to Almansour et al. (2023) behavioral finance also suggests that cognitive biases can amplify market volatility, making fear indices a reflection of collective sentiment that may precede large price movements. Mahjoubi et al. (2024) find that according to many researchers have proposed behavioral biases and feelings as a reason why crises have expanded.

2.2.1 Herding behavior

The influence of risk perception on stock returns initiates herding behavior. Many investors follow the crowd to avoid risk. During herding behavior, individuals who typically act rationally begin to behave irrationally by relying on the judgments of others. This phenomenon may stem from a lack of investment knowledge or an inherent tendency to conform to the opinions and actions of peers. Herding behavior increases during times of market uncertainty and volatility. This intensified behavior increases investment risk, as decisions are made more often based on market sentiment than on rational evaluation of risks (Almansour et al. 2023). As the phenomenon intensifies, it may offer an opportunity to predict returns as the market reaction intensifies as investors join in the selling on the very early stage of a market crash.

Covid-19 was a great example of herding behavior. Many investors began massive sales, following the behavior of others, even though the long-term prospects of the companies were not yet fully clear. Herding behavior significantly increased volatility and accelerated the price decline. However, many markets fixed quite fast. The decrease in the stock prices was mostly fear which did not last long (Çütcü, 2020). Covid-19 will be examined more specifically in chapter 3.

2.2.2 Overconfidence

Overconfidence is a cognitive bias whereby investors overestimate their investment skills, frequently leading to the assumption of unnecessary risks. Confident investors have a positive perception of risk, and this can be seen when making investment decisions (Almansour et al. 2023). They identify overconfidence as one of the key behavioral biases shaping investor decision-making. Mahjoubi et al. (2024) argue that overconfidence bias can help explain the stock market volatility. The role of overconfidence before and throughout the Global Financial Crisis might be vital. As examined in chapter 3, there were only few people who took early warnings of the crisis seriously. Investors were too confident to slow down and took too much risk, which boosted the crisis (Crotty, 2009).

2.2.3 Loss aversion

Loss aversion posits that individuals tend to be more sensitive to losses than to equivalent gains. A loss hurts about twice as much as a gain of the same size makes you happy (Kahneman & Tversky, 1979). This behavioral bias leads to investors reacting more strongly to negative news than to positive news. This means that investors may overreact and sell off, causing predictable movements in the stock market. Loss-averse investors quickly sell off unsafe assets, adding to the downward pressure.

2.2.4 Disposition effect

The disposition effect, characterized by the propensity to prematurely sell winning investments while holding the loss-making stocks too long, is also one of the behavioral biases observed in investor behavior. This behavior is driven by a desire to avoid realizing losses, even at the expense of potential gains. The disposition effect is particularly pronounced in long positions compared to short ones and can distort market reactions as well as affect price development. Previous research offers substantial evidence supporting the existence of the disposition effect and its impact on investment decision-making (Almansour et al., 2023).

From a critical perspective, the disposition effect may weaken the predictive power of risk indicators in the early stages of market crashes, as investors might delay reacting to deteriorating market conditions. Avoiding loss realization can create a false sense of market stability just before a downturn.

Overall, behavioral biases play a significant role in stock market dynamics. These biases can lead to systematic deviations from rational decision-making, contributing to market inefficiencies and volatility (Almansour et al., 2023). Generally, behavioral finance provides a theoretical foundation to understand why fear and risk indices may serve as early indicators of financial instability. By acknowledging the role of human psychology in investment behavior, this framework offers a deeper understanding of market dynamics, particularly during periods of stress and uncertainty.

3 Market crashes

Several studies have reached a consensus on the importance of monitoring unsustainable developments across various segments of the financial market. This includes not only the traditional banking sector and capital markets, but also rapidly evolving structured financial instruments and financial innovations. The systemic risk implications of many of these newer instruments remain insufficiently understood (Financial Cycles Around the World, 2022). This section examines recent market crashes and their causes.

A market crash is a sudden and significant decline in stock prices across a broad market, often triggered by economic instability, financial crises, or investor panic. These crashes can lead to widespread financial losses, reduced consumer confidence, and economic recessions. Historical examples, such as the 2008 Financial Crisis and the Covid-19, highlight the devastating impact of market crashes on global economies. Crises are always different. For instance, the environment in general and the causes during the next presented crises were totally different. It is still important to learn the reasons behind them to not make the same mistakes again. Nevertheless, it is quite sure that the world will face many crises regardless of how prepared all the institutions are for it.

3.1 The Global Financial Crisis

The 2008 financial crisis, commonly referred to as the Global Financial Crisis (GFC), was a worldwide economic collapse that originated in the United States and quickly spread globally. It was one of the most severe economic shocks after the Great Depression of the 1930s. The crisis was driven by several factors related to banking and financial sector practices, regulatory shortcomings, and structural and behavioral issues in the financial markets (Crotty, 2009).

Yalamova and McKelvey (2011) demonstrate how the 2007 liquidity crisis and the subsequent global financial crisis emerged from a combination of excessive leverage, derivative trading, and unstable investment instruments. They argue that financial experts on

Wall Street and within the U.S. government likely possessed sufficient knowledge to foresee and mitigate the progression toward the crash. It is interesting that if they have the knowledge, why did they not act. According to Crotty (2009), the root cause of the global financial crisis lies in the fundamentally flawed institutions and practices associated with the so-called New Financial Architecture. This term refers to the integration of contemporary financial markets with the period's minimal regulatory oversight. This arrangement has been defended and praised within the Efficient Market Hypothesis. It is understandable that theory has been criticized. The theoretical basis has been widely challenged, as observed in the previous chapter, and this has also led to practical challenges and problems.

3.2 The COVID-19 Crisis

The COVID-19 Crisis was above all a health crisis, but also a significant economical and financial crisis. Table 1 presents the key dates of rapid spread of the virus to global pandemic. The crisis spread to the stock market at the end of February 2020 causing a market crash. Major indices fell by up to 30 percent (Çütcü, 2020). In addition, the economical environment was challenging to manage financial crisis. Interest rates were histrically low and supply and demand disruptions occured simultaneously. It can be said that the crisis was very different from what had been faced before and, especially since the world was truly integrated, the crisis quickly spread worldwide. Prediction of a crisis like this might be challenging because of the dissimilarity with previous crises. There still was some early signs of the market crash.

Date	Event
December 31, 2019	Cases of pneumonia detected in Wuhan, China, are first reported to the WHO. During this reported period, the virus is unknown. The cases occur between December 12, and December 29, according to Wuhan Municipal Health.
January 1, 2020	Chinese health authorities close the Huanan Seafood Wholesale Market after it is discovered that wild animals sold there may be the source of the virus.
January 5, 2020	China announces that the unknown pneumonia cases in Wuhan are not SARS or MERS
January 7, 2020	Chinese authorities confirm that they have identified the virus as a novel coronavirus, initially named 2019-nCoV by the WHO.
January 11, 2020	The Wuhan Municipal Health Commission announces the first death caused by the coronavirus. A 61-year-old man, exposed to the virus at the seafood market, died on January 9, after respiratory failure caused by severe pneumonia.
January 13, 2020	First cross-border transmission as Thai authorities report a case of infection caused by the coronavirus. The infected individual is a Chinese national who had arrived from Wuhan.
January 30, 2020	WHO declares 2019-nCoV to be a "Public Health Emergency of International Concern"
February 11, 2020	WHO announces a new name for the virus, COVID-19
March 11, 2020	WHO declares COVID-19 to be a Pandemic

Table 1. Key dates in the Chinese COVID-2019 outbreak (Corpet et al., 2020).

Overall, financial crises and market crashes are complex phenomena with causes that can vary significantly over time. As demonstrated above, past crises have been triggered by different underlaying factors. Therefore, accurately predicting them requires careful attetntion to the most relevant indicators. Changes in the real economy can increase exposure to specific types of risks, making it essential to identify and monitor those shifts. A deep understanding of the broader economic context, market dynamics, and potential triggers is crucial for developing a reliable predictive perspective.

4 Indices

This chapter introduces the chosen indices and explores their role in previous market crashes, especially in the Global Financial Crisis (GFC), COVID-19, and the Russia-Ukraine War. The indices under study have been selected based on their significance in relation to previous research, and each choice is justified in the following subsections.

4.1 Chicago Board Options Exchange Volatility Index

The Chicago Board Options Exchange Volatility Index (VIX) is a volatility index calculated by the Chicago Board Options Exchange (CBOE) that measures the expected volatility of the market over the next 30 days. Volatility refers to fluctuations in asset prices, ranging from frequent small movements to occasional large swings, with market crashes representing the most extreme form of volatility (Yalamova and McKelvey, 2011). The index is based on the implied volatility of options on the S&P 500 index and is generally considered a measure of market risk or "fear" (Whaley, 2009). The VIX has its roots in financial economics research, where Brenner and Galai (1989) propose the creation of a set of volatility indices, starting with the stock market volatility index and subsequently extending to interest rate and exchange rate volatility. The current value, the charts and the data of VIX is available from CBOE website (Chicago Board Options Exchange, n.d.).

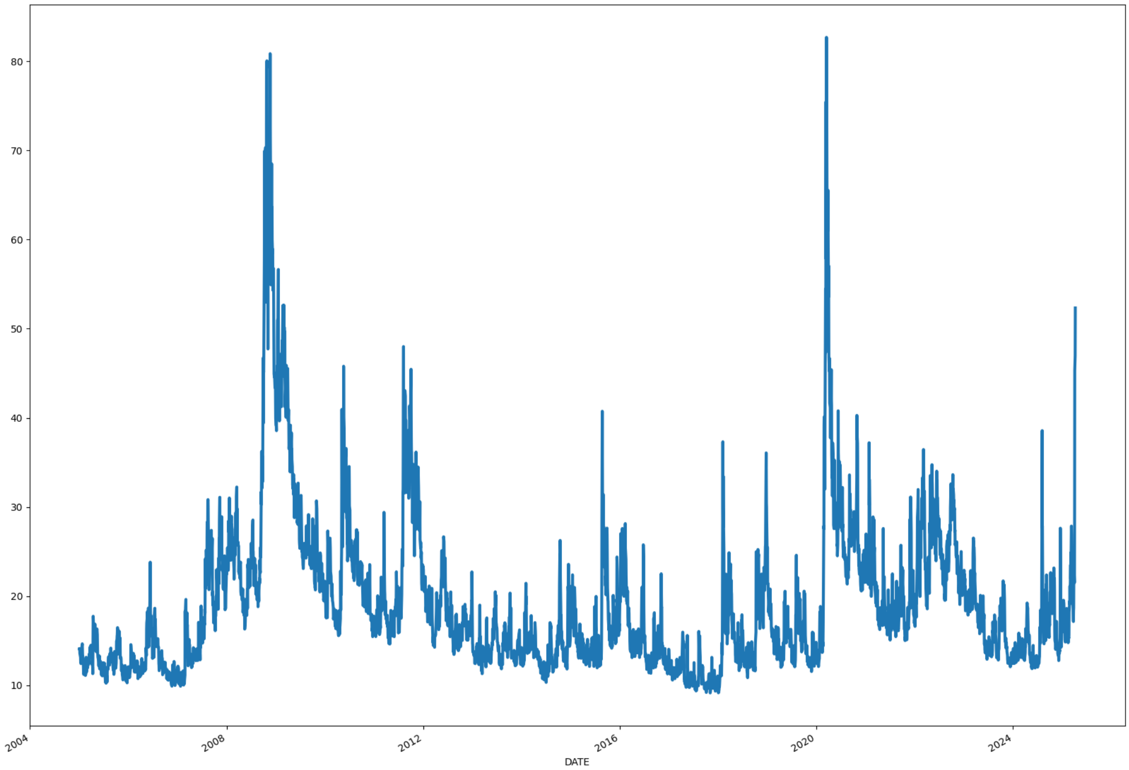

Figure 1. The chart of VIX Index from January 1, 2005 to April 8, 2025 (Chicago Board Options Exchange, n.d.).

VIX's position and recent research support the theory of behavioral finance, in which investors' reactions, often exaggerated ones, influence market prices. VIX may therefore act as an effective mirror of collective emotional decision-making. As seen in figure 1, VIX has been historically high in the last days and its movements are cyclical. The three largest peaks in the chart are the Global Financial Crisis at 2008, COVID-19 at 2020, and the latest peak can be attributed to tariffs imposed by the United States.

The status of the VIX is undoubtedly significant in current research field and practical investment use, but it still has its limitation relying too much to the United States stock market. Rubbaniy et al. (2014) find that VIX is positively related to short term stock returns. Results of their study show that implied volatility indices (VIX, VXN and VDAX) are able to predict forward looking 20- and 60-day returns. They highlight a slightly more consistent and more significant relationship between the VIX and the returns of the S&P

500. Similarly, Liang et al. (2020) examine the predictive ability of the VIX across eight international stock markets; the results indicate that the VIX index has strong predictive power from October 24, 2006, to December 31, 2018, including Global Financial Crisis. In crises like Global Financial Crisis which expanded from United States, VIX might have better predictability, than in the crises which start from somewhere else. However, it is crucial to adapt the fact that United States stock market is the biggest and the most important market when discussing or reviewing stock market overall. Is VIX a truly global indicator, or does it primarily reflect the psychology of US investors, which is then reflected in other markets as well?

Despite the high relationship with the United States stock market, VIX has proven to have a good predictive ability even in the crashes not highly related to United States. Rahman et al. (2022) evaluate the predictive accuracy of IV indices and their information efficiency during the initial phase of the Covid-19 pandemic. They find significant connection between IV indices and stock market returns. These indices, including VIX, provide critical information efficiently and can predict the returns not only in the United States, but also in Europe.

VIX has managed its accuracy even in the latest events on the market. Bossman et al. (2023) emphasize the VIX's effectiveness as a hedging instrument against the downside risk of EU stocks, particularly during recent periods of heightened uncertainty, such as the Russia–Ukraine conflict. While their results reinforce VIX’s position as a significant predictor also in non-US crises, its generalizability to wider market contexts needs to be critically examined.

4.2 Economic Policy Uncertainty Index

The Economic Policy Uncertainty (EPU) Index is a measure of economic policy uncertainty developed by Baker, Bloom, and Davis (2016). It quantifies the level of uncertainty in economic policy by analyzing the content of major newspapers and other news sources. The index is based on keyword searches that identify terms related to the economy, policy, and uncertainty. The index is calculated for multiple countries and regions. It is available on the research group's website (Economic Policy Uncertainty, n.d.). The study by Du et al. (2021) demonstrates that economic policy uncertainty plays a critical role in amplifying the risk of abrupt stock price declines.

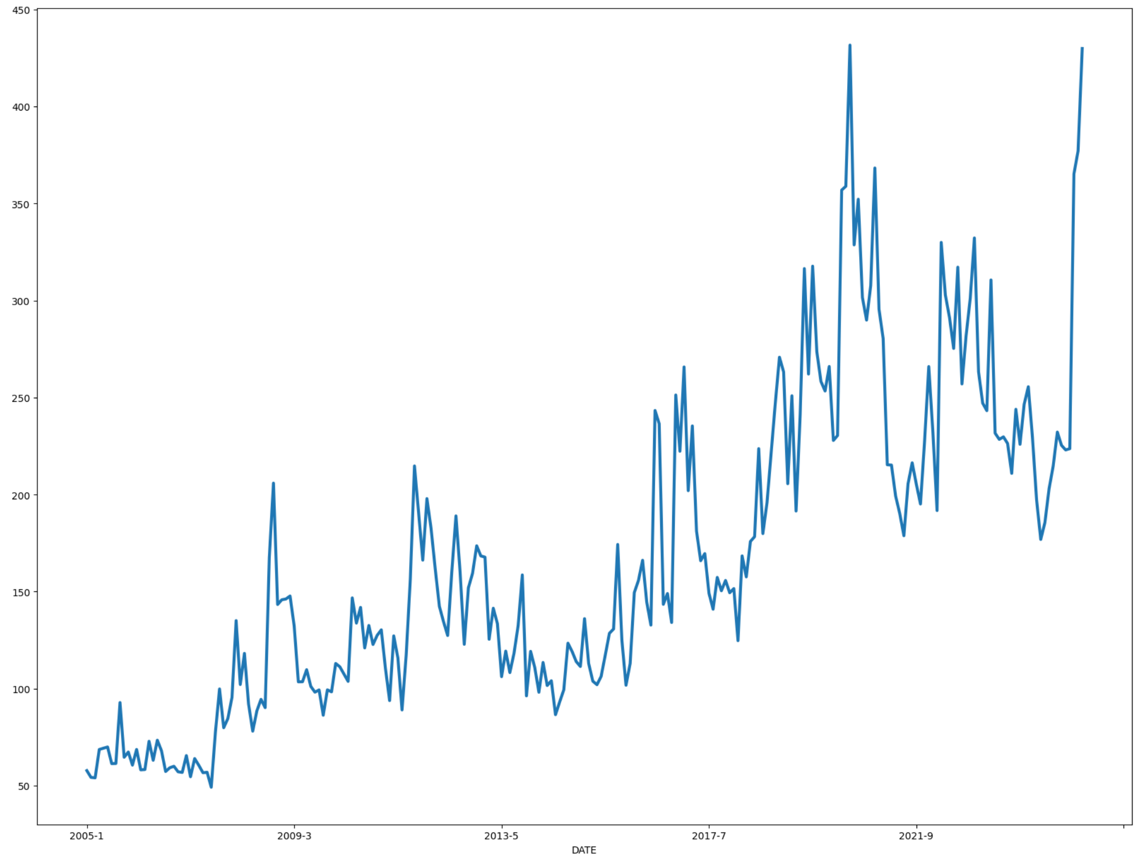

Figure 2. The chart of Economic Policy Uncertainty Index from January 2005 to January 2025 (Economic Policy Uncertainty, n.d.).

The peaks during some crashes can be seen clearly, but the increasing trend seems to be more interesting observation (see Figure 2). The lowest values of the index after 2019 are more than 100% higher than in the period before 2018. The reasons behind that might be related to increased role of the governments. The crises themselves might increase uncertainity.

Dai et al. (2021) find a significant positive correlation between EPU and stock market crash risk, indicating that an increase in EPU, increases crash risk. Furthermore, the positive correlation strengthens after the global COVID-19 pandemic, suggesting that EPU has a greater impact on the crash risk of the U.S. stock market during the epidemic. Tutuncu et al. (2024) demonstrate that the Economic Policy Uncertainty indices of the United States, the United Kingdom, and Germany had the most significant impact not only on their respective stock markets but also on those of other G7 countries.

The war between Ukraine and Russia increased uncertainty, negatively affecting the functioning of global financial markets and driving up commodity prices. These market reactions seem to diminish over time as the war persists. Additionally, Boungou and Yatié (2024) observe that market reactions to uncertainties induced by war are more pronounced in Europe and the Americas. More specifically, a one percent increase in uncertainty leads to a 0.06 percent decline in global stock market indices. There are also contradictory findings. Yao and Sun (2018) observe that in 2016 higher EPU did not indicate lower returns of observed stock returns. Instead, it increased the prices of stocks.

4.3 Geopolitical Risk Index

Geopolitical Risk (GPR) Index is a measure that assesses the impact of geopolitical tensions and crises on the economy and financial markets. Developed by Caldara and Iacoviello (2022), the index is constructed based on an analysis of newspaper articles that track adverse geopolitical events, such as wars, terrorist attacks, and international conflicts. By quantifying the frequency of such events in media coverage, the GPR Index provides insights into the economic and financial implications of geopolitical uncertainty. The GPR index is built using eight geopolitical-related categories: War Threats, Peace Threats, Military Build-ups, Nuclear Threats, Terror Threats, Beginning of War, Escalation of War and Terror Acts. The data and the chart is published daily on their website (Matteoiacoviello, n.d.).

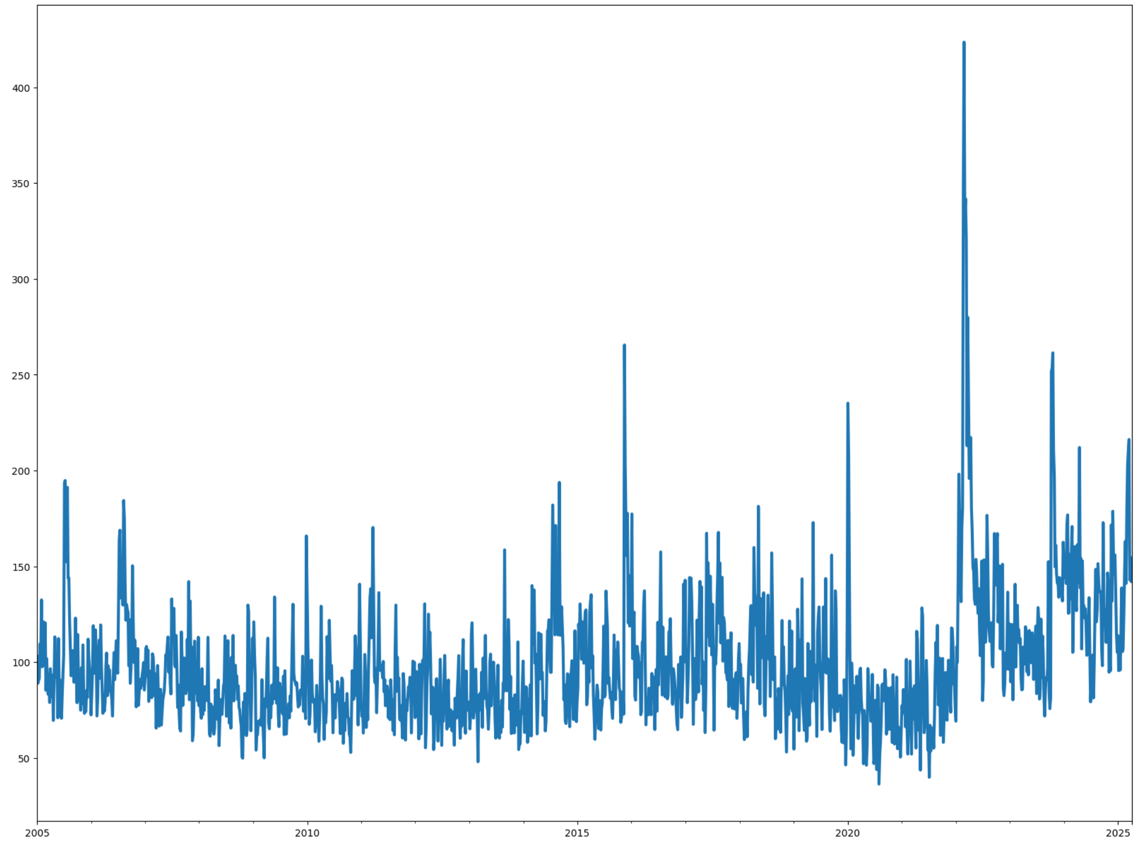

Figure 3. The chart of Geopolitical Risk Index from January 1, 2005 to April 8, 2025 (Matteoiacoviello, n.d.).

As seen in figure 3, the chart of Geopolitical Risk Index appears relatively stable in certain crises. This is because not all crises originate from geopolitical or political events. For example, the Global Financial Crisis. In contrast, during the Russia-Ukraine war, the index shows a clear and strong response, reflecting the political nature of the event.

Geopolitical Risk Index has been identified as a significant predictor of stock returns in nearly all advanced economies, including the G7 countries and Switzerland (Salisu et al., 2022). Several studies highlight the significance of Geopolitical Risk (GPR) in influencing stock returns, both in the short term and, more notably, over the long term (Cokro Darsono et al., 2024; Chen et al., 2024). Stock markets suffer more from the threats of geopolitical risks than from their actual occurrences. So, even if the responsiveness is not clearly seen in figure 3, it actually manages quite well, especially in the long term.

Salisu et al. (2022) demonstrate that advanced markets are vulnerable to geopolitical risk and, therefore, cannot be considered effective hedges against it. This underscores their vulnerability to global shock factors and challenges the conventional assumption that international diversification inherently enhances portfolio resilience. Furthering this perspective, Hao et al. (2024) offer deeper insight by illustrating that geopolitical risk (GPR) functions not merely as a broad macroeconomic backdrop, but as a dynamic variable with rapid and observable effects on risk transmission across markets, even with a one-day lag. These findings position GPR as a highly relevant and actionable indicator in contemporary risk management practices. Overall, the findings presented in this paragraph contribute to an important discussion regarding the influence of geopolitical risks on advanced stock markets and their perceived role as safe havens or tools for effective risk management.

4.4 Global Financial Stress Index

The Global Financial Stress Index (GFSI) is a key international indicator of economic and financial fundamentals. It is designed to capture vulnerabilities in global financial intermediation and assess systemic risks within the financial system. Additionally, the index serves as a tool for monitoring conditions in global financial markets. Specifically, the GFSI is constructed from 33 market variables (Office of Financial Research, n.d.). It covers information about stress from 5 asset classes (stocks, interest rates, credit, foreign exchange, and commodity markets) and 3 financial market pressures in different regions (risk, hedging demand, and investor risk appetite) (Liang et al., 2023). GFSI is obtained from the Office of Financial Research. The data and the charts are published on their website (Office of Financial Research, n.d.). According to the Office of Financial Research, the index takes on positive values when financial stress levels are above average, and negative values when stress levels fall below the historical average.

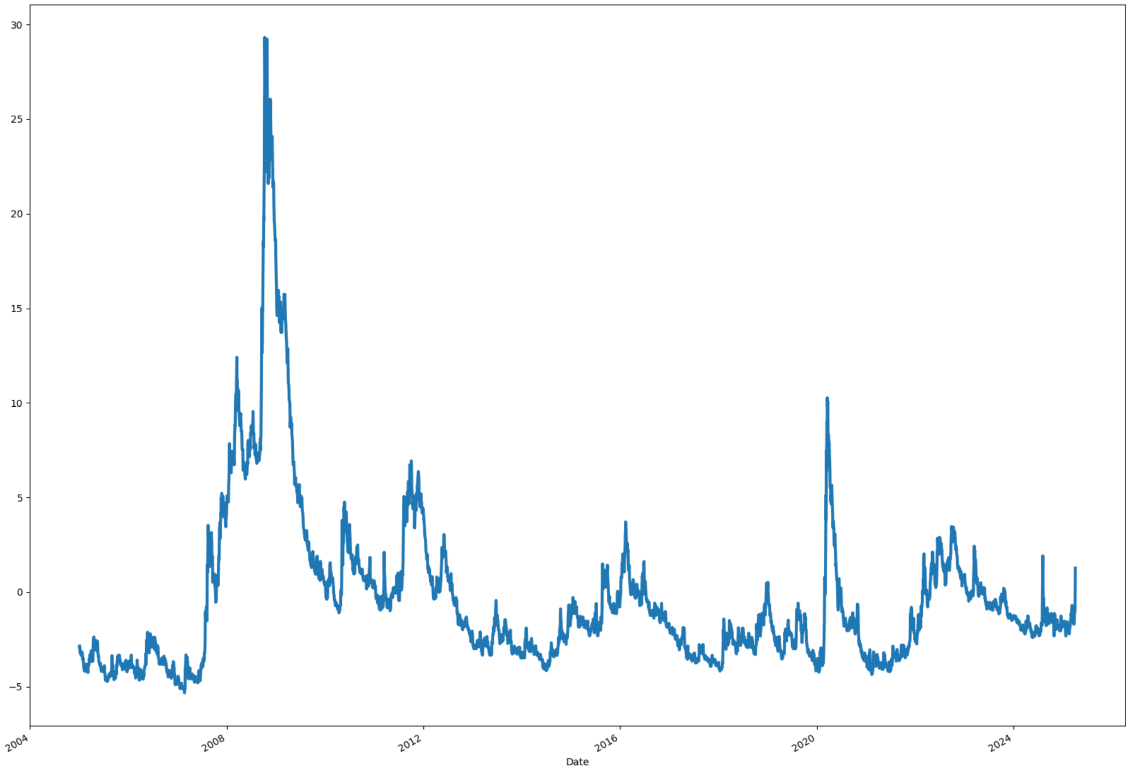

Figure 4. The chart of the Global Financial Stress Index from January 1, 2005 to April 4, 2025 (Office of Financial Research, n.d.).

The responsiveness of GFSI can be clearly seen in figure 4. The Global Financial Crisis, COVID-19, and the Russia-Ukraine War have significantly increased the stress level. Based on the chart it is still hard to make a conclusion about predictability even if the responsiveness is clear. It is reasonable to examine the literature more specifically.

The Global Financial Stress Index has not been extensively studied, yet a few studies present bold insights into its effectiveness from a forecasting perspective. Liang et al. (2023) demonstrate that the GFSI exhibits significant predictive capability over the long term and the findings remain robust even during the COVID-19 pandemic. Hoque et al. (2024) examine the volatility linkages between the Global Financial Stress Index (GFSI) and U.S. financial sectors under low, moderate, and extreme volatility conditions. Their findings indicate that the interdependence between financial stress and U.S. indices intensifies during periods of extreme volatility.

Hoque et al. (2024) demonstrate the predictive role of the Global Financial Stress Index in the realized volatility of global equity indices. Their findings show that the five component-based categories and three region-based categories of the GFSI yield more accurate forecasts than the raw GFSI itself. Specifically, during the COVID-19 pandemic and the 2008 global financial crisis, the combination model outperformed the raw GFSI. It may be important not only to use these indicators, but also to enhance their effectiveness through more sophisticated applications and modeling techniques. Hoque et al. (2024) provide compelling evidence that the categorized structure of the Global Financial Stress Index significantly enhances the prediction of stock market volatility. This finding challenges the simplified assumptions of market efficiency and validates the ability to predict market crashes more reliably. Notably, the success of the combination model raises important questions about the temporal dynamics of forecasting models.

5 Predictability

In this chapter, hypotheses are reviewed. Ability to predict is examined and indices presented in the previous chapter are compared. In the second subchapter, the combination is examined.

5.1 Predictive power overall

As demonstrated above, chosen indices have the ability to predict market crashes. Because of the different nature of the indices, there are some differences in predictability accuracy in different crises. In this chapter, indicators will be compared by examining the existing literature.

Li et al. (2024) examine the predictability of EPU and GPR in China's stock market, especially Shanghai Stock Exchange 50-index. They use GARCH-MIDAS model. GARCH-MIDAS allows combining samples with different frequence to one model. In this case, it is about daily and monthly data samples. They find that when compared to other's countries EPU indices China's EPU index is the most effective in forecasting the volatility of the Chinese stock market.

VIX is still held as a more accurate predictor in general and in wider research. Especially long-term predicting ability of VIX is better as EPUs, as Liang et al. (2023) find in their study. They find also that GFSI is even more accurate. Given the composite nature of the GFSI, this result is not unexpected. Nevertheless, further empirical validation is required to firmly establish GFSI's reliability and position in the literature.

Wang et al. (2020) examine the effectiveness of popular predictors in forecasting international stock markets during the COVID-19 pandemic, comparing the Volatility Index and Economic Policy Uncertainty Index. Their findings indicate that the VIX index serves as a more reliable predictor of future volatility across most stock markets during the crisis. They find that the VIX index has the best ability to predict for most of the stock market. Shaikh (2019) finds that VIX seems to react before the news and EPU after the news. That makes the VIX faster to respond to the possible fears, thus making it better predictor.

Overall, the hypothesis 1 is supported by several studies (Cokro Darsono et al., 2024; Chen et al., 2024; Rubbaniy et al., 2014; Liang et al., 2020; Rahman et al., 2022; Bossman et al., 2023; Dai et al., 2021; Tutuncu et al., 2024; Boungou and Yatié, 2024; Salisu et al., 2022; Boungou and Yatié, 2024; Hoque et al., 2024; Hao et al., 2024). These studies provide empirical evidence that the selected risk and uncertainty indicators possess predictive power in identifying potential stock market downturns. However, Yao and Sun (2018) present a contrasting view. They identify periods during which the Economic Policy Uncertainty (EPU) index yielded negative or inconclusive results in relation to the hypothesis.

5.2 The combination of indices

Even if some of the indices, especially VIX and GFSI, have strong predictive ability, they have their own limitations. Stock markets are complex and often exhibit random behavior, which limits the ability of a single model to fully capture market dynamics. The forecast combinations approach is an effective way to manage model uncertainty and enhance the robustness of forecasts. Hoque et al. (2024) state that in the future, they aim to incorporate other significant global macroeconomic indicators and new combination predicting methods to enhance the predictability of stock market volatility. According to Wang et al. (2020), forecasting accuracy is improved based on forecast combinations. Similarly, Rubbaniy et al. (2014) propose that the VIX has a good predicting power, it is not able predict the returns alone. Therefore, other factors also should to be considered when predicting future returns.

In other indices as well, combining appears to improve forecast accuracy. Li et al. (2024) find that when combining EPU and GPR, it improves the overall predictive accuracy of the model presented in chapter 4.5. It is natural that two indices which have good predictability by themselves, have better predictability when combined with each other. Overall, the combination of indices seems to increase the predicting ability.

In general, the combination can be held as a improving method. The combination notices more factors, which is mandatory in the comprehensive stock market. Baumeister & Kilian (2013) find that suitably constructed forecast combinations give better results than traditional predicting methods when predicting the real price of oil. Similarly, Zhang et al. (2018) come to the same conclusion when examining the forecasting the prices of crude oil. They use 18 variables related to macroeconomics and 18 technical indicators.

Based on the papers discussed in this chapter, hypothesis 2 receives limited support. The findings are not significantly clear due to the small number of papers. This highlights the need for further research on the topic. In particular, the approach taken by Zhang et al. (2018) in combining a large number of indicators, offers valuable direction for future research.

6 Conclusion

This thesis examines how different risk and fear indices perform to predict market crash and how the combination of them would affect the predicting ability. Volatility Index, Economic Policy Uncertainty Index, Geopolitical Risk Index and Global Financial Stress Index are examined individually and compared with each other. Their ability to predict market crashes is examined during previous crashes including the Global Financial Crisis, COVID-19 Crisis and current Russia-Ukraine War.

In this study, it is shown that predicting stock market crashes is possible. Behavioral finance recognizes behaving biases that seem to happen repeatedly and the markets are not always that efficient. The findings of many studies support the first hypothesis (Cokro Darsono et al., 2024; Chen et al., 2024; Rubbaniy et al., 2014; Liang et al., 2020; Rahman et al., 2022; Bossman et al., 2023; Dai et al., 2021; Tutuncu et al., 2024; Boungou and Yatié, 2024; Salisu et al., 2022; Boungou and Yatié, 2024; Hoque et al., 2024; Hao et al., 2024). According to several studies the ability to predict overall is robust. Especially, VIX index in the short term and GFSI in the long term. EPU and GPR do not necessarily react fast enough to the changing circumstances. There are differences in how indices react depending on the crisis. Because of this, the second hypothesis is settled.

The second hypothesis that states a combination of indicators enhances the accuracy of market crash prediction, is supported by few previous studies (Wang et al., 2020; Rubbaniy et al., 2014; Li et al., 2024). There is evidence from oil market that combination method improves accuracy of predicting (Baumeister & Kilian, 2013; Zhang et al., 2018). Although some studies provide evidence regarding the combination of indicators, no clear conclusion can be drawn about the hypothesis. Based on the understanding of how different market crashes might occur, many potential risk factors and predictors must be considered. Crises give different signals depending on their type. Because of this, it suggested that creating a more comprehensive predicting model might improve predicting accuracy.

The study's findings have important implications for private and institutional investors, fund managers, and governments. Awareness of how risk perception contributes to the prediction of market crashes enables financial professionals to refine their investment strategies and risk management approaches. Private and institutional investors and fund managers should pay attention to these insights in their investment processes, enabling more effective portfolio and risk management. Governments are able to take preventive measures and/or prepare for market crashes and their consequences. Overall, this thesis offers new ways to leverage the predictive capabilities of the VIX, EPU, GPR, and GFSI indices in predicting stock market movements before and during crashes. Based on the improvement in predicting accuracy as a result of combining indices, new predicting model should be developed.

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