NUI MAYNOOTH

Ollscoil na hÉireann Má Nuad

PERFORMANCE AND FACTOR STRUCTURE OF GREEN, GREY AND RED SECURITIES IN EUROPEAN UNION COUNTRIES

by

Ferdinantos Kottas,

MSc Data Science, MSc Business Analytics, MPhil Econ, MSc Fin, BSc Math

National University of Ireland Maynooth

A thesis submitted in the fulfilment of the requirements for the degree of
Doctor of Philosophy (Ph.D.) in the School of Business,
Maynooth University, Maynooth, Co. Kildare

Jun 2025

Supervised by Thomas Flavin & Gregory Connor, Professors of Finance

Table of Contents

List of Figures 4

List of Tables... 5

Acknowledgements 7

Conferences and Publications 8

Chapter 1: Introduction 9

1.1 Background and Context 9

1.2 Purpose and Significance of the Study 10

1.3 Definitions and Categorization of Securities..11

1.4 Theoretical Framework and Asset Pricing Models 11

1.5 Impact of Financial Crises on Green, Grey and Red Securities 12

1.6 Comparative Performance Analysis of Green and Red Securities 13

1.7 Influence of Sentiment and Economic Uncertainty 14

1.8 Contribution to Knowledge and Implications 15

1.9 Structure of the Dissertation 16

Chapter 2: Factor Structure of the Green, Grey and Red EU securities 18

Abstract 18

2.1 Introduction 18

2.2 Identifying the Asset Class: Green, Grey and Red...................................19

2.3 Factor Models and Extensions 23

2.4 Data Collection 25

2.5 Independent and Control Variables 27

2.6 Methodology 27

2.7 Empirical Results and Findings 32

1.7.1 Summary statistics of Green, Grey, and Red securities returns..32

1.7.2 Factor structure of Green, Grey, and Red securities 34

2.8 Robustness tests...53

2.9 Application Based on Asset Class and Factor Exposures 55

2.10Conclusion and Discussion 56

Chapter 3: Performance of Green vis-à-vis Red EU Securities 61

Abstract 61

3.1 Introduction 61

3.2 Asset Class, Factor Models and Two-Step Regression 63
3.3 Methodology 66
3.4 Performance of Green over Red 68
3.4.1 Summary statistics of Green, and Red risk-adjusted alpha 68
3.4.2 Statistical Analysis of Alpha values 74
3.4.3 Green vis-à-vis Red risk-adjusted alpha performance 76
3.5 Conclusion 80
Chapter 4: European Green, Grey, Red Securities and crisis sentimental 83
Abstract 83
4.1 Introduction 83
4.2 Exploring Sentimental Indexes: Historical Insights and Cases for applying Sentimental Indexes 86
4.3 Data Description and Methodology 89
4.3.1 Data Description 89
4.3.2 Crisis Indexes: Methodologies and Construction 91
4.4 Empirical Results and Findings 105
4.4.1 Analysis of Time-Series Factors 105
4.4.2 Model Results 108
4.5 Conclusion 125
Chapter 5: Conclusion, Discussion and Future Research...............................130
References...133
Appendices...145

List of Figures

Figure 4.1: Fears Indexes ………………………………………………………………………....95
Figure 4.2: US & EU General CSI Indexes …………………………………………………………98
Figure 4.3: Google Search Volume Indices for crisis-related search terms ………………………...99
Figure 4.4: Global Economic Policy Uncertainty (GEPU) Index - Level ……………………….....101
Figure 4.5: Global Economic Policy Uncertainty (GEPU) Index – Return (%) …………………...101
Figure A3.1: Density plot for the risk adjusted alphas of monthly excess returns from 3FFM for the Green & Red assets……………………………………………………………………………159
Figure A3.2: Density plot for the risk adjusted alphas of monthly excess returns from 4CM for the Green & Red assets……………………………………………………………………………159
Figure A3.3: Histogram and Density plot for the adjusted alphas of monthly excess returns from 5FF for the Green & Red assets…………………………………………………………………………160
Figure A3.4: Density plot for the adjusted alphas of monthly excess returns from 3FF +QMJ+BAB for the Green & Red assets………………………………...160
Figure A3.5: Density plot for the adjusted alphas of monthly excess returns from 4CM +QMJ+BAB for the Green & Red assets…………………………………………………………………………161
Figure A3.6: Density plot for the adjusted alphas of monthly excess returns from 5FF +QMJ+BAB for the Green & Red assets…………………………………………………………………………162
Figure A3.7: Density plot for the adjusted alphas of monthly excess returns from 5FF +MOM for the Green & Red assets……………………………………………………………………………162
Figure A3.8: Density plot for the adjusted alphas of monthly excess returns from 5FF +FEAR for the Green & Red assets……………………………………………………………………………163
Figure A3.9: Density plot for the adjusted alphas of monthly excess returns from 5FF+FEAR+MOM for the Green & Red assets……………………………………………………………………....163
Figure A3.10: Density plot for the adjusted alphas of monthly excess returns from 5FF +UK/EUR for the Green & Red assets…………………………………………………………………………164
Figure A3.11: Density plot for the adjusted alphas of monthly excess returns from 5FF + GOLD for the Green & Red assets………………………………………………………………………….165
Figure A3.12: Density plot for the adjusted alphas of monthly excess returns from 5FF+UK/EUR +GOLD for the Green & Red assets………………………………………………………………166

List of Tables

Table 2.1: Contentious, grey, red and green sectors……………………………………………….…..20
Table 2.2: Industry classification matching………………………………………………………21
Table 2.3: Cross-sectional averages of time-series moments for monthly simple returns from the three categories before and after winsorization…………………………………………………...33
Table 2.4: Empirical results for Green simple returns (for the period 2000-2019 and the sub-periods) ……………………………………………………………………………………………….34
Table 2.5: Empirical results for Grey simple returns (for the period 2000-2019 and the sub-periods) ……………………………………………………………………………………………….36
Table 2.6: Empirical results for Red simple returns (for the period 2000-2019 and the sub-periods) ……………………………………………………………………………………………….39
Table 2.7: Empirical results for Green returns-extension (period 2000-2019 and the sub-periods)...44
Table 2.8: Empirical results for Green returns-extension II (period 2000-2019 and the sub-periods) ………………………………………………………………………………………………45
Table 2.9: Empirical results for Grey returns-extension (period 2000-2019 and the sub-periods)…46
Table 2.10: Empirical results for Grey returns-extension II (period 2000-2019 and the sub-periods) ……………………………………………………………………………………………….47
Table 2.11: Empirical results for Red returns-extension (period 2000-2019 and the sub-periods)…48
Table 2.12: Empirical results for Red returns-extension II (period 2000-2019 and the sub-periods) ……………………………………………………………………………………………….49
Table 3.1: Cross-sectional risk-adjusted alphas moments of monthly excess returns from three asset pricing models and for two asset classes Green and Red…………………………………………69
Table 3.2: Cross-sectional adjusted alphas moments of monthly excess returns from the three asset pricing models and for the two asset classes Green and Red……………………………………..70
Table 3.3: Cross-sectional adjusted alphas moments of monthly excess returns from the three asset pricing models and for the two asset classes Green and Red……………………………………..71
Table 3.4: Cross-sectional adjusted alphas moments of monthly excess returns from the three asset pricing models and for the two asset classes Green and Red……………………………………..72
Table 3.5: Statistical Analysis of Alpha Values Across Categories and models…………………... 75
Table 3.6: Empirical results for comparing the Red versus Green returns (for the period 2000-2019 and the sub-periods) ………………………………………………………………………………77
Table 3.7: Empirical results for comparing the Red versus Green returns using extension models (for the period 2000-2019 and the sub-periods) …………………………………………………………78
Table 4.1: FEARS Google Search terms……………………………………………………….....92
Table 4.2: CSI Google Search terms………………………………………………………………97
Table 4.3: Empirical results of the sentimental factors for Red excess returns for the period 2004-8/2009 (ex-Global crisis) …………………………………………………………………………..109
Table 4.4: Empirical results of the sentimental factors for Red excess returns for the period 9/2009-20019 (Global crisis and Post-ante EU crisis) …………………………………………………..110
Table 4.5: Empirical results of the sentimental factors for Red excess returns for the period 2004-2019 (Entire period) ……………………………………………………………………………..111
Table 4.6: Empirical results of the sentimental factors for Grey excess returns for the period 2004-8/2009 (ex-Global crisis) …………………………………………………………………………..115
Table 4.7: Empirical results of the sentimental factors for Grey excess returns for the period 9/2009-20019 (Global crisis and Post-ante EU crisis) …………………………………………………….116
Table 4.8: Empirical results of the sentimental factors for Grey excess returns for the period 2004-

2019 (Entire period) …………………………………………………………………………117
Table 4.9: Empirical results of the sentimental factors for Green excess returns for the period 2004-8/2009 (ex-Global crisis) ………………………………………………………………………120
Table 4.10: Empirical results of the sentimental factors for Green excess returns for the period 9/2009-20019 (Global crisis and Post-ante EU crisis) ……………………………………………121
Table 4.11: Empirical results of the sentimental factors for Green excess returns for the period 2004-2019 (Entire period) …………………………………………………………………………122
Table A2.1: FTSE environmental sectors and sub-sectors………………………………………..145
Table A2.2: Classical factors Variable names, definition and description………………………..146
Table A2.3: Additional factors Variable names, definition and description………………………147
Table A2.4: Commodities Variable names, definition and description…………………………...147
Table A2.5: Currency Variable names, definition and description………………………………..148
Table A2.6: First four moments of time-series classical factors…………………………………..148
Table A2.7: First four moments of time-series additional macro-factors……………………….....149
Table A2.8: First four moments of time-series commodities factors……………………………..149
Table A2.9: First four moments of time-series currency factors…………………………………150
Table A2.10: Correlation of the six factors the period 2000-2009………………………………..150
Table A2.11: Correlation of the four commodities factors the period 2000-2009………………..150
Table A2.12: Correlation of the five currency factors the period 2000-2009…………………….150
Table A2.13: Correlation for all factors the period 2000-2009…………………………………...151
Table A2.14: Correlation of the six factors the period 2010-2019………………………………..152
Table A2.15: Correlation of the four commodities factors the period 2009-2019………………..152
Table A2.17: Correlation of the five currency factors the period 2009-2019…………………….152
Table A2.18: Correlation for all factors the period 2009-2019…………………………………...152
Table A2.19: Correlation of the six factors the period 2000-2019………………………………153
Table A2.20: Correlation of the four commodities factors the period 2000-2019……………….153
Table A2.21: Correlation of the five currency factors the period 2000-2019……………………153
Table A2.22: Correlation for all factors the period 2000-2019…………………………………..154
Table A2.23: Terminology and portfolio construction…………………………………………...155
Table A2.25: Empirical results of the extension models in the Green returns including the period 2000-2019 and the sub-periods ex and post EU crisis……………………………………………156
Table A2.26: Empirical results of the extension models in the Grey returns including the period 2000-2019 and the sub-periods ex and post EU crisis. …………………………………………..157
Table A2.27: Empirical results of the extension models in the Red returns including the period 2000-2019 and the sub-periods ex and post EU crisis…………………………………………………158
Table A4.1: EU crisis events ………………………………………………………………….167
Table A4.2: Impact of sentiment: Author Name, Market Analyzed, Time period and Conclusion….……………………………………………………………………………168
Table A4.3: Cross-sectional averages of time-series moments for monthly excess simple returns from the two categories before and after winsorization………………………………………..169
Table A4.4: First four moments of the time-series factors………………………………………..169
Table A4.5: Correlation of the six factors………………………………………………………...170
Table A4.6: Correlation of the six sentimental crisis factors……………………………………..171
Table A4.7: Correlation of the six sentimental crisis factors and the six proxy portfolios factors ……………………………………………………………………………………………172

Acknowledgements

I would like to acknowledge with gratitude the support of the following people without whose guidance and assistance this Ph.D. thesis would not have been possible.

I would first like to thank from my heart, my supervisor Professor Thomas Flavin and Professor Gregory Connor for their guidance, insight and commitment over the course of my doctoral studies. I am truly thankful that he was always there to provide continuously valuable feedback and comments. His tutelage proved both invaluable and inspiring during my time at Maynooth University.

I would like to express my gratitude to the Financial Mathematics and Computational Research Cluster (FMC^2) for giving me the opportunity to conduct Ph.D. research. This research is based upon works supported by Science Foundation Ireland under Grant Number 16/SPP/3347. I thank the FMC^2 professors and all my colleagues at the FMC^2.

I would also like to thank Professor Valerio Potti, Dr. Fotini Economou and Dr. Konstantinos Loizos for all of her comments and much appreciated advice, to Professor Aggelos Tsaklaganos for their guidance throughout and to all the members and my fellow Ph.D. students at the Department of Finance at NUI Maynooth.

I would like to thank my family from the bottom of my heart. I special thanks to **my mother Sotiria Kapsali** for their inspiration and personal sacrifices. They single-handedly offered the necessary inspiration and motivation. Completing this thesis would not have been possible otherwise.

I would like to thank my friends especially for the love gave me, the help and the provided comments in my research prof. Grigoria Chlomou, prof. Anastasios Megaritis. Katerina Katsarou as a great friend and for her helping. They will never truly understand the role they played during the completion of my Ph.D thesis.

Conferences and Publications

I have presented Chapter 1 and 2 titled "*Performance and factor structure of Green, Grey and Red securities"*, at the 11th Financial Engineering & Banking Society (FEBS) Conference (December 2021), at the 20th Annual Conference of the Hellenic Finance and Accounting Association (HFAA) (December 2021) and I was invited at the 18th Summer School in Risk Finance & Stochastics (September 2021) with limited international participants. These papers are included in the Conference Proceedings of the Hellenic Finance and Accounting Association and Financial Engineering & Banking Society. Chapter 1, titled "*Factor Structure of Green, Grey and Red EU Securities*" the half has been submitted to Journal of Financial Management, Markets and Institutions and the other half is published in the *Journal of Risk and Financial Management* (Special Issue: *Bridging Financial Integrity and Sustainability*) with title *"Empirical Asset Pricing Models for Green, Grey, and Red EU Securities: A Fama-French and Carhart Model Approach"*. Additionally, the Chapter 2 titled as "*Performance of Green vis-à-vis Red EU Securities*" presented at the 32nd Southern African Finance Association's (SAFA) Conference (Jan 2024) and have been published to the Journal of Investment Analyst.

I was invited to present the Chapter 3 with title "*EU Green, Grey and Red securities and crisis sentiment"* at the International Ph.D. Workshop Data science in business of the HERMES University Network that took place in Athens, Greece, on June 7th-8th, 2023. Furthermore, I was invited to the 20th Summer School in Risk Finance & Stochastics (4-8th September 2023) with limited international participants. This chapter is accepted to publish in the Review of Behavioral Economics.

Chapter 1: Introduction

1.1 Background and Context

Financial market dynamics and investor preferences have significantly evolved over the last few decades, influenced by a growing awareness of environmental issues and the social push towards sustainable investing. The European Union (EU) market, in particular, has witnessed a rapid increase in the categorization and investment in securities based on their environmental impact (e.g. Miroshnychenko et al.,2017; Molina-Azorín et al., 2009) or corporate social responsibility (e.g. Dhaliwal et al, 2011; Eccles et al., 2014; Margolis et al.,2009; McGuire et al., 1988). This shift has given rise to the concept of 'Green assets' which are financial products that are connected to environmentally responsible practices. The magnitude of the global market for Green bonds grew from just $257.7 billion in 2019 to over $5 trillion by 2024, reflecting the asset preferences of the investor priorities (Climate Bonds Initiative[1],2020; 2024). Furthermore, green stocks, which are shares of companies that actively engage in environmentally sustainable practices, follow similar significant growth. According to the Global Sustainable Investment Alliance institution, funds in Europe with financial assets focused on environmental, social, and governance (ESG), which includes a portion of Green stocks under management, grew from $12 trillion in 2020 to $14 trillion in 2022 (Global Sustainable Investment Alliance Review[2], 2022). For 2022, sustainable investment assets in Europe comprise around 40% of global totals (GSIA, 2022). This trend of examining financial assets through the lens of environmental impact underscores the importance of these types of assets and creates a space for additional study.

For our research, the securities are categorized into Green (eco-friendly), Grey (neutral), and Red (eco-enemy) stocks, each reflecting varying levels of environmental responsibility. This dissertation aims to identify multiple factors affecting the returns of these categorized securities within EU financial markets.

The study spans several critical periods, including the pre-and post-Global Financial Crisis (2008) and the EU Financial Crisis (2010), offering a comprehensive analysis of how

[1] www.climatebonds.net (Accessed: 2 October 2024)
[2] http://www.gsi-alliance.org (Accessed: 2 October 2024)

these crises influenced the returns of Green, Grey, and Red securities (Claessens et al., 2010; Lane, 2012; Brunnermeier, 2009; Laeven & Valencia, 2013; Mody & Sandri, 2012). The primary objective is to examine the inherent factor structure within these categorized groups of stocks using enhanced asset pricing models and sentimental indexes. Additionally, the study pursues the financial performance of Red versus Green securities.

1.2 Purpose and Significance of the Study

The fundamental purpose of this study is to investigate the macroeconomic, fundamental, and sentimental factors that impact the returns of Green, Grey, and Red securities within the EU market. This research utilizes established asset pricing models such as the Fama-French three and five-factor model, the Carhart four-factor model, and their extensions, aiming to construct the factor structure of these types of securities. The multi-factor model will clarify the characteristics of this classification of securities by explaining their different risk exposures and the relationship with the diversified portfolio proxies. These models (Fama & French, 1993; Carhart, 1997; Fama & French, 2015; Cakici, 2015; Hou et al., 2015; Harvey et al., 2016; Griffin, 2002) are tested across various financial markets and economic conditions proving their merit as asset pricing models.

The significance of this study lies in its potential to provide valuable insights for investors, policymakers, and academics. As previously noted from the reports, investor demand for environmentally sustainable portfolios continues to grow significant, particularly in Europe. Notably, among investors seeking to align financial performance with environmental values, is crucial to understand the differences in risk and reward between Green (eco-friendly) and Red (eco-enemy) industries. This research will help portfolio managers better assess how these industries perform and how they can optimize portfolios by balancing sustainability with asset returns. By analyzing Green, Grey and Red stock's risk and return dynamics, investors can either diversify portfolios to reduce risk or employ hedging strategies to mitigate potential losses. For policymakers, the insights gained from this study can inform regulations and policies that encourage sustainable investing and help reduce systemic financial risks. For the academic community, this research contributes to the growing body of knowledge on asset pricing and sustainable finance, particularly within the

EU market (Friede et al., 2015; Giese et al., 2019; Dorfleitner et al., 2015; Busch et al., 2016).

1.3 Definitions and Categorization of Securities

To facilitate a better understanding of the securities, a classification is essential. Below is how our study defines the categorization of the securities under investigation:

- **Green Securities**: These are stocks of companies that are considered environmentally friendly, engaging in sustainable practices, and minimizing their carbon footprint. For instance, the type of companies involved is in renewable energy, waste management, and efficient energy activities. The literature has many different classifications of Green (e.g. Clark et al., 2015; Cojoianu, et al., 2020; Bolton et al., 2021, 2022; In et al., 2019; Cheema-Fox et al., 2021, Bauer et al., 2022; Pastor et al, 2022; Ardia, et al, 2022) and mostly connected with the carbon footprint.
- **Grey Securities**: These stocks belong to companies that have a neutral stance towards environmental impact. This type of securities neither actively harm the environment nor engage in significant eco-friendly practices.
- **Red Securities**: These are stocks of companies that are considered environmentally unfriendly, with substantial negative impacts on the environment. For example, these companies belong in the fossil fuel sector which produces high carbon emissions. Comparative analyses across studies reveal nuanced variations when incorporating sectors characterized by high carbon emissions, as highlighted in recent research (e.g., Dyck et al., 2019).

1.4 Theoretical Framework and Asset Pricing Models

In every chapter, the famous asset pricing models are applied as base models. This research is grounded in the theoretical framework and the practical use of asset pricing models, which are essential tools for understanding the relationship between risk and return. The primary models employed in these studies include:

- **Fama-French Three-Factor Model**: This model expands on the Capital Asset Pricing Model (CAPM) by adding size risk and value risk factors to the market risk factor, providing a more comprehensive explanation of stock returns (Fama & French, 1993).

- **Carhart Four-Factor Model**: This model further extends the Fama-French model by including a momentum factor, which captures the tendency of stocks that have performed well in the past to continue performing well (Carhart, 1997).
- **Extended Asset Pricing Models**: Various extensions of the basic models are utilized to capture additional risk factors and dynamics specific to the categorization of Green, Grey, and Red securities. These models help in understanding the changing exposures to global factors over time due to financial crises (Lins et al., 2017).

The study starts with the factor structure of Green, Grey and Red assets using classical multi-factor models and their extensions. Primarily, the aim is to identify which factors (e.g. market, size, value, or growth factor) influence the returns of these environmentally differentiated securities. Followed by assessing whether there are differences in the factors that determine the returns of Green, Grey and Red securities. The analysis is also broken into two subperiods: the pre-Global Financial Crisis (GFC), and post-GFC. Financial crises provide a unique opportunity to study how macroeconomic disruptions affect the performance of securities distinguished by environmental criteria. The results show that, during such crises, these asset classes generally underperform relative to the market index and other macroeconomic factors. Enhanced models reveal that the sensitivities to global factors evolve over time due to the impact of financial crises. In the post-crisis period, Grey and Red assets demonstrated a stronger relationship with the factors by increasing their sensitivity, indicating that these industries became more vulnerable to external shocks. In contrast, Green assets showed more stable results by not changing or shifting hugely the sensitivities before and after the crisis period, this suggests that type of securities may provide a more consistent risk-return profile across different economic conditions.

1.5 Impact of Financial Crises on Green, Grey and Red Securities

The study examines the impact of financial crises on Green, Grey, and Red securities returns by analyzing different periods, including the pre-Global Financial Crisis (GFC), and post-GFC. The financial crises serve as natural experiments to observe how macroeconomic shocks influence the performance of environmentally differentiated securities. The findings indicate that the asset classes underperform compared to the market index and other macro-factors during crises. Extension models[3] enhance explanatory power, revealing changing exposures to global factors over time due to the financial crises. Grey and Red assets exhibit greater sensitivity to these changes in the post-crisis period than Green assets (Nofsinger & Varma, 2014). The contrasting impacts may arise due to variations in the underlying characteristics of these securities; for example, Green securities may be more sensitive to policy changes and long-term sustainability concerns, while Grey and Red securities as traditional companies, could be more connected with the market that can explain the experience of sharper declines during economic downturns.

1.6 Comparative Performance Analysis of Green and Red Securities

This thesis next proceeds to investigate the comparative performance of Green versus Red securities. By employing asset pricing models to determine the risk-adjusted alphas for each asset class, the study seeks to compare the performance of these securities over time. The findings suggest that there is no statistically significant performance difference between Red securities and Green securities. Practically, Red securities neither outperform nor underperform green securities, suggesting that financial performance cannot be attributed to any inherent advantage or disadvantage associated with the environmental impact of the portfolio. In contrast, the previous research of Derwall et al. (2011), which followed a similar approach, found that eco-friendly companies have better risk-adjusted returns before the crisis period in 2008.

The practical implication of the study carries significant weight for the financial perspective of the investors and portfolio managers by suggesting there is no clear advantage to favouring one asset class over another (Green vs Red Assets). As investors seeking to maximize returns, they may need to look beyond simple asset class selection and instead consider other factors, such as risk tolerance, or mix the assets of Red and Green for diversification strategies, or the sensitivities of external economic conditions, to allocate their portfolio strategies. For example, suppose one asset class yields higher realized returns and volatility and the other

[3] Extension models refer to asset pricing models that build upon foundational frameworks, in our case the foundantion models are the Fama-French three/five-factor model and the Carhart four-factor model and appending additional factors is the exentation models. These models aim to better capture variations in asset returns by extending the original set of explanatory variables.

lower realized returns and volatility over time. In this case, the investors might focus on diversifying their investments using low-correlated assets for achieving a well-rebalanced portfolio by reducing the concentration risk for the long-term financial goals rather than attempting to increase the risk by creating one asset class portfolio (e.g. crude oil crisis 2020 the covid period; negative price of the futures which passed to the Red type of securities). In simple terms, this diversification strategy balances risk-reward across multiple asset types, rather than concentrating on a single class with the expectation of outperformance, allowing investors to adopt an approach that combines exactly opposite environmental asset classes without concerns of missing out on superior financial gains. In conclusion, financial advisors or portfolio managers can support advising their clients using these results to offer a way to maintain balanced portfolios that do not overemphasize one asset class over another based purely on the expectation of higher realized returns.

1.7 Influence of Sentiment and Economic Uncertainty

Chapter 4 of this dissertation examines the influence of crisis sentiment indexes on the returns of Green, Grey, and Red securities. The study establishes the impact of investor sentiment and economic uncertainty on monthly returns by utilizing crisis factors derived from Google query volumes, alternative news, and policy sentiment indexes. A behavioural view of investing whereby sentiment indexes can potentially influence the market by leading to a sell-off of securities, regardless of their environmental classification. Higher values of these crisis sentiment indexes indicate heightened fear in the financial market, which is primarily associated with decreasing equity price returns. The sentimental and economic uncertainty indexes during crises are found to decrease equity price returns across the Red and mainly in the Grey category. The research applies extended CAPM and Fama-French models to measure the impact of investor sentiment and economic uncertainty levels. Different periods are analyzed, including pre-Global Crisis, post-Global Crisis, and the entire period, providing valuable insights for environmentally conscious investors and policymakers (Baker & Wurgler, 2006; Tetlock, 2007; Da et al., 2011).

1.8 Contribution to Knowledge and Implications

This dissertation makes several contributions to the understanding of the financial performance of environmental and non-environmental securities and the link between these returns and macroeconomic, fundamental, and sentimental factors. By constructing a factor structure for these categories of assets in the European financial markets, the study offers insights into their responses to periods with and without financial distress. These findings hold valuable implications for investors aiming to manage portfolios and mitigate contagion risks and for policymakers striving to promote sustainable investing practices. For instance, the integration of Green and Red assets can broaden the diversification strategies by adopting a balanced risk-reward portfolio across different types of assets without seeking a constant superior return.

Another case is considering a portfolio constructed on Green assets, and include other diversified portfolios, such as a market portfolio. Based on our study, Green assets mainly generate negative alpha, suggesting that investors can achieve stable financial performance by implementing a short strategy for the Green portfolio while taking a long position in the market portfolio. Furthermore, the strategy can implement short-long strategy with other diversified portfolios (such as the size and value portfolios) relative to their relationship with Green assets. The alpha-seeking strategy can also be employed similarly for our two additional asset classes (Grey and Red).

Another strategy can involve leveraging the crisis sentiment indices with diversified portfolios and an asset class (Grey and Red). Investors may perceive a strategic advantage by adopting a (short-long) strategy position of the asset class and diversified portfolios in relationship with the asset class based on the crisis sentiment index. Sentiment-based strategies can improve decision-making by giving direction to portfolio allocation of our asset class and diversified portfolios.

Even for marginal investors operating in efficient markets, understanding these exposures matters since asset prices reflect aggregate beliefs about future risks and returns. Additionally asset class respond differently to macro shocks, their inclusion in a portfolio affects the portfolio's aggregate exposure to those risks. The Green/Red/Grey stocks are having systematically different and similarities in their macro sensitivities, that macro sensitivities could affect equilibrium pricing, required returns, and portfolio rebalancing strategies. Decomposing returns based on macro factors helps investors and asset managers evaluate what drives performance and under what conditions (e.g. finacial crisis period). This is particularly relevant for strategies that aim to tilt toward sustainability assets without unconsciously taking on unintended macro exposures.

1.9 Structure of the Dissertation

The dissertation is structured as follows:

- **Chapter 2**: Study the factor structure of the Green, Grey, and Red securities, utilizing various famous asset pricing models and their extensions.
- **Chapter 3**: Compares the performance of Green and Red securities over time, employing asset pricing models to determine risk-adjusted alphas for each asset class.
- **Chapter 4**: Examines the influence of crisis sentiment indexes on the returns of Green, Grey, and Red securities, utilizing various crisis factors and extended asset pricing models.
- **Chapter 5**: Concludes the dissertation by summarizing key findings, contributions, implications and offering suggestions for future research.

In conclusion, this dissertation aims to provide a thorough investigation of the factors affecting the returns of Green, Grey, and Red securities within the EU market, offering valuable insights for investors, policymakers, and academicians. By understanding the financial performance and risk factors associated with these environmentally differentiated securities, stakeholders can make more informed decisions in the context of sustainable investing and financial market dynamics.

Chapter 2: Factor Structure of the Green, Grey and Red EU Securities

Abstract

The purpose of this research is to determine the factors that are important in explaining Green (eco-friendly), Grey (neutral), and Red (eco-enemy) EU securities returns. This study investigates the factors that influence performance over time, before and after the Global Financial Crisis (GFC) in 2009. The primary objective of our study is to examine the factor structure inherent within the categorized groups of stocks. We define Green stocks, as those in the primary business that are relatively beneficial to the environment, and Red as, harmful to the environment. Our analysis applies the following asset pricing models: the Fama-French 3-factor and 5-factor models, the Carhart Model (4-factor model) and extension models (Asness et al., 2013, 2019; Connor & Korajczyk, 2022; Durand et al., 2011; Frazzini & Pedersen, 2014). The research findings show that every asset class after the crisis period underperforms relative to the market index and the other portfolio proxies. The extension models significantly improve the explanatory power of the returns. Moreover, the exposures to the global factors are changing from period to period, and shows that the downturn affected asset sensitivity to these factors. Lastly, we observe that Grey and Red assets were affected more than Green stocks after the slump (GFC) period.

Keywords: Asset Pricing Models, European Stock Market, Factor Analysis, Green Securities, Red Securities, Grey Securities

JEL classification: C5, G11, G12

2.1 Introduction

The global landscape is witnessing a significant surge in environmental consciousness, with reusing, recycling, and other eco-friendly acts emerging as key drivers of change. Companies with environmental awareness have captivated the attention of researchers, organizations, firms, institutions, and lawmakers. The firm's aim is profit maximization, but firms competitive environment drive them to facilitate actions and behaviors that bring about environmental improvements for the betterment of society and nature. Consequently, green stocks possess an inherent allure for investors of all kinds, creating a perception of potentially safe returns by enclosing to environmental companies. This research seeks to find answers to the following research questions: a) Which securities are characterized as green, grey and red/brown? b) How do expected returns vary across these assets? c) What are the risk exposures that define the asset category returns of Green, Grey, and Red investments? By exploring these questions, this study aims to contribute to a comprehensive understanding of the nature and implications of sustainable investments, thereby informing investment strategies and decision-making in the financial markets.

In the context of financial markets, the terminology associated with 'green' financial instruments, such as eco-investment, green investment, green banking, green stocks, green bonds, green mutual funds, green savings accounts, and green certificates of deposit, can indeed seem multifaceted and potentially perplexing. However, it's important to clarify that these designations collectively signify a concerted effort towards environmentally responsible investments and sustainable practices. If it is not Green, is it Red or Grey? Unlike their counterparts that might fall into 'Red' or 'Grey' or unspecified categories, which often involve industries and practices with harmful ecological footprints, 'Green' instruments exclude such ventures from their purview.

The following section presents how previous research categorized stocks by at the industry level and how the classification is ambiguous. Even though the institutions have a different type of sector classification, the greatest problem is figuring out if the company's business activity is ('really') beneficial for the environment. Previous research (Badia et al., 2019; Brammer et al., 2009; Climent & Soriano, 2011; Ibikunle & Steffen, 2017) focuses on the performance of portfolios or funds, which include Green and Red stocks or just Green or just subsector of Red category. This research contributes to bridging the gap in the prior literature and seeks to find the common relationship and at the same time, the differences between Green, Grey and Red security returns by studying the macro-factor exposure. By looking at the overall exposure of environmentally friendly, moderately environmentally friendly, and less environmentally friendly securities to these factors and analyzing how they react to the economy's ups and downs, we can gain a deeper understanding of the dynamic interactions between environmental sustainability and financial performance.

In this study, the stock sample is generated from the European market securities. Our analysis explores the factors over time and also separates them into two time periods, (i) ex-crisis and (ii) post-crisis level (with a breakpoint in the year 2009). For this purpose, the analysis has two parts. The first part is about how the stocks are grouped. The classification stems from a specific table which is collected from previous research and reports of financial institutions (see table 2.1). Furthermore, the other part is assessing how the specific class of securities performs in the market with the asset pricing models, which describe the securities' return based on equilibrium theories and the models from previous literature.

The paper is organized as follow: The coming sections discusses how previous researchers classified the Green, Grey, and Red/Brown categories, as well as the asset pricing models, which are used for these three categories. Section three describes the data collection process and filtering among the Green, Red (or Brown), and Grey stocks. The next part of this research illustrates the methodology and the notion behind the Fama-French models (3FF and 5FF) and Carhart Model (4-factor model) and the extension of these models. Section five examines the main research questions with the use of empirical models. Section five describes the main findings of this research and includes a discussion of improvements and applications of these models.

2.2 Identifying the Asset Class: Green, Grey and Red

This section aims to review prior research that provided classifications for Green, Red (or Brown), and Grey securities. By examining previous research contributions, we can gain a comprehensive understanding of the categorizations and definitions associated with these distinct types of securities. The primary measure is the business activities that the company engages in as an entity that offers a classification in a specific group as a Green, Red (or Brown), or Grey asset.

According to the report by Kepler Cheuvreux Transition Research (2015) institution, the FTSE (Financial Times Stock Exchange) was the pioneering institution to introduce the Low Carbon Economy Industry Classification Scheme (LCEIC). This scheme categorizes industries into seven high-level sectors and 29 sub-sectors, as outlined in Table A1.1 provided in the appendix. Another institution is MSCI, which employs a different classification type comprising five themes and 37 technologies. Themes that we can identify as 'contentious' or 'Grey' (e.g., biofuels and general waste management) are included in both the FTSE and MSCI classifications. In order to distinguish the 'Green' from the others, these classifications have their benchmarks and are best tailored to industry-level research. In this potentially controversial environment, clarity and transparency are essential. Investors and researchers need to decide which research to follow—whether a consistent classification or a dubious one that varies over time or across databases. It is crucial for them to understand the industry of the companies and exercise caution with category fits in contentious areas. FTSE classification is based on the 'industrial test of utility', which evaluates how the investor is economically involved in the solution, including both mitigation and adaptation operations. Therefore, Green stocks are concentrated mainly in areas such as alternative energy, pollution control, carbon reduction, and recycling (Table 2.1).

Table 2.1: Contentious, grey, red and green sectors

Contentious	Grey	Red	Green
Gas-fired power, bioenergy, hydropower, nuclear power		Fossil fuels	Solar, wind
Energy efficiency without credentials/standards or from the perspective of fossil fuels or at risk of "rebound effect"			Energy efficiency
	Agri-food		
	Real estate		
	Forestry		
Waste management			Recycling, composting
	Transport		Electric and alternative mobility
	ICT		

Source: Kepler Cheuvreux, CBI, FTSE, MSCI

Cojoianu et al. (2020) adapts different types of classification by studying the environmental policies and also the new regional environmental knowledge which affects the

Green (environmental), Red (fossil fuel), and Grey (unrelated to natural resources) technologies. Furthermore, his paper refers to the industries that aim to minimize or facilitate the responsible use of environmental degradation as 'Green'. Within the Grey category, certain industries have been excluded from consideration due to damage to the environment, exploitation of environmental policies for company gains, and reliance on natural resources. The final category is the "Brown"; those industries are expected to be significantly influenced by further environmental policies due to their dependency on natural resources and environmental externalities. Additionally, this category is concentrated on non-renewable resources (Table 2.2).

Table 2.2: Industry classification matching.

SASB Industry Classification	Crunchbase Classification	Paper Terminology
Renewable Resources, Alternative Energy & Infrastructure (Utilities and Waste Management).	Battery, Biofuel, Biomass Energy, Clean Energy, CleanTech, Electric Vehicle, Electrical Distribution, Energy Efficiency, Energy Management, Energy Storage, Environmental Consulting, Environmental Engineering, Fuel Cell, Green Building, Green Consumer Goods, GreenTech, Paper Manufacturing, Pollution Control, Power Grid, Renewable Energy, Smart Building, Smart Home, Solar, Sustainability, Timber, Waste Management, Water, Water Purification, Water Transportation, Wind Energy, Wood Processing, Recycling	**Green**
Non-Renewable Resources	Fossil Fuels, Fuel, Mineral, Mining Technology, Natural Resources, Oil and Gas, Precious Metals, Mining	**Brown**
Healthcare, Financials, Technology and Communications, Transportation, Services, Consumption, Infrastructure (Infrastructure and Real Estate).	Software, Biotech, Healthcare, Telecommunications, Real Estate and other sectors excluding the ones above.	**Grey**

Source: Cojoianu, T., et al. (2020). " Entrepreneurs for a low carbon world: How environmental knowledge and policy shape the creation and financing of green start-ups."

Previous work by Bolton et al. (2021, 2022) classified the securities into two categories: Brown and Green. The classification based on carbon emissions is a different approach from our research to measure the Green and the Brown companies. The "Brown" securities represent higher-emitting firms, while the "Green" securities represent lower-emitting firmsIn the classification of securities into Green and Brown categories, In et al.

(2019) and Cheema-Fox et al. (2021) proposed an alternative approach based on emissions scaled by firm size, known as emission intensity. This method allows for a more nuanced assessment of a company's carbon footprint by considering emissions relative to its operational scale, providing a valuable perspective for investors and policymakers aiming to make informed decisions in the context of climate change and finance. Bauer's et al. (2022) applied a combination of the previous two. The methodology is employed to assess the degree of "greenness" by quantifying the level or intensity of CO_2 emissions reported by the emitting entities. By utilizing this approach, they aim to evaluate the environmental impact of various entities and identify the extent of their carbon footprint. The utilization of CO_2 emissions as a metric enables us to gauge the environmental performance of different entities and discern their commitment to sustainable practices. Lastly, Pastor et al. (2021a, 2022) employed the classification based on Environmental, Social, and Governance (ESG) ratings using the "E" component. By leveraging this approach, they were able to determine the environmental sustainability of individual companies and subsequently shortlisted them into distinct two categories, namely Green and Brown. This method allowed them to effectively categorize securities based on their environmental practices, aiding investors and stakeholders in making more environmentally-conscious investment decisions. The drawbacks of these methods manifest in the variability and consistency of both scores, and carbon emissions across different databases.

Our research adopts Table 2.1 to classify our stock universe based on environmental activity. The adoption of an industry-level classification system is to provide a clear and consistent framework for analysis. This approach mitigates the inconsistencies and variability found in classifications that rely solely on environmental policies, carbon emissions, or ESG ratings. By focusing on industry-specific classifications, my research offers a more stable and comparable basis for understanding different sectors' environmental impacts and financial performance. The categorization is aimed at organizing the stocks into meaningful groups, which will enable us to analyze and compare their environmental performance within specific segments. By using reliable institutional reports and adhering to established standards, we ensure the accuracy and consistency of our classification, which is crucial for drawing meaningful conclusions and implications from our research findings.

2.3 *Factor Models and Extensions*

The factor models apply firm-specific and other characteristics that were documented as predicting differences in return among stocks. The general form to study a specific-asset class returns with the factor models can be estimated in their linear form for a fixed time t as equation 2.1:

$$r = Bf + e \tag{2.1}$$

where r is the Nx1 column vector of the N asset returns in our investment universe (in our case Green, Red, or Grey), B is the NxK matrix that contains the factor exposures or loadings for the K factors for each asset, f is the Kx1 column vector of factors and e is the error term or asset-specific component of the returns r.

In theory, the single factor model refers to CAPM and suggests the variation of the expected returns on the risky security is explained by the market's excess return (to a certain degree). The beta coefficient measures the asset's sensitivity to market movements, the change of the asset's return in relation to the changes in the overall market portfolio's return. On the other hand, the alpha coefficient (or Jensen alpha), named after economist Michael Jensen (1967), is a measure of the alpha returns of an asset. In other words, the alpha quantifies the generated returns beyond what is expected given the asset's level of market risk. This concept, introduced by William Sharpe in 1964 and later expanded upon by John Lintner in 1965, helps us understand how expected returns on assets are influenced by their exposure to systematic market risk. Empirical studies (e.g. Choudhry, 2002, 2004) show that the CAPM is not adequate (the performance is poor) to explain the variation of the returns. The most recent literature presents models with higher explanatory power than the CAPM (Black, 1972), such as the multi-factor models from Fama-French (1993) and Carhart (1997). While in 1993, Fama and French took the first step on the asset pricing multi-factor models with the 3-factor model, which included the already market excess factor (market return minus the risk-free rate) from CAPM and added the book-to-market factor (HML, i.e., the difference of high book-to-market values and low book-to-market values stocks on the returns) and the size factor (SMB, i.e., the difference of small Size and Big size stocks on the returns) [4]. The three-factor model proposed is then (2.2):

[4] Fama French(1993), refer to the additional factors as market index "anomalies" and add them to the market factor analysis. This term is accepted among academics, but investors refer to them as predictive signals.

$$E(r_{i,t}) - r_f = \beta_{i,M} * (E(R_M) - r_f) + \beta_{i,SMB} * E(SMB) + \beta_{i,HML} * E(HML), \tag{2.2}$$

where r_f is the risk-free interest rate; $E(MKT) = E(R_M) - r_f$, $E(SMB)$ and $E(HML)$ are the expected premiums, and the factor sensitivities from the time-series regression are measured by the coefficients $\beta_{i,M}$, $\beta_{i,SMB}$ and $\beta_{i,HML}$.

As previously noted, the application of multi-factor models, as demonstrated by Fama and French (1993, 1998, 2008) and Carhart (1997), has yielded noteworthy outcomes in explaining securities returns. These findings have generated substantial interest among researchers and investors alike (Fama & French 1993, 1998, 2008; Bali 2012). Carhart (1997) extends the model by adding one more factor to the FF model, the cross-sectional momentum factor MOM (in some research papers this factor is called the Up minus Down factor (UMD)), which is the difference of risen (winners) and fallen (losers) in value stocks. The proposed Carhart model is then (2.3):

$$E(r_{i,t}) - r_f = \beta_{i,M} * (E(R_M) - r_f) + \beta_{i,SMB} * E(SMB) + \beta_{i,HML} * E(HML) + \beta_{i,MOM} * E(MOM), \tag{2.3}$$

Later, another famous paper about the multi-factor models was introduced by Fama & French (2015) and called the 5-factor Model. The extended model builds upon the previous 3-factor model by introducing two additional factors, widely recognized as 'quality' factors in the literature. Their inclusion enriches the analysis and expands the existing framework, providing a more comprehensive understanding of the underlying securities dynamics. These factors are the profitability factor (the difference between high and low operating profitability stocks) and the investment factor (the difference between high and low total asset growth stocks). The proposed five-factor model is then (2.4):

$$E(r_{i,t}) - r_f = \beta_{i,M} * (E(R_M) - r_f) + \beta_{i,SMB} * E(SMB) + \beta_{i,HML} * E(HML) + \beta_{i,RWA} * E(RWA) + \beta_{i,CMA} * E(CMA), \tag{2.4}$$

Even though the 5-factor model ignores the momentum of the Carhart model, both the 5-factor Fama French model and the 4-factor Carhart model are extension models from the 3-factor model, which considerably improves the explanatory power of the 3-factor model.

The extension of equity factor models is becoming more prevalent in academic and financial institutions. The additional factors attempt to explain the random noise that impacts the returns. The Fear (VIX) model proposed by Durand et al. (2011) is accompanied by various extended models that stem from the Fama-French's five or three-factor model framework. For instance, Asness et al. (2013, 2019) introduces the Quality factor, Frazzini & Pedersen (2007) contributes the Value II factor (also referred to as the HML devil factor) and the betting against beta factor, Dirkx et al. (2020) incorporates the momentum factor into the 5-factor model, and Connor & Korajczyk (2022) introduces commodity and currency factors. These models collectively aim to elucidate the distinctions within return-generating processes that exert an influence on different asset classes. Furthermore, their objective is to uncover shared characteristics among various securities.

In response to the need for greater flexibility in capturing evolving financial market conditions, several factor models have emerged (Feng, 2020). These models are designed to adapt more swiftly, enabling a timely adjustment to changing market circumstances. Our study includes the Asness model, Frazzini model and Durand model and a combination of them as an extension (Appendix A2.2-A2.5).

2.4 Data Collection

The data sample consists of stocks from twenty-eight (28) European Union countries separated into three categories (Green, Red, and Grey), based on the criteria in Table 2.1. The data set contains 2007 Grey, 150 Green, and 367 Red stocks. The data in this study is collected or aggregated at a monthly frequency. The sample data are collected from 1st January 2000 to 31st December 2019. Our aim is to study the sensitivity of our risk factors over time and also with a separation in 2009. The European union crisis began in the second-half of 2009 leading to a shift in systemic risk across EU economies, thereby substantially shaping the influence of various factors[5] (Begg, 2012; Bouvet & King, 2013). The financial crisis event had a profound and enduring impact in particular European countries (Greece, Portugal, Spain, Cyprus, Italy and Ireland), exacerbating the challenges faced during the period spanning from 2010 to 2012. Our "classical" risk factors come from the library of Kenneth R. French[6] ,the BAB, HML^{DEVIL} and QML from Asness and Frazzini database and the closing stock prices, the EU volatility index, commodity and currency prices from the Thomson Reuters Eikon[7]. The variables include the "market excess", "risk free rate", "momentum",

[5] We apply the Chow test for the structural point.
[6] http://mba.tuck.dartmouth.edu
[7] https://eikon.thomsonreuters.com/

“size”, “value”, “profitability”, “investment”, “fear”, “value II”, “quality”, “currency”, “commodities”, and “systematic risk” portfolios (Appendix Table A2.2 till A2.5).

The stock selection process entails considering companies that were listed on the public stock exchange prior to 2015. However, it is essential to acknowledge certain limitations stemming from missing values and varying sizes within each stock universe. The securities without variation (or nulls) are dropped from the sample. These securities aren’t traded very often so prices are stale and uninformative. An implicit assumption in our analysis is that stocks are traded across European markets, and we ignore the country in which they are issued. European markets have free access and stocks can be purchased through ADRs, EDRs, or GDRs between countries, with little or no constraints. It is also worth mentioning that we filter our data and remove the stocks with more than 80% missing values and clean the data from errors (e.g., stocks with zero prices/missing values between prices, not survive, huge irrational returns et cetera).

Lastly, we winsorize the data to mitigate the influence of extreme values within the sample, thereby minimizing the potential impact of outliers that may be spurious in nature. The winsorization is set at 95%, which means every security (i) returns belongs within a specific internal ($average_i \pm 1.96*s.d._{(i)}$), and the observation above and below the boundaries are sharing 2.5% of the sample and are the outliers. One plausible explanation could be attributed to the occurrence of massive volume of one-sided position trading in isolated illiquid securities within the market and the rapid market declines during the financial crisis. This phenomenon can lead to substantial fluctuations in the returns of these securities.

2.5 Independent and Control Variables

The independent variables (Appendix Table A2.2-A2.5) seek to capture the Green, Grey and Red stocks' variation in European markets. Past studies highlight the Fama-French models and Carhart models as the most popular asset pricing models that explain the stock's behaviour in any liquid market. Table A2.6-A2.9 provides descriptive statistics of our sample variables. Tables A2.10-A2.22 independent variables' correlation matrix. Based on the correlation matrix presented in tables A2.10-A2.22, it becomes evident that there exists a strong correlation among the factors, with correlations often surpassing 40% and even exceeding 60%. This strong relationship is particularly pronounced after the crisis period. This heightened correlation among the risk factors can be attributed to the aftermath of the crisis, which has caused a reshaping of market dynamics and interdependencies. The financial upheaval likely led to a greater synchronicity in the behavior of these factors, reflecting a heightened level of interconnectedness and shared influences on asset movements. This could be a result of changed investor behavior, market regulations, or shifts in economic fundamentals that have collectively strengthened the interrelation among these factors. Thus, these risk factors (Erdinç, 2018) are not only valued as theoretical instruments, but they also provide practical results for explaining the securities returns in any liquid market (such as the turkey financial market).

2.6 Methodology

The Fama-French Model (including the Carhart model) is employed as a hybrid factor model that integrates estimation techniques derived from both macroeconomic and fundamental factor models. The Fama-French Model is estimated in a two-stage regression; the first stage is a Time Series (TS) regression, while the second stage involves a cross-section (CS) regression. Specifically, for the Fama-French Model (1993), three macroeconomic factors are identified; the market index return, the SMB portfolio return (that corresponds to Size), and the HML portfolio return (that corresponds to value). After the construction of those portfolios (computed in the Fama French library), the excess returns of asset i for a time period [t-T, t] are regressed on returns of the market, SMB, and HML portfolio using a time-series approach, the same follows with the 5-factor Model and the Carhart Model.

Our statistical model is estimated as a panel data model with random effects[8], which take into consideration the individual class of the Green, Grey and Red securities heterogeneity. Random effects are more appropriate when you are interested in estimating the average relationship between the independent variables and the dependent variable while allowing for variation[9] in the stock return.

In asset pricing research within the EU stock market, employing random effects panel data models offers distinct advantages. These models efficiently manage unobserved heterogeneity when this heterogeneity is uncorrelated with the independent variables, allowing for the inclusion of time-invariant variables typically excluded in fixed effects models (Baltagi, 2005; Greene, 2012). Additionally, random effects models provide more efficient estimators under certain assumptions, making them particularly useful in financial data analysis (Hsiao, 2014). They also facilitate broader inferences to the population rather than being restricted to the sample, which is crucial given the diversity among EU countries (Wooldridge, 2010). Moreover, random effects models facilitate broader generalizations across the entire population of EU stocks, rather than being limited to specific samples, thus enhancing the robustness and applicability of the results (Arellano, 2003). Empirical studies, such as those by Bekaert and Harvey (1995), Fama and French (1998), and Harvey (1991), underscore the utility of random effects models in examining international market integration, stock returns, and covariance risk, respectively. Thus, the robust capabilities of random effects models make them a compelling choice and well-suited for examining how different environmental classifications impact stock returns in the EU market, providing valuable insights for investors and policymakers.

The random effects model is effective where it concentrates the possible association within the same group of data observations, accounting for within-group correlation. Our dataset is unbalanced because companies list on the stock exchange at different times (e.g.,

[8] Note: the factors are repeated observations for every security, and the securities are belonging in the similar activity sector with large number in the cross-section regression, therefore it is difficult to apply another method. Additionally, the RE estimate the parameters with greater efficient (using N-1 degrees of freedom) and the coefficients are time-invariant with the regressors (Cameron & Trivedi, 2009).

[9] Hausman test is recommended in certain cases for determining the suitability of time-specific fixed effects. However, given our research question and the underlying assumptions, our study does not aim to capture time-specific effects or control for unobserved heterogeneity across securities. Therefore, the use of the Hausman test is not applicable in our context.

missing values) and the different size for every category. The dependent variable derives from three sectors as Green, Red (or Brown), and Grey. These sectors returns are evaluated with the regression equation (2.2 - 2.4) in the form [2.5]-[2.7], below:

$r_{i,t}^{j}$ - $r_{f,t}$ $= a_i + b_{1,i}^{j} MKTRF_t + b_{2,i}^{j} SMB_t + b_{3,i}^{j} HML_t + e_{i,t}^{j}$, 3-factor Fama Frech model (2.5)

$r_{i,t}^{j}$ - $r_{f,t}$ $= a_i + b_{1,i}^{j} MKTRF_t + b_{2,i}^{j} SMB_t + b_{3,i}^{j} HML_t + b_{4,i}^{j} MOM_t + e_{i,t}^{j}$, 4-factor model/ Carhart model (2.6)

$r_{i,t}^{j}$ - $r_{f,t}$ $= a_i + b_{1,i}^{j} MKTRF_t + b_{2,i}^{j} SMB_t + b_{3,i}^{j} HML_t + b_{4,i}^{j} RMW_t + b_{5,i}^{j} CMA_t + e_{i,t}^{j}$, 5-factor Fama Frech model (2.7)

with i = 1,…,n, the n is 150 for Green stocks, 2007 for Grey stocks, and 367 for Red stocks. The n depends on the Size of the stock category, and j is an index that groups the stock (0-Green,1-Grey,2-Red). The t represents the time period.

$r_{i,t}^{j}$ is the return of asset i at time t (within the period, 2000-2019); $r_{f,t}$ is the risk-free rate at time t; the $MKTRF_t$ is the return on a European region's (Stoxx Europe 600 Index)[10]value-weighted market portfolio at time t; the SMB_t is Small Minus Big size companies; the HML_t is high minus low based on the value of the companies; the RMW_t is Robust Minus Weak based on the operating profitability of the companies at time t; the CMA_t is conservative minus aggressive and based on the investment of the companies at time t; the MOM_t is the monthly momentum. (see Appendix Table A2.3) The a_i is the stock's alpha performance, and b_k is the coefficient from the specific k-factor (with k=1,..,5). As the $r_{i,t}^{j}$ - $r_{f,t}$ denotes the excess return of portfolio i in the time t with the specific asset class j.

The Fama and French model is constructed with the help of SMB, HML, RMW, and CMA factors (and some of these factors are also used in the Carhart model). To build these factors, we sort stocks into two market caps (Small and Big) and three individual layers as book-to-market equity (B/M), operating profitability (OP), and investment (INV) portfolios

[10] Our stock portfolio includes only European securities

(see Appendix Table A2.2 and Table A2.23). To create the MOM factor for the Carhart model, we sort stocks by Size and lagged momentum. The lagged momentum return is a stock's cumulative return for day t–250 to day t–20. Big stocks are those in the top 90% of June market cap in the Europe stock region, and small stocks are those stocks appearing in the bottom 10%. The B/M, OP, INV, and momentum breakpoints for a region are the 30^{th} and 70^{th} percentiles of respective ratios and the lagged momentum returns for the region's big stocks.

In order to gain insights into the factors that impact asset returns and to ascertain the number of factors in situations where the economic environment undergoes changes, it becomes crucial to examine alternative risks factors and combinations of them in different time periods. The expansion of factor models allows the linking of new factors that enhance the explanation of financial performance and help to differentiate the factor structure of the Green, Grey, and Red securities. Asness et al. (2013) and Frazzini & Pedersen (2014) introduce three additional factors in the classical models, which are the value-devil (HML^{Devil}), quality (QMJ) and betting against beta (BAB) factor. The creation of the Fama-French value portfolios is done by calculating the book-to-price (B/P) using the lagged book and price data ignoring recent price fluctuations and maintaining these values constant until the next rebalancing at the fiscal year-end. The HML^{Devil} (Asness et al., 2013) overcomes the limitation of classical HML models, which rely on outdated or less timely book-to-price data, by employing more recent price data while maintaining the necessary information regarding the value of the book-to-price. The updated Value portfolio based on the most recent measurements (HML^{Devil}) generates statistically significant results for the explanation of the common variation of the securities returns. The Bet Against Beta factor (Frazzini & Pedersen, 2014) is associated with the capital asset pricing model (CAPM). The CAPM is based on the rationality of the agents who desire to invest in the highest Sharpe ratio or, based on their risk appetite, allocate their investments to the market portfolio and decide to borrow or lend at the risk-free rate. This beta-tilting trend implies that high-beta securities demand lower risk-adjusted returns than low-beta securities. The betting-against-beta (BAB) portfolio, created by combining a portfolio that focuses on low-beta stocks with another portfolio that bets against high-beta stocks. This helps to create a more neutral position in the market. The other factor is the "Quality Minus Junk" (QMJ), which is the difference in the portfolio of high-quality stocks (such as firms with high profitability characteristics and well management) and low-quality stocks, known as junk (such as firms with low or without profitability and poor management).

Likewise, the above factors are not exhaustive, as the search for factors influencing returns remains ongoing to discover new risk factors to enhance the understanding and explanation of asset performance. Alternative factors applied in our study are the Semi-factor structure (Connor & Korajczyk, 2022) which employs the currency and the commodity factors. These factors represent a contemporary approach to understanding and modeling asset returns. The methodology acknowledges the significance of currency and commodities factors in shaping investment outcomes. Currency factors reflect the influence of exchange rate movements on investment performance, while commodities factors capture the impact of changes in commodity prices on asset returns.

Institutional investors utilize currency and commodities factor strategies to hedge unfavorable investment assets in globally diversified portfolios (Pojarliev & Levich, 2008). The utility of commodities is the protection against inflation and the low correlation relationship with the stocks, that provides significant value on the stock portfolios (Blitz & De Groot, 2014). Although, during the 2008/2009 Global Financial Crisis, the commodity prices fell faster than other asset classes and caused a rethinking regarding the advantages of the commodities factors (Bartram & Bodnar, 2009). Incorporating currency and commodities factors aligns with the objective of creating more robust and resilient portfolios. By recognizing the importance of these factors, institutional investors seek to enhance their ability to navigate the complexities of global financial markets and manage risks more effectively. Additionally, these factors play a pivotal role in the strategies of institutional investors, who leverage them to safeguard against risks and optimize portfolio performance in globally diversified settings.

According to Dirkx & Peter (2020), another approach is to augment the five-factor model with the momentum factor and create the 6-factor model. Lastly, the Fear factor (VIX) from Durand et al. (2011), commonly known as the "investor fear gauge" captures investors' expectations of market volatility and influences the return of stocks. All of the mentioned factors revealed significant results for the structure of the securities.

2.7 Empirical Results and Findings

Table 2.3 reports summary statistics for the Green, Grey, and Red (or brown) stocks returns and compare them before and after the winsorization method. At the end of the specific period, we mention the dimension of the sample.

2.7.1 Summary statistics of Green, Grey, and Red securities returns

Table 2.3 reports summary statistics on Green, Red, and Grey asset returns with Green having 120 assets in the first half period and 150 assets in the second half period and for the whole period. The Red stocks are comprised of 286 assets in the first period and 367 assets in the second half period, and the whole sample. For Green assets, the mean return for the period 2000 - 2009 was 1.16% per month, decreasing to 0.89% after winsorization. For the period 2010 - 2019, the mean return decreased from 0.68% to 0.15% after winsorization. Over the entire period 2000 - 2019, the mean return decreased from 0.86% to 0.42% after winsorization. Winsorization also led to reductions in variance, skewness, and kurtosis, indicating a more stable return distribution, a reduction in volatility and tail risk. The opposite type of securities (Red) observes before winsorization that the mean return for the period 2000 - 2009 was 0.7%, decreasing to 0.4% (after winsorization). For the period 2010 - 2019, the mean return decreased from 0.85% to 0.59% after winsorization. Over the entire period 2000 - 2019, the mean return decreased from 0.8% to 0.51% after winsorization. Lastly, for the neutral type of securities (Grey), the mean return for the period 2000 - 2009 was 1.18%, decreasing to 0.99% after winsorization. For the period 2010 - 2019, the mean return decreased from 0.35% to 0.05% after winsorization. Over the entire period 2000 - 2019, the mean return decreased from 0.65% to 0.39% after winsorization. Winsorization significantly impacted variance, skewness, and kurtosis, resulting in a more robust data representation. Comparing the effects of winsorization across the three categories, we observe that Grey Securities experienced the most significant reduction in mean returns after winsorization, indicating a substantial impact on their performance. On the other hand, Red Securities showed more moderate changes, while Green Securities experienced a relatively moderate decrease in mean returns.

The analysis of monthly simple returns for Green, Grey, and Red Securities reveals that winsorization effectively mitigates the influence of outliers and stabilizes the distribution of the simple returns. The reduction in moments (Mean, Variance, Skewness, and Kurtosis) indicates a more reliable representation of the underlying data. The comparison across categories highlights varying degrees of impact, with Grey Securities being most affected and Red Securities and Green Securities showing more resilience. These findings provide valuable insights for investors and researchers seeking to better understand the behavior of different categories of securities and the effect of the extreme values in the distribution.

Table 2.3: Cross-sectional averages of time-series moments for monthly simple returns from the three categories before and after winsorization

Asset Class		Green Securities Returns		Grey Securities Returns		Red Securities Returns	
Period	Summary stats	Winsorization Before	After	Winsorization Before	After	Winsorization Before	After
2000 - 2009	Mean	1.16	0.89	0.7	0.4	1.18	0.99
	Variance	328.18	201.4	310.81	171.83	222.99	133.37
	Skewness	4.27	1.19	5.87	0.89	5.03	0.83
	Kurtosis	65.83	7.30	135.59	6.2	96.12	7.41
	Min	-95.8	-51.06	-95.66	-59.44	-96.94	-60.92
	Max	437.38	140.12	698.02	199.11	414.37	125.57
	T; n	120;120	120;120	120; 1652	120; 1652	120; 286	120; 286
2010 - 2019	Mean	0.68	0.15	0.85	0.59	0.35	0.05
	Variance	395.95	186.7	224.25	133.83	298.15	186.11
	Skewness	9.5	1.26	8.24	1.67	6.01	1.75
	Kurtosis	203.93	8.95	223.26	19.01	107.18	18.77
	Min	-94.64	-57.59	-98.91	-74.13	-95.71	-73.97
	Max	621.19	140.12	687.66	275.62	526.91	233.94
	T; n	120;150	120;150	120; 2007	120; 2007	120; 367	120; 367
2000 - 2019	Mean	0.86	0.42	0.8	0.51	0.65	0.39
	Variance	371.04	192.24	258.77	148.99	271.11	167.23
	Skewness	7.92	1.23	7.08	1.29	5.77	1.51
	Kurtosis	165.5	8.29	178.88	12.56	106.14	16.51
	Min	-95.8	-57.59	-98.91	-74.13	-96.94	-73.97
	Max	621.19	140.12	698.02	275.62	526.91	233.94
	T; n	240; 150	240; 150	240; 2007	240; 2007	240; 367	240; 367

The table shows the first four moments of Green, Red, and Grey returns (in percentage, %) and the minimum and maximum return within the two subperiods, and the whole period (the observations time is between 1/2000 till 12/2019 and with separation in 12/2009). The table includes the results from before and after winsorization at 95% and the number of cross-sectional (n) securities, and the total months include every security (T).

In our research, we analyze data on a monthly frequency, and we test the optimal level of winzorization at 0.01, 0.05 and 0.10 and the most suitable level was 0.05 to draw conclusions. The reason we employ the standardization technique known as Winsorization is to mitigate the impact of extreme price fluctuations.

2.7.2 Factor structure of Green, Grey, and Red securities

In this subsection, we combine the asset pricing models from Fama-French, Carhart and extension models to characterize the factor structure of the Green, Grey, and Red stock universe. The study analyzes the empirical results obtained from random effect regression using simple returns for the period 2000-2019, along with sub-periods (2000-2009 and 2010-2019).

In Tables 2.4,2.5 and 2.6, we present the results from three prominent asset pricing models (3-factor model, 4-factor model, and 5-factor model) and the corresponding table for each of the three-asset class returns (Green, Grey, and Red) and using the explanatory factors provided by the Kenneth R. French library and Asness library. Furthermore, the first 3 models using exclusively the factors from the Kenneth R. French library and the last 3 models (4, 5 and 6) are the same models but substitute the HML with HML II (or Devil).

Table 2.4: Empirical results for Green simple returns (for the period 2000-2019 and the sub-periods)

Period	Model	Alpha	MktRf	SMB	HML/ HML II*	MOM	RMW	CMA	R-sq within	R-sq between	R-sq overall
2000 – 2009	[1]	0.27	**0.95**	**0.58**	**0.15**				17.54%	1.39%	17.36%
	[2]	0.27	**0.95**	**0.58**	**0.15**	0.01			17.55%	1.39%	17.36%
	[3]	0.18	**0.98**	**0.59**	**0.13**		0.11	0.11	17.57%	1.78%	17.39%
	[4]*	0.27	**0.94**	**0.58**	**0.10**				17.52%	1.59%	17.34%
	[5]*	0.18	**0.97**	**0.57**	**0.19**	**0.09**			17.56%	1.54%	17.38%
	[6]*	0.14	**0.98**	**0.61**	**0.1**		0.14	**0.16**	17.57%	2.07%	17.4%
2010 – 2019	[1]	**-0.54**	**1.03**	**0.84**	**0.35**				14.51%	1.33%	14.33%
	[2]	**-0.46**	**1.02**	**0.84**	**0.31**	**-0.10**			14.54%	1.41%	14.36%
	[3]	**-0.52**	**1.02**	**0.83**	**0.36**		-0.06	-0.12	14.52%	1.4%	14.33%
	[4]*	**-0.49**	**1.04**	**0.82**	**0.35**				14.44%	1.49%	14.26%
	[5]*	**-0.49**	**1.04**	**0.83**	**0.29**	-0.08			14.46%	1.5%	14.27%
	[6]*	**-0.42**	**1.03**	**0.8**	**0.24**		**-0.27**	-0.01	14.46%	1.5%	14.27%
2000 – 2019	[1]	**-0.31**	**0.98**	**0.69**	**0.30**				15.49%	2.68%	15.39%
	[2]	**-0.30**	**0.98**	**0.69**	**0.29**	-0.01			15.50%	2.67%	15.39%
	[3]	**-0.33**	**1.00**	**0.70**	**0.27**		0.01	0.08	15.50%	2.72%	15.39%
	[4]*	**-0.29**	**0.99**	**0.69**	**0.22**				15.41%	2.28%	15.30%
	[5]*	**-0.34**	**1.00**	**0.68**	**0.28**	0.06			15.42%	2.57%	15.32%
	[6]*	**-0.31**	**1.01**	**0.72**	**0.15**		-0.07	**0.22**	15.47%	2.59%	15.36%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, and CMA factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library. Additionally, the results report both dependent variables that are the returns. We denote the models 1, 2, and 3; the 3 Factor Fama and French model, 4 Factor Carhart Model, and 5 Factor Fama and French Model, respectively. The models 4,5 and 6 are the same models but substitute the HML with HML II (or Devil). The table reports the results from equation [2.2] till [2.4]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table 2.4 presents the results for the Green asset class. The coefficients show interesting dynamics over different time periods and models. For the period 2000-2009, all three models (1, 2, and 3) consistently display non-significant alphas. On the other hand, for the period 2010-2019 and the whole period, the alphas are negative for the returns, indicating that assets in the Green category underperformed the market on a risk-adjusted basis. Generally, the coefficients for MktRf, SMB, HML and HML II are positive, suggesting that these factors had a positive impact on the Green asset class's returns and RMW (statistical significant in few models) negative impact suggesting the opposite effect. The coefficients for MktRf (market factor), SMB (size factor) and HML (value factor) remain relatively stable when comparing the 2000-2009 and 2010-2019 periods. This consistency suggests that market movements, the value and the size of the firms continue to be influential factors for the returns of the Green asset. In practical terms, this implies that investors with portfolios sensitive to market performance, value and firm size may have experienced consistent effects on their Green asset holdings throughout these two decades. Positive HML coefficients suggest that stocks characterized by high book-to-market ratios outperformed those with lower ratios in the context of the Green asset. This finding holds practical significance for investors. Investors with a preference for value stocks, typically associated with higher book-to-market values, may have seen favorable returns when allocating their portfolios to the Green asset. During the 2010-2019 period, the MOM and RMW factors exhibit, in particular models, a negative impact on Green asset returns. In contrast to HML, the RMW and MOM factors show a negative impact on Green asset returns in the 2010-2019 period based on the construction of the factor model. This observation implies that stocks of firms with robust profitability profiles or momentum may not have performed as well within the Green asset context during this decade. Investors focusing on factors related to firm profitability or momentum should take note of this influence when crafting their investment strategies. This finding bears practical significance for investors seeking to enhance their risk-adjusted returns and gain a deeper understanding of underlying market dynamics and combine a strategy using the proxies' portfolios. Incorporating HML devil into asset pricing models isn't clear that it can provide more accurate risk assessments, facilitating informed investment decisions. The empirical results reveal nuanced insights that can guide investors in their decision-making processes. Understanding the positive or negative exposures to factors such as HML and RMW, alongside the choice between HML and HML devil, empowers investors to tailor their portfolio strategies to different market conditions and financial goals. The stability of MktRf, HML (both) and SMB coefficients highlights their enduring significance for Green asset returns. Conversely, the fluctuations in RMW, MOM, and CMA coefficients across time periods and models underscore the importance of adapting to evolving market dynamics. This variability of the factors suggests that different factor models are attempting to capture the common variation of the asset returns in distinct ways. Climent & Soriano (2011) for the period 1987-2009 found similar results for the green asset returns regarding the coefficients of the market and growth factors in the US market. The opposite empirical results for US Green and a sub-sector of our Red asset class were found in Ibikunle & Steffen (2017) for the period 1991-2014 in which the adjusted alpha is negative for black and green portfolios and the MOM is a significant factor for the Green portfolio returns.

Table 2.5: Empirical results for Grey simple returns (for the period 2000-2019 and the sub-periods)

Period	**Model**	**Alpha**	**MktRf**	**SMB**	**HML/ HML II***	**MOM**	**RMW**	**CMA**	**R-sq within**	**R-sq between**	**R-sq overall**
2000 – 2009	[1]	-0.01	**0.91**	**0.62**	**-0.21**				17.32%	12.24%	17.22%
	[2]	**0.09**	**0.87**	**0.65**	**-0.22**	**-0.11**			17.44%	11.59%	17.34%
	[3]	**0.23**	**0.88**	**0.65**	**-0.37**		**-0.52**	**0.08**	17.67%	13.03%	17.57%
	[4]*	**-0.17**	**0.90**	**0.62**	**-0.02**				17.14%	12.95%	17.04%
	[5]*	0.07	**0.85**	**0.66**	**-0.18**	**-0.17**			17.31%	12.67%	17.21%
	[6]*	**0.13**	**0.82**	**0.60**	**-0.08**		**-0.45**	**-0.18**	17.41%	13.61%	17.32%
2010 – 2019	[1]	-0.05	**0.86**	**0.76**	**0.16**				13.15%	0.56%	13.01%
	[2]	0.02	**0.85**	**0.76**	**0.13**	**-0.07**			13.17%	0.53%	13.04%
	[3]	**-0.06**	**0.87**	**0.77**	**0.17**		**-0.06**	**0.08**	13.16%	0.55%	13.02%
	[4]*	**-0.06**	**0.88**	**0.75**	**0.09**				13.09%	0.58%	12.96%
	[5]*	0.01	**0.88**	**0.76**	0.01	**-0.10**			13.13%	0.53%	12.99%
	[6]*	-0.06	**0.89**	**0.76**	0.002		**-0.09**	**0.18**	13.13%	0.56%	13.00%

2000 – 2019	[1]	**-0.13**	**0.90**	**0.68**	**-0.04**				14.92%	1.13%	14.83%
	[2]	-0.04	**0.88**	**0.69**	**-0.07**	**-0.09**			14.99%	1.09%	14.91%
	[3]	0.04	**0.88**	**0.68**	**-0.22**		**-0.41**	**0.06**	15.09%	0.93%	15.00%
	[4]*	**-0.14**	**0.90**	**0.68**	0.01				14.91%	1.21%	14.83%
	[5]*	-0.02	**0.87**	**0.70**	**-0.10**	**-0.13**			15.00%	0.99%	14.92%
	[6]*	0.01	**0.86**	**0.66**	**-0.06**		**-0.31**	**-0.09**	15.02%	1.09%	14.94%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, and CMA factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library. Additionally, the results report both dependent variables that are the returns. We denote the models 1, 2, and 3; the 3 Factor Fama and French model, 4 Factor Carhart Model, and 5 Factor Fama and French Model, respectively. The models 4,5 and 6 are the same models but substitute the HML with HML II (or Devil). The table reports the results from equation [2.2] till [2.4]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

In Table 2.5, the coefficients for the Grey asset class also demonstrate diverse patterns over different time periods and models. For the periods 2000-2009 exhibit mostly positive alphas, indicating that assets in the Grey asset class outperformed the market on a risk-adjusted basis. The coefficients for MktRf, and SMB, are positive and significant, suggesting that these factors had a positive impact on the Grey asset class's returns. On the contrary, the coefficients for MOM, and RMW, are negative and significant, suggesting that these factors had a negative impact on the Grey asset class's returns. However, HML coefficients show slight variations across periods, specifically in the second half change from negative to positive. Furthermore, the CMA coefficients demonstrate variations across models, particularly noticeable when transitioning from the HML to the HML devil factor.

The calculated alpha values for the Grey asset class are noteworthy behavior. The alpha is mostly positive for the models in the first half and in the second half mostly statistically insignificant. The adjusted alpha coefficient becomes insignificant, implying that the systematic risk factors included in the model sufficiently capture the variation in the returns of the Grey asset. In other words, the added factors are explaining more of the variation in asset returns, rendering the adjusted alpha term statistically insignificant. This divergence highlights the importance of return measurement methods in assessing the performance of the Grey asset class. Across the observed periods, the coefficients for the market factor (MktRf), size factor (SMB), momentum factor (MOM), and robust-minus-weak (RMW) demonstrate a remarkable level of consistency. This stability suggests that these factors have an enduring influence on the Grey asset class's returns, reinforcing their relevance in asset pricing models. However, it is essential to note the variations observed in the HML factor, particularly during the second half of the study period. These variations indicate that the HML may have responded to changing market conditions or specific economic events. This underscores the dynamic nature of factors and their potential impact on asset returns. An intriguing observation arises from the post-crisis period analysis, where a significant decrease is evident in the coefficients' magnitude. The observed decline in the magnitude of coefficient estimates for assets can be primarily attributed to an increase in idiosyncratic risk following the global financial crisis. In the aftermath of the crisis, market dynamics underwent significant shifts, leading to a greater emphasis on asset-specific factors over systemic market influences. This rise in idiosyncratic risk diminished the correlation between individual asset returns and overall market movements, thereby reducing the sensitivity of assets as measured by their beta coefficients. Additionally, changes in investor behavior, market liquidity, and regulatory adjustments post-crisis further contributed to this decline. As a result, assets displayed lower beta values, reflecting a market environment where individual risks became more pronounced relative to broad market risks. It emphasizes the importance of considering historical context and events when interpreting asset pricing results. Consistently, our analysis reaffirms the superiority of HML models compared to the HML II (or Devil) model in explaining the returns of the Grey asset class. The practical implication here is that employing HML factor enables better risk-adjusted performance and a more comprehensive capture of the underlying market dynamics specific to the Grey asset class.

For investors and financial institutions, these findings hold crucial practical implications. Firstly, recognizing the influence of return measurement methods on alpha calculations can help investors make more informed decisions when assessing the performance of the Grey asset class within their portfolios. The choice between the HML and CMA models can significantly impact perceived asset performance, leading to different allocation strategies. Secondly, the stability of factors such as MktRf, SMB, MOM, and RMW underscores their enduring relevance for constructing asset portfolios. Financial institutions can utilize this stability to design more robust investment strategies and tailor their product offerings to align with the risk-return preferences on their portfolios. Lastly, the observed variations in factor coefficients, especially during unique periods like the post-crisis era, highlight the importance of dynamic asset management. Investors and financial institutions should remain agile and adapt to changing market conditions, incorporating updated factor insights into their investment strategies to mitigate risks and seize opportunities effectively.

Table 2.6: Empirical results for Red simple returns (for the period 2000-2019 and the sub-periods)

Period	Model	Alpha	MktRf	SMB	HML/ HML II*	MOM	RMW	CMA	R-sq within	R-sq between	R-sq overall
2000 – 2009	[1]	**0.30**	**0.80**	**0.69**	**0.17**				19.15%	23.46%	19.02%
	[2]	**0.24**	**0.83**	**0.66**	**0.20**	**0.08**			19.24%	23.05%	19.11%
	[3]	0.12	**0.84**	**0.69**	**0.21**		**0.33**	0.08	19.33%	24.23%	19.19%
	[4]*	**0.31**	**0.79**	**0.70**	**0.14**				19.16%	23.81%	19.03%
	[5]*	-0.02	**0.86**	**0.65**	**0.38**	**0.25**			19.62%	22.54%	19.48%
	[6]*	0.04	**0.85**	**0.72**	**0.19**		**0.39**	**0.16**	19.43%	24.27%	19.28%
2010 – 2019	[1]	**-0.54**	**0.92**	**0.58**	**0.37**				11.72%	1.27%	11.62%
	[2]	**-0.44**	**0.91**	**0.59**	**0.32**	**-0.12**			11.76%	0.95%	11.67%
	[3]	**-0.58**	**0.93**	**0.6**	**0.41**		0.12	0.08	11.72%	1.35%	11.64%
	[4]*	**-0.31**	**0.87**	**0.54**	**0.70**				12.18%	1.24%	12.09%
	[5]*	**-0.33**	**0.87**	**0.54**	**0.74**	0.05			12.19%	1.36%	12.09%
	[6]*	**-0.34**	**0.87**	**0.55**	**0.74**		0.11	0.01	12.19%	1.33%	12.10%
2000 – 2019	[1]	**-0.29**	**0.86**	**0.64**	**0.33**				13.67%	11.03%	13.63%
	[2]	**-0.33**	**0.87**	**0.63**	**0.35**	**0.04**			13.68%	11.19%	13.64%
	[3]	**-0.41**	**0.89**	**0.66**	**0.36**		**0.22**	**0.13**	13.72%	12.14%	13.69%
	[4]*	**-0.26**	**0.85**	**0.64**	**0.35**				13.76%	12.21%	13.72%
	[5]*	**-0.45**	**0.88**	**0.61**	**0.54**	**0.22**			13.97%	13.52%	13.94%
	[6]*	**-0.40**	**0.89**	**0.68**	**0.34**		**0.19**	**0.25**	13.84%	13.05%	13.81%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, and CMA factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library. Additionally, the results report both dependent variables that are the returns. We denote the models 1, 2, and 3; the 3 Factor Fama and French model, 4 Factor Carhart Model, and 5 Factor Fama and French Model, respectively. The models 4,5 and 6 are the same models but substitute the HML with HML II (or Devil). The table reports the results from equation [2.2] till [2.4]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 4th decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table 2.6 illustrates a range of coefficient patterns associated with Red asset returns across various timeframes and models. Specifically, throughout the 2000-2009 period, the models (1, 2, and 4) exhibit mostly positive alphas. This suggests that assets within the Red asset class consistently overperformed the market when considering risk-adjusted performance.

In our analysis, we observed that the coefficients for market factor (MktRf), size factor (SMB), and value factor (HML) are positive and statistically significant, indicating that these factors have historically exerted a positive influence on the returns of the Red asset class. For the first half period and whole period the momentum factor (MOM), profitability factor (CMA) and robust-minus-weak factor (RMW) are predominantly positive and statistically significant. Conversely, the momentum factor (MOM) exhibited a negative impact on Red asset returns in the second half. However, it's crucial to note that the value factor (HML II or Devil) displayed an improving role across different models. These variations may reflect subtle differences in the measurement or modeling of this factor but generally confirm its positive influence on Red asset returns.

The results for the Red asset class in the period from 2010 to 2019 take a divergent turn. During this period, our models indicate negative alphas for the Red asset class. This shift in alpha sign may raise questions for potential investors who seek clarity on what to expect going forward. The change in alpha sign for Red stocks hinges on several factors. It is essential to recognize that historical performance patterns do not guarantee future outcomes. Instead, alpha's direction may depend on evolving market conditions, economic variables, and the unique characteristics of the Red asset class. Investors should consider these elements when forming expectations for alpha. For investors, this implies that relying solely on historical alpha trends may not provide a clear-cut forecast. Instead, they should maintain a forward-looking perspective and continuously assess the evolving landscape. Alpha's sign may depend on factors such as market sentiment, economic cycles, or shifts in investor preferences. Therefore, potential investors should exercise caution, conduct thorough due diligence, and remain adaptable in their investment decisions. It's worth noting that while alpha may change, the coefficients for MktRf, SMB, and HML remain relatively consistent with the previous period in the 2010-2019 era. However, there are variations in profitability factor (CMA) and robust-minus-weak factor (RMW) coefficient, which is not statistically significant, and the momentum factor (MOM), which exhibits a negative impact on Red returns during this period. Considering the entire period from 2000 to 2019, our models consistently display negative alphas for the Red asset class. This consistent pattern suggests that investors should approach the Red asset class with caution, particularly if they have a historical perspective.

However, it's important to recognize that past performance may not always mirror future results, and investors should consider the broader context.

In conclusion, the change in the sign of alpha for Red stocks underscores the dynamic nature of financial markets. Investors should approach their decisions with caution, considering a broader set of factors and recognizing that historical trends are not infallible predictors of future outcomes.

Comparing the beta coefficients of different securities across two distinct sub-periods reveals significant changes in risk sensitivities and exposures. For Red and Grey securities, we observe notable fluctuations in their beta values, indicating either an increase or a decrease in their sensitivity to market risk. This suggests that the risk profiles of these securities have altered over time. Furthermore, there is a noticeable change in risk exposures, particularly for Green and Red securities. This variation indicates shifts in how these securities respond to broader market movements, reflecting changes in their market behavior and risk profiles. These findings enhance our understanding of how economic conditions have evolved between the two periods. The observed changes in beta values and risk exposures underscore that shifts in the economic environment have impacted the risk behavior of different types of securities. This underscores the broader implication that market conditions and investor perceptions have undergone significant transformations over time, influencing the risk dynamics of securities categorized as Red, Grey, and Green.

The coefficient of the SMB is positive; this suggests that the securities have exposure to small-cap stocks, but the degree of exposure depends on the beta value of the SMB which for Green and Grey stocks is increasing from sub-period to subperiod. The positive coefficient of the HML in Green and Red assets suggests that the stocks have exposure to high book-to-market (value) stocks and the Grey assets have exposure to low value stocks (in the first half). The momentum (MOM) coefficient has a negative sign for Grey assets, which suggests that these types of assets have exposure to a portfolio with aggressive losers momentum. In other words, these assets tend to perform worse when it comes to stocks that have been experiencing strong negative momentum or losing streaks. Negative momentum implies that stocks with a history of poor recent performance will continue to perform poorly in the short term. Investors typically view negative momentum as a sign of weakness or distress in those stocks. It could be due to factors such as poor earnings, unfavorable news, or market sentiment turning against them. For investors and financial institutions, it has practical implications. It suggests that when constructing portfolios that include Grey assets, they should be aware of the potential impact of stocks with aggressive losers momentum. These assets may be more susceptible to underperformance during periods when stocks with negative momentum are struggling. Additionally, investors should assess their risk tolerance and portfolio diversification strategies, especially when considering investments in assets with negative momentum exposure. It may be important to balance such assets with other investments to manage risk effectively. For example, they might choose to allocate smaller proportions of their portfolios to Grey assets during periods when negative momentum stocks dominate the market. Alternatively, they may implement risk mitigation strategies, such as stop-loss orders or hedging techniques, to protect their portfolios in the face of adverse momentum trends.

The CMA estimated coefficients are negative and statistically significant (at 5%), which means our asset class is exposed to the firms investing aggressively. Corresponding to the findings of the profitability (RMW) factor coefficient, the Red stock exposes to high operating profitability firms, and contrariwise, the Grey stock indicates exposure to low operating profitability firms. Furthermore, the Green and Red stocks increase their exposure to the market (MktRf) factor substantially, even though this exposure has the most significant impact among the other factors. In contrast, Grey securities decrease their exposure to the global market from the first to the second half period.

In some cases, the assets show similar behaviour (or risk exposure) since the economy represents the systematic risk where it cannot diversify away. That means during periods of economic turbulence or significant market events, many assets may respond in a similar way because they are influenced by the same underlying economic or market forces. This phenomenon is often observed when economic conditions lead to increased correlations between the risk factors (as indicated in Appendix tables A2.10-A2.22). Diversification is an investment strategy where investors spread their investments across different asset classes to reduce risk. However, systematic risk cannot be diversified away because it affects all assets within a particular market or the entire economy. Even a well-diversified portfolio may still be exposed to systematic risk, as it is inherent to the broader economic environment. In some cases, it can be challenging to generate alpha consistently because systematic risk dominates, leaving limited room for active managers or investors to outperform the market.

Moreover, the R-sq overall and the relatively consistent coefficients between the subperiods underscores the robustness of our results, and ensures it detects meaningful relationships between the asset class and the factors from the asset pricing models. The principles of the asset pricing models contribute to accurately capturing the distinct characteristics of the asset class returns and the significant results enhancing the confidence in the reliability of our conclusions.

The empirical results have several implications for investors. The positive alphas observed for the Grey and Red asset (for the first half period) imply that it has provided excess returns beyond what could be explained by traditional risk factors. This finding may attract investors seeking higher returns. On the other hand, the mixed results observed for the Green, Grey and Red asset (for the second period and the whole period) suggest that they may not always outperform the market on a risk-adjusted basis. Investors interested in these asset classes should exercise caution and conduct further analysis to understand the underlying risk factors driving their performance.

Tables 2.7-2.8, 2.9-2.10, and 2.11-2.12 exhibit the findings from the extensions of two asset pricing models: the 3-factor, and 4-factor models. Each pair of tables corresponds to a specific asset class return (Green, Grey, and Red respectively), employing explanatory factors sourced from the Kenneth R. French library, Datastream, and Asness database. The empirical results are produced from the estimation of equations 2.2-2.3 and their extensions by employing additional European factors for the construction of our models. Additionally, Tables A2.25 to A2.27 (refer to Appendix) present the results from the extension asset pricing models from the Fama French 5-factor model. These three tables in the appendixes correspond to each of the three-asset class returns (Green, Grey, and Red). The empirical results are produced from the estimation of the extended equation 2.4.

Table 2.7: Empirical results for Green returns-extension (period 2000-2019 and the sub-periods)

Period	Model	Alpha	MktRf	SMB	HML/ HML II*	BAB	QML	FEAR	R-sq within	R-sq between	R-sq overall
2000 – 2009	[1]	0.27	**0.95**	**0.57**	**0.15**	0.01			17.54%	1.39%	17.36%
	[2]	0.29	**0.94**	**0.56**	**0.14**	0.02	-0.03		17.54%	1.36%	17.36%
	[3]	0.27	**0.94**	**0.57**	**0.15**	0.01		-0.01	17.55%	1.41%	17.36%
	[4]*	0.26	**0.94**	**0.55**	**0.11**	0.04			17.53%	1.56%	17.36%
	[5]*	**0.25**	**0.94**	**0.55**	0.11	0.04		-0.001	17.53%	1.57%	17.36%
2010 – 2019	[1]	**-0.56**	**1.03**	**0.83**	**0.35**	0.03			14.52%	1.34%	14.33%
	[2]	**-0.48**	**1.00**	**0.79**	**0.26**	0.06	-0.16		14.53%	1.38%	14.34%
	[3]	**-0.55**	**1.00**	**0.86**	**0.36**	0.05		-0.01	14.53%	1.36%	14.34%
	[4]*	**-0.54**	**1.04**	**0.79**	**0.37**	0.09			14.46%	1.56%	14.27%
	[5]*	**-0.51**	**0.99**	**0.83**	**0.39**	**0.11**		-0.02	14.48%	1.62%	14.29%
2000 – 2019	[1]	**-0.30**	**0.99**	**0.69**	**0.30**	-0.01			15.50%	2.67%	15.39%
	[2]	**-0.28**	**0.98**	**0.68**	**0.28**	-0.00	-0.03		15.50%	2.65%	15.39%
	[3]	**-0.29**	**0.97**	**0.70**	**0.30**	0.001		-0.01	15.50%	2.72%	15.40%
	[4]*	**-0.32**	**0.99**	**0.66**	**0.23**	0.05			15.42%	2.50%	15.31%
	[5]*	**-0.32**	**0.97**	**0.67**	**0.24**	**0.06**		-0.01	15.42%	2.57%	15.32%

The table shows the alpha and beta value of the MktRf, SMB, HML, BAB, QML, and FEAR factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French, Datastream and Asness data library. Additionally, the results report both dependent variables that are the simple returns. We denote the models 1, 2, and 3; as extension the 3 Factor Fama and French model by applying additional factors from the Asness and Durand. Respectively, the models 4, and 5 are the same models but substitute the HML with HML II (or Devil). The table reports the results using extension factors from equation [2.2]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table 2.8: Empirical results for Green returns-extension II (period 2000-2019 and the sub-periods)

Period	Model	Alpha	MktRf	SMB	HML/ HML II*	MOM	UK/ EUR	GOLD	R-sq within	R-sq between	R-sq overall
2000 – 2009	[1]	0.2	**0.93**	**0.61**	**0.13**		**0.18**		17.64%	0.94%	17.46%
	[2]	0.27	**0.95**	**0.57**	**0.15**			0.002	17.54%	1.4%	17.36%
	[3]	0.2	**0.93**	**0.61**	**0.13**		**0.18**	0.01	17.64%	0.94%	17.46%
	[4]	0.2	**0.93**	**0.61**	**0.13**	-0.01	**0.18**		17.64%	0.93%	17.46%
	[5]	0.27	**0.95**	**0.57**	**0.15**	0.01		0.001	17.55%	1.39%	17.36%
	[6]	0.19	**0.93**	**0.61**	**0.13**	-0.01	**0.19**	0.01	17.64%	0.93%	17.46%
	[7]*	0.18	**0.92**	**0.63**	**0.12**		**0.21**		17.65%	0.93%	17.48%
	[8]*	0.3	**0.94**	**0.58**	**0.1**			-0.003	17.52%	1.58%	17.34%
	[9]*	0.17	**0.92**	**0.62**	**0.12**		**0.22**	0.01	17.66%	0.93%	17.48%
2010 – 2019	[1]	**-0.54**	**1.03**	**0.84**	**0.33**		**0.15**		14.57%	2.07%	14.38%
	[2]	**-0.57**	**1.04**	**0.85**	**0.38**			**0.07**	14.56%	1.66%	14.37%
	[3]	**-0.57**	**1.04**	**0.85**	**0.36**		**0.15**	**0.07**	14.61%	2.45%	14.43%
	[4]	**-0.42**	**1.02**	**0.85**	**0.27**	**-0.13**	**0.19**		14.62%	2.37%	14.43%
	[5]	**-0.49**	**1.03**	**0.85**	**0.34**	**-0.09**		**0.06**	14.58%	1.75%	14.4%
	[6]	**-0.46**	**1.03**	**0.85**	**0.3**	**-0.12**	**0.18**	**0.06**	14.66%	2.75%	14.47%
	[7]*	**-0.47**	**1.03**	**0.82**	**0.35**		**0.19**		14.53%	2.6%	14.35%
	[8]*	**-0.5**	**1.04**	**0.82**	**0.35**			0.01	14.45%	1.54%	14.26%
	[9]*	**-0.48**	**1.04**	**0.82**	**0.34**		**0.19**	0.02	14.45%	1.54%	14.26%
2000 – 2019	[1]	**-0.32**	**0.98**	**0.71**	**0.28**		**0.17**		15.57%	3.17%	15.47%
	[2]	**-0.34**	**0.99**	**0.68**	**0.31**			**0.04**	15.51%	2.86%	15.41%
	[3]	**-0.35**	**0.98**	**0.70**	**0.29**		**0.17**	**0.04**	15.59%	3.37%	15.48%
	[4]	**-0.29**	**0.97**	**0.71**	**0.26**	-0.03	**0.18**		15.58%	3.18%	15.47%
	[5]	**-0.32**	**0.99**	**0.69**	**0.31**	-0.09		**0.04**	15.51%	2.86%	15.41%
	[6]	**-0.32**	**0.97**	**0.71**	**0.28**	-0.03	**0.18**	**0.04**	15.59%	3.39%	15.49%
	[7]*	**-0.30**	**0.97**	**0.71**	**0.23**		**0.21**		15.53%	3.15%	15.42%
	[8]*	**-0.30**	**0.99**	**0.69**	**0.22**			0.01	15.41%	2.31%	15.30%
	[9]*	**-0.31**	**0.98**	**0.71**	**0.23**		**0.21**	0.02	15.53%	3.21%	15.42%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, UK/EUR, and Gold factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French, Datastream and Asness data library. Additionally, the results report both dependent variables that are the simple returns. We denote the models 1, 2, and 3; as extension the 3 Factor Fama and French and 4 factor Carhart models by applying additional factors of commodities and currencies. Respectively, the models 7,8 and 9 are the same models but substitute the HML with HML II (or Devil). The table reports the results using extension factors from equation [2.2] till [2.3]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table 2.9: Empirical results for Grey returns-extension (period 2000-2019 and the sub-periods)

Period	Model	Alpha	MktRf	SMB	HML/ HML II*	BAB	QML	FEAR	R-sq within	R-sq between	R-sq overall
2000 – 2009	[1]	**0.08**	**0.91**	**0.72**	**-0.18**	**-0.12**			17.45%	11.54%	17.34%
	[2]	**0.31**	**0.78**	**0.58**	**-0.32**	0.01	**-0.37**		17.56%	12.53%	17.46%
	[3]	**0.07**	**0.93**	**0.73**	**-0.18**	**-0.14**		**0.01**	17.46%	11.48%	17.36%
	[4]*	0.002	**0.90**	**0.74**	**-0.06**	**-0.15**			17.34%	12.42%	17.24%
	[5]*	-0.002	**0.92**	**0.75**	**-0.06**	**-0.17**		**0.01**	17.35%	12.41%	17.25%
2010 – 2019	[1]	**-0.11**	**0.86**	**0.72**	**0.16**	**0.10**			13.18%	0.56%	13.04%
	[2]	**-0.08**	**0.85**	**0.71**	**0.13**	**0.11**	**-0.06**		13.18%	0.56%	13.04%
	[3]	**-0.10**	**0.84**	**0.75**	**0.16**	**0.11**		**-0.01**	13.19%	0.54%	13.05%
	[4]*	**-0.12**	**0.88**	**0.71**	**0.11**	**0.11**			13.13%	0.58%	12.99%
	[5]*	**-0.11**	**0.85**	**0.73**	**0.13**	**0.13**		**-0.01**	13.14%	0.57%	13.01%
2000 – 2019	[1]	**-0.08**	**0.90**	**0.73**	**-0.03**	**-0.08**			14.95%	1.08%	14.87%
	[2]	**0.12**	**0.81**	**0.62**	**-0.16**	**0.02**	**-0.32**		15.04%	0.97%	14.96%
	[3]	**-0.08**	**0.91**	**0.72**	**-0.03**	**-0.08**		0.002	14.95%	1.08%	14.87%
	[4]*	**-0.08**	**0.90**	**0.73**	-0.01	**-0.08**			14.95%	1.13%	14.87%
	[5]*	**-0.08**	**0.90**	**0.73**	-0.01	**-0.09**		0.002	14.95%	1.12%	14.87%

The table shows the alpha and beta value of the MktRf, SMB, HML, BAB, QML, and FEAR factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French, Datastream and Asness data library. Additionally, the results report both dependent variables that are the simple returns. We denote the models 1, 2, and 3; as extension the 3 Factor Fama and French model by applying additional factors from the Asness and Durand. Respectively, the models 4, and 5 are the same models but substitute the HML with HML II (or Devil). The table reports the results using extension factors from equation [2.2]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2^{nd} decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table 2.10: Empirical results for Grey returns-extension II (period 2000-2019 and the sub-periods)

Period	Model	Alpha	MktRf	SMB	HML/ HML II*	MOM	UK/ EUR	GOLD	R-sq within	R-sq between	R-sq overall
2000 – 2009	[1]	-0.04	**0.90**	**0.64**	**-0.23**		**0.13**		17.37%	12.02%	17.27%
	[2]	0.03	**0.91**	**0.63**	**-0.22**			**-0.03**	17.33%	12.33%	17.23%
	[3]	-0.007	**0.90**	**0.65**	**-0.23**		**0.12**	**-0.03**	17.37%	12.11%	17.27%
	[4]	0.06	**0.84**	**0.69**	**-0.27**	**-0.12**	**0.16**		17.53%	11.01%	17.42%
	[5]	**0.11**	**0.87**	**0.66**	**-0.25**	**-0.10**		**-0.02**	17.45%	11.68%	17.34%
	[6]	0.06	**0.84**	**0.69**	**-0.27**	**0.12**	**0.16**	-0.01	17.53%	11.06%	17.42%
	[7]*	**-0.21**	**0.89**	**0.63**	-0.02		**0.10**		17.17%	12.88%	17.07%
	[8]*	**-0.15**	**0.90**	**0.62**	**-0.02**			**-0.01**	17.14%	12.98%	17.04%
	[9]*	**-0.20**	**0.89**	**0.64**	-0.02		**0.10**	-0.01	17.17%	12.90%	17.07%
2010 – 2019	[1]	-0.04	**0.86**	**0.76**	**0.14**		**0.14**		13.22%	0.62%	13.08%
	[2]	-0.05	**0.86**	**0.76**	**0.16**			0.01	13.15%	0.56%	13.01%
	[3]	-0.04	**0.86**	**0.76**	**0.14**		**0.14**	0.003	13.22%	0.62%	13.08%
	[4]	0.05	**0.85**	**0.76**	**0.09**	**-0.10**	**0.17**		13.26%	0.57%	13.12%
	[5]	0.05	**0.86**	**0.76**	**0.13**	**-0.07**		0.002	13.17%	0.53%	13.04%
	[6]	0.05	**0.85**	**0.76**	**0.09**	**-0.10**	**0.17**	-0.0003	13.26%	0.57%	13.12%
	[7]*	-0.04	**0.87**	**0.75**	**0.09**		**0.16**		13.18%	0.66%	13.05%
	[8]*	-0.04	**0.87**	**0.75**	**0.10**			**-0.02**	13.10%	0.55%	12.96%
	[9]*	-0.03	**0.87**	**0.75**	**0.10**		**0.16**	**-0.02**	13.18%	0.63%	13.05%
2000 – 2019	[1]	**-0.14**	**0.90**	**0.69**	**-0.06**		**0.14**		14.98%	1.24%	14.90%
	[2]	**-0.12**	**0.90**	**0.68**	**-0.05**			**-0.02**	14.92%	1.08%	14.84%
	[3]	**-0.13**	**0.89**	**0.69**	**-0.06**		**0.14**	**-0.02**	14.98%	1.19%	14.90%
	[4]	-0.04	**0.86**	**0.71**	**-0.10**	**-0.11**	**0.16**		15.08%	1.21%	14.99%
	[5]	-0.03	**0.87**	**0.70**	**-0.08**	**-0.09**		**-0.02**	14.99%	1.05%	14.91%
	[6]	-0.03	**0.86**	**0.72**	**-0.10**	**-0.11**	**0.16**	**-0.01**	15.08%	1.17%	15.00%
	[7]*	**-0.14**	**0.89**	**0.69**	0.01		**0.13**		14.97%	1.33%	14.89%
	[8]*	**-0.13**	**0.89**	**0.68**	0.01			**-0.01**	14.91%	1.18%	14.83%
	[9]*	**-0.14**	**0.89**	**0.69**	0.01		**0.13**	**-0.01**	14.97%	1.31%	14.89%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, UKEUR, and Gold factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French, Datastream and Asness data library. Additionally, the results report both dependent variables that are the simple returns. We denote the models 1, 2, and 3; as extension the 3 Factor Fama and French and 4 factor Carhart models by applying additional factors of commodities and currencies. Respectively, the models 7,8 and 9 are the same models but substitute the HML with HML II (or Devil). The table reports the results using extension factors from equation [2.2] till [2.3]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table 2.11: Empirical results for Red returns-extension (period 2000-2019 and the sub-periods)

Period	Model	Alpha	MktRf	SMB	HML/ HML II*	BAB	QML	FEAR	R-sq within	R-sq between	R-sq overall
2000 – 2009	[1]	0.18	**0.80**	**0.51**	**0.11**	**0.22**			19.68%	20.72%	19.54%
	[2]	0.19	**0.80**	**0.50**	**0.11**	**0.22**	-0.004		19.68%	20.70%	19.54%
	[3]	0.19	**0.77**	**0.49**	**0.13**	**0.25**		**-0.02**	19.75%	20.21%	19.60%
	[4]*	0.07	**0.78**	**0.49**	**0.20**	**0.27**			19.93%	20.11%	19.77%
	[5]*	0.08	**0.74**	**0.47**	**0.20**	**0.30**		**-0.02**	19.99%	19.63%	19.83%
2010 – 2019	[1]	**-0.61**	**0.93**	**0.55**	**0.37**	**0.09**			11.73%	1.34%	11.64%
	[2]	**-0.58**	**0.92**	**0.54**	**0.34**	**0.10**	-0.05		11.73%	1.32%	11.64%
	[3]	**-0.61**	**0.93**	**0.55**	**0.37**	**0.09**		-0.0006	11.73%	1.34%	11.64%
	[4]*	**-0.42**	**0.86**	**0.47**	**0.73**	**0.19**			12.26%	1.39%	12.17%
	[5]*	**-0.40**	**0.83**	**0.50**	**0.75**	**0.21**		-0.01	12.27%	1.38%	12.18%
2000 – 2019	[1]	**-0.41**	**0.86**	**0.53**	**0.31**	**0.17**			13.8%	11.43%	13.77%
	[2]	**-0.46**	**0.89**	**0.56**	**0.35**	**0.15**	**0.09**		13.81%	11.64%	13.78%
	[3]	**-0.40**	**0.83**	**0.54**	**0.32**	**0.19**		**-0.01**	13.82%	11.40%	13.79%
	[4]*	**-0.44**	**0.84**	**0.49**	**0.40**	**0.26**			14.07%	12.82%	14.04%
	[5]*	**-0.43**	**0.80**	**0.50**	**0.41**	**0.28**		**-0.01**	14.10%	12.68%	14.08%

The table shows the alpha and beta value of the MktRf, SMB, HML, BAB, QML, and FEAR factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French, Datastream and Asness data library. Additionally, the results report both dependent variables that are the simple returns. We denote the models 1, 2, and 3; as extension the 3 Factor Fama and French model by applying additional factors from the Asness and Durand. Respectively, the models 4, and 5 are the same models but substitute the HML with HML II (or Devil). The table reports the results using extension factors from equation [2.2]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table 2.12: Empirical results for Red returns-extension II (period 2000-2019 and the sub-periods)

Period	**Model**	**Alpha**	**MktRf**	**SMB**	**HML/ HML II***	**MOM**	**UK/ EUR**	**GOLD**	**R-sq within**	**R-sq between**	**R-sq overall**
2000 – 2009	[1]	**0.31**	**0.80**	**0.68**	**0.17**		-0.02		19.15%	23.39%	19.02%
	[2]	**0.27**	**0.80**	**0.68**	**0.17**			0.03	19.16%	23.53%	19.03%
	[3]	**0.27**	**0.80**	**0.68**	**0.17**		-0.01	0.03	19.16%	23.48%	19.03%
	[4]	**0.25**	**0.84**	**0.65**	**0.21**	**0.09**	-0.05		19.25%	22.87%	19.12%
	[5]	0.22	**0.83**	**0.66**	**0.20**	**0.08**		0.02	19.24%	23.13%	19.11%
	[6]	**0.35**	**0.84**	**0.65**	**0.21**	**0.08**	-0.04	0.01	19.25%	22.94%	19.12%
	[7]*	**0.30**	**0.78**	**0.70**	**0.14**		0.02		19.16%	23.85%	19.03%
	[8]*	**0.28**	**0.79**	**0.69**	**0.14**			0.03	19.17%	23.86%	19.03%
	[9]*	**0.26**	**0.79**	**0.70**	**0.14**		0.02	0.03	19.17%	23.91%	19.04%
2010 – 2019	[1]	**-0.54**	**0.92**	**0.58**	**0.37**		0.03		11.72%	1.24%	11.63%
	[2]	**-0.59**	**0.94**	**0.59**	**0.42**			**0.11**	11.83%	1.30%	11.74%
	[3]	**-0.59**	**0.94**	**0.59**	**0.42**		0.03	**0.11**	11.83%	1.28%	11.74%
	[4]	**-0.42**	**0.91**	**0.59**	**0.30**	**-0.14**	**0.07**		11.78%	0.87%	11.68%
	[5]	**-0.49**	**0.93**	**0.60**	**0.37**	**-0.11**		**0.10**	11.87%	1.01%	11.78%
	[6]	**-0.48**	**0.93**	**0.60**	**0.36**	**-0.12**	0.06	**0.10**	11.88%	0.93%	11.79%
	[7]*	**-0.31**	**0.86**	**0.54**	**0.70**		**0.07**		12.20%	1.18%	12.10%
	[8]*	**-0.34**	**0.88**	**0.54**	**0.69**			**0.04**	12.20%	1.18%	12.10%
	[9]*	**-0.33**	**0.87**	**0.54**	**0.69**		**0.07**	**0.04**	12.21%	1.20%	12.12%
2000 – 2019	[1]	**-0.29**	**0.86**	**0.64**	**0.33**		0.001		13.67%	11.03%	13.63%
	[2]	**-0.35**	**0.87**	**0.62**	**0.36**			**0.08**	13.74%	12.10%	13.71%
	[3]	**-0.36**	**0.87**	**0.63**	**0.36**		0.001	**0.08**	13.74%	12.11%	13.71%
	[4]	**-0.33**	**0.87**	**0.63**	**0.35**	**0.04**	-0.001		13.68%	11.17%	13.64%
	[5]	**-0.38**	**0.88**	**0.62**	**0.37**	**0.03**		**0.08**	13.75%	12.20%	13.71%
	[6]	**-0.38**	**0.88**	**0.62**	**0.37**	**0.03**	-0.003	**0.08**	13.75%	12.19%	13.71%
	[7]*	**-0.27**	**0.84**	**0.65**	**0.35**		**0.05**		13.77%	12.36%	13.73%
	[8]*	**-0.30**	**0.86**	**0.64**	**0.35**			**0.05**	13.79%	12.53%	13.75%
	[9]*	**-0.31**	**0.85**	**0.64**	**0.35**		**0.05**	**0.05**	13.80%	12.67%	13.76%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, UKEUR, and Gold factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French, Datastream and Asness data library. Additionally, the results report both dependent variables that are the simple returns. We denote the models 1, 2, and 3; as extension the 3 Factor Fama and French and 4 factor Carhart models by applying additional factors of commodities and currencies. Respectively, the models 7, 8 and 9 are the same models but substitute the HML with HML II (or Devil). The table reports the results using extension factors from equation [2.2] till [2.3]. The last 3 columns are the R squared for within, between, and overall. Numbers in bold indicate statistical significance at the 5% level. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

In analyzing the behavior of various stock categories within portfolios, our study reveals noteworthy patterns regarding Green, Red and Grey stocks, particularly during distinct time periods. Notably, the alpha for the Green, Red (except the first half period) and Grey (except the first half period) asset class is mostly negative, suggesting potential underperformance (Tables 2.7-2.12). The adjusted alpha decreases for the Red and Grey assets by switching from positive to negative alphas. The value of the beta MktRf for the Red, Green and Grey asset classes are consistently around 0.9, indicating a positive strong correlation with market movements. Coefficients for other factors (HML, MOM, RMW, CMA, FEAR, BAB and QML) exhibit variations across sub-periods, with some factors being statistically significant in certain periods. Comparing the previous table's 5FF model and the 5-factor model substitute with HML(devil), we can conclude that HML(devil) isn't adding significant information on the Green and Grey stocks. However, for the Red securities, the HML(devil) shows a considerable improvement on the model comparing the results between table 2.11 and 2.12.

Every asset class has similar significant factors with dissimilar relative exposure, and the level of exposure changes significantly from model to model. Most common observations indicate that stocks classified as Red and Grey (during the post-crisis period and whole period) tend to exhibit high beta portfolios. Grey assets during the first half of the period typically demonstrate exposure to low beta portfolios, while those classified as Red (in the first half period) and Grey (in the second half period) are adversely affected by high volatility that means are impacted by the high level uncertainty in the market. Notably, within the Grey category, three factors—HML, FEAR, and BAB—exhibit switching behavior from the pre-crisis to the post-crisis period. This shift may be attributed to changing market dynamics and investor sentiments during these distinct periods. This phenomenon underscores the dynamic nature of market influences on Grey stocks, necessitating further examination to elucidate the underlying mechanisms driving these shifts. Moreover, the coefficient for the momentum (MOM) factor is negative for Grey stocks and, in the second half, for Green and Red stocks. Conversely, in the first half period, it is positive for Red stocks. The coefficient representing the change in the exchange rate of the UK currency (with the euro as the base currency) is positive for Green and Grey stocks. Conversely, Conversely, the negative coefficient for the Quality Minus Junk (QMJ) factor in Grey stocks highlights exposure to lower quality or 'junks' stocks, suggesting a higher risk profile compared to stocks with stronger financial fundamentals. Also, the favorable influence of the UK pound exchange rate underscores the significance of currency factors, aligning with the findings of Pojarliev & Levich (2008) that establish a connection between stock returns and currencies. One notable dissimilarity observed in our analysis is the positive impact of changes in Gold on the Red & Green asset class (in the second half period), contrasting with the negative impact on the Grey asset class. This finding aligns with the assumption made by Bams et al. (2017) regarding the strong relationship between stocks and commodities, particularly the Gold and Oil price. Red stocks are typically linked to industries heavily reliant on non-renewable energy sources and commodities, such as oil. This assumption suggests that Red stocks tend to exhibit a positive exposure to fluctuations in commodity prices, especially oil and Gold. This expectation stems from the observation that industries like energy, mining, and materials are directly influenced by changes in commodity prices. When commodity prices, including oil, rise, companies operating within these sectors often experience increased revenues and profitability. This, in turn, leads to higher stock prices. Thus, the sensitivity of Red stocks to commodity price fluctuations may result in a positive relationship between Red stocks and Gold prices. Investor sentiment and market perception play a significant role in influencing asset prices. The assumption acknowledges the impact of positive sentiment surrounding the energy sector. Factors such as rising global energy demand, geopolitical events, or supply constraints can foster optimistic outlooks for the energy sector, prompting increased investments in Red stocks. This heightened investor interest can subsequently drive up the prices of Red stocks in response to surges in commodity prices, particularly in the case of Oil and Gold (see Appendix Table A2.27).

In conclusion, the premise of Red stocks displaying a positive exposure to changes in Gold and Oil prices aligns with the assumption of a robust stock-commodity relationship, particularly for sectors closely intertwined with non-renewable energies. Nevertheless, it is imperative to acknowledge the intricacies of these relationships and their susceptibility to variations over time and under diverse circumstances. Another application is when you want to adopt portfolio diversification strategies that encompass assets from various sectors, including those associated with non-renewable energies. This assumption recognizes that such diversification strategies may inadvertently result in positive exposures to commodity price changes. By diversifying across sectors, investors may indirectly embrace the broader market dynamics influenced by commodity movements. Both investors and researchers should take into account these multifaceted factors when engaging in the analysis and interpretation of asset pricing models and the broader dynamics of financial markets.

Over the two subperiods and the whole inquiry period, we observed a sharp change or shifting in the risk sensitivities and the significant level of the betas, which strengthened our belief that the financial crisis changed the economic environment from the first to the second subperiod.

The findings from this research analysis offer valuable insights for investors and their understanding of the financial market for these asset classes. The Grey asset class shows potential for underperformance, especially in the post-ante EU crisis period. The Green asset class exhibits relatively consistent performance with negative alpha values, albeit smaller in magnitude. The Red asset class consistently displays negative alpha values, indicating the potential for unattractive risk-adjusted returns. Investors should consider these results while making investment decisions and building diversified portfolios. The variations in coefficients for risk factors highlight the importance of assessing each asset class's unique risk-return profile and tailoring investments to align with individual investment goals and risk tolerance. Overall, this research analysis emphasizes the importance of rigorous analysis when evaluating asset classes and the need for continuous monitoring of their performance to optimize portfolio outcomes.

Based on the R squared from the multi-factor models that explain better the returns' behaviour is the five-factor Fama and French model for the Red and Green assets and also Grey assets. Except for the second subperiod, in which the performance is slightly better with the 4-factor model. Subsequently, the R squared for the extended model is increased and the full extent to show superior performance compared with the other models. In most cases, the R squared values for Green, and Grey stocks is low in cross-sectional data compared to time series data. This discrepancy arises due to the relatively higher heterogeneity present in the cross-sectional data, where each stock represents a distinct entity, and our dataset is predominantly cross-sectional in nature, and not time dominant. This means that the R square between is lower than the R square within and, therefore, the R square overall. An optimal model is the trade-off for the R-sq between and after within, that model explains the variation within time and cross sectional the asset returns.

During periods of crisis, the behavior of Red asset returns group is of particular interest due to the heightened market volatility and disruptions in financial markets. In our analysis, we observed that the R-squared within the asset (Green, Grey and Red) group was notably lower compared to ex-crisis period, sometimes exceeding 14%. This suggests that a significant proportion of the variability in the dependent variable can be attributed to factors specific to our assets within the group. This phenomenon is likely influenced by several factors specific to crisis periods. Firstly, heightened idiosyncratic risk within individual assets (or sectors) may play a significant role, stemming from company-specific factors, operational challenges, or market sentiment. Additionally, market dislocations and disruptions during crises contribute to significant deviations in asset prices from their fundamental values within each asset group, leading to increased variability in asset returns.

Furthermore, flight to safety behavior among investors during crises may lead to increased correlations within certain asset classes or sectors, further contributing to higher variability in returns within the asset group. Additionally, liquidity constraints may exacerbate variability in asset returns within the group as investors face challenges in executing trades.

Overall, the observed lower R-squared within the asset group during crisis periods underscores the complexity of asset pricing dynamics in turbulent market conditions, which are not captured within our factors. It highlights the importance of analyzing and understanding the behavior of asset returns within specific asset groups during periods of crisis, as this variability may provide valuable insights into the underlying factors driving market fluctuations and investor behavior.

2.8 Robustness tests

In our analysis, robustness testing in asset pricing models involves evaluating the stability and reliability of the model's results across different factor models and data samples. Specifically, robustness tests are conducted on the monthly returns for each asset group within the asset pricing models. This is achieved by testing the robustness of our factor models through adjustments in their specifications, such as adding or removing variables based on relevant literature, and employing various estimation techniques (e.g., panel data regression vs. robust panel data regression with random effects).

As indicated in Tables 2.4 to 2.12 (and Appendix Tables A2.25-A2.27), the performance of our model against alternative models remains relatively unchanged. This comparative analysis encompasses the classical 3FF model and over 20 different extensions of asset pricing models (e.g., 5FF, Carhart, Assens, among other asset pricing models). Additionally, an alternative method to assess the stability of our model's results involves using different time periods for estimation. In our case, the model is estimated using data from subperiods both before and after the financial crisis within the overall dataset. This approach helps to ascertain whether the relationships captured by the model hold consistently over time.

The results reveal that core factors remain consistent before and after the crisis, but some factors exhibit temporal variations, either in sign or in their significance levels. By systematically conducting these robustness tests on our asset pricing model using monthly returns data, we enhance confidence in the reliability and stability of the model's results. Moreover, these tests enable the identification of potential limitations or areas for improvement, such as the changes observed in factors before and after the crisis.

In our models, certain factors exhibit strong correlations (see Appendix Table A2.10-A2.22), which can account for the changes in the sign of the factors within our multi-factor models. This indicates robust interdependence among the variables under consideration. High correlations imply that some factors may be redundant or overlapping in their explanatory power, leading to fluctuations in their significance levels when additional factors are integrated into the models. Understanding and addressing these interrelationships is crucial for refining the structure model and improving the performance. This emphasizes the importance of conducting robustness tests to confirm the model's stability and identify areas where adjustments to model specifications may be needed to better capture the underlying dynamics of asset pricing models.

2.9 Application Based on Asset Class and Factor Exposures

The classification of Green, Grey, and Red equities reveals distinct patterns of risk exposure that can be directly applied to portfolio design and asset allocation decisions. Understanding these differentiated factor loadings offers investors a framework for tailoring investment approaches that align with specific financial objectives and risk preferences, particularly in the context of environmentally differentiated equity segments.

The observed significant exposure of Green stocks to the size, value, and currency factors provides a rationale for asset managers to tilt portfolios towards small-cap, high-value Green equities with favourable currency dynamics. These factor sensitivities suggest that such stocks may offer enhanced returns while contributing to diversification, especially when market conditions favour these characteristics. Asset managers can apply smart beta techniques by constructing factor-tilted portfolios that overweight these characteristics, potentially enhancing returns while simultaneously contributing to factor diversification. Furthermore, profitability-related factors—especially the robust negative loading of Red stocks on the RMW factor—underscore their association with weak fundamentals, while Grey stocks tend to exhibit stronger profitability signals. This divergence supports relative value or factor-based rotation strategies, whereby allocations are dynamically shifted away from underperforming Red stocks towards more fundamentally sound Grey equities. Additional factors enrich the framework, and investors can leverage these exposures by emphasizing securities within each asset class that score positively on these dimensions, particularly in periods of heightened market dispersion. For instance, QMJ and BAB factors show stronger explanatory power in specific classes, offering an opportunity to refine allocations through systematic screening for high-quality or low-beta stocks. The distinct behavior of Green, Grey, and Red stocks with respect to factor sensitivities suggests that macroeconomic conditions can inform active asset allocation. These dynamics could be employed in a tactical overlay, where shifts in the specific factor trigger rebalancing decisions across asset classes. However, Green equities exhibit relatively more stable market-adjusted risk compared to Grey and Red stocks, particularly around periods of financial stress. This finding implies a potential role for Green stocks in defensive portfolio construction, offering resilience during downturns or heightened uncertainty. In contrast, Grey and Red stocks may be more suited to cyclical or opportunistic strategies. In addition to strategic asset allocation, the differentiated factor exposures identified across asset group equities offer a compelling foundation for alpha-seeking strategies, particularly by exploiting relative mispricings between environmental asset equities and their factor proxy portfolios. Thus, investors can actively extract alpha from inefficiencies not captured by the factors by using the spread between environmental portfolios and their analogue factors weighted portfolios.

Lastly, the heterogeneous factor exposures identified in this research provide a foundation for constructing more nuanced equity portfolios. By aligning investment decisions with the risk-return attributes of each environmental classification, investors can better navigate the complex trade-offs between financial performance, factor risk, and environmental considerations.

2.10 Conclusion and Discussion

The primary purpose of this research is to examine the factor structure of Green, Grey, and Red stock returns. In essence, this research examines the risk sensitivities of EU Green, Grey, and Red securities. As mentioned, a Red asset return is the return associated with the equity returns of environmentally-unfriendly companies. Conversely, a Green asset return is an implicit return associated with environmentally-friendly equities. In our analysis, we also include "Grey" equities, which are neither Red nor Green (essentially, all other equities in the database after excluding unspecified activities or unknown industry companies or securities without any variation from our sample).

The study based on the combination of previous research which provides a solid background for academics and practitioners to understand Green, Grey, and Red's classification and our research to assess their risk-return profile. The significance of certain factors in explaining the specific asset group returns can lead to a deeper understanding of the underlying market dynamics. For instance, the positive and significant coefficients of certain factors for the Green asset class may suggest that size, value, and currency have a substantial impact on returns in this type of group. Similarly, exploring the factors that significantly influence the Red and Grey asset classes can offer insights into their unique risk-return profiles. Overall, the analysis underscores the importance of asset pricing models and the need for investors to carefully consider market dynamics when making investment decisions. The findings contribute to a more nuanced understanding of asset pricing for different asset classes and encourage further research to develop more sophisticated models for improved investment outcomes. Investors should remain vigilant and tailor their investment strategies based on the specific risk factors driving each asset class's returns to achieve their financial goals effectively.

One of the significant findings of this research is the presence of negative alpha within the majority of asset class categories when evaluated within the framework of factor models.

This negative alpha is consistently observed in comparison to the market proxy portfolio, and the other proxies portfolios that contribute to explaining the risk-adjusted returns. Every asset class diverges either the exposure on the global factor or the significance level (see table 2.4-2.12 and Appendix A2.25-2.27). Despite that fact, we have different business activities between the asset classes, we have similar risk behaviours, and a reason is an adaptation in the economic environment or possible behavioural herding for these asset classes. According to our findings, the Green and Red stocks are exposed to small-cap and generally in high value stocks, and contrarily, the Grey stocks are exposed to low value stocks in the first half and whole period. Our analysis reveals that Red stocks exhibit a notable affinity for low-profitability stocks, as indicated by the RMW (Robust Minus Weak) factor. Conversely, Grey stocks display a predilection for investments associated with higher levels of profitability. This highlights the contrasting investment profiles between the two categories of stocks based on their exposure to the RMW factor. For all the periods, the market factor mostly occurs the highest risk exposure compared to the other factors for any asset class. These differences give insight into risk and return and help understand the vulnerabilities better for every asset class. An important consideration in assessing asset risk is how an asset reacted before and after the economic downturn; the green assets show a stable risk profile compared to the other two asset classes. Looking at the prominent models' risk exposures indicate at least three stable factors and at least five on the extension models for every class in our European monthly stock returns.

Cochrane (2001) and Bartram et al. (2021) emerged the case of the "factors zoo" and offered a new technique to differentiate between beneficial, worthless, and redundant factors, which systematically examines and assesses potential factors on the asset price model. In our research, we expand the five-factor model and implement over fourteen additional factors, volatility, value II, betting against beta, quality, currency, and commodity. Compared to the models (3FF,4CM and 5FF), the expansion models show increases in the coefficient of determination by adding valuable factors to explain the Green, Red and Grey securities returns. In isolation, the new aspects of the FEAR, BAB, QMJ and specific commodities and currency factors based on the asset class are appealing, statistically significantly improving the model's explanation. The EU VSTOXX (Fear index) captures the market's fear and expectations that don’t appear to impact on the securities through the multi-factor asset pricing models and modify the rest of the factor's exposures. The Grey (second half), and Red show similar behavior following high beta portfolio returns and opposite relationship with the change of the Gold commodity prices, due Bams et al. (2017) research reveals similar results with the negative relationship between stocks and oil-gold. Lastly, the high minus low devil factor isn't improving the models in Green and Grey securities, but only in the Red securities observe a notable enhancement in the model.

The findings compared to the classical factor model (3FF, 4CM & 5FF) results show a significant increase in the explanatory power with the average adjusted R-squared to jump on the whole model. The combination of portfolio proxies sharpens the performance's view and gives a better understanding of the asset class return dynamic. Apparently, the global financial crisis caused a regime shift, changing the nature or number of the excess factors and the risk exposures on the market. By elucidating these findings, our study contributes to a deeper understanding of the dynamics within stock portfolios, shedding light on the nuanced behavior of various stock categories in response to market conditions and underlying factors.

According to Jegadeesh et al. (2019), portfolios are extensively used to evaluate asset pricing models to mitigate an inherent errors-in-variables bias; yet, portfolios may obscure significant risk-return-related aspects of individual equities. Implying instrumental variables technique allows for the use of particular Green, Grey and Red assets while still producing consistent ex-post risk premiums estimates.

Every asset class includes a lot of securities from different countries; thereby, the data density for that is hard to explain with a small partition of signals/factors. Also, we observe that the factor exposure is changing from period to period, which is consistent with mispricing history, and we need to broaden our analysis with recent data and additional market signals. The inducement in the crisis showed that the previous conditions could lead to complacency and the underpricing of risk that the financial world was arguably lulled into a false sense of confidence by the quiet-good economic conditions in earlier (pre-crisis) years. Our methodology grants the relationships held between security returns and risk factors that had been observed in the past could not be expected to continue to hold in the future. Also, the complexity of the securities market infrastructure change the risk models life cycle and obviously after the EU crisis event.

Since all studies face limitations, focusing on the results from the first subperiod may possibly produce for a misleading outcome for the later years. The results are based on stocks within the European markets and are affected by the EU policies. In our models, we require a liquid market, which is reflected in the securities' returns. However, in some rare cases, we have access to illiquid securities on which we applied the transformation method for revealing the impact of the factors. Additionally, we can explore other macro factors or create them for the European securities, such as the liquidity (LIQ) factor (Pastor & Stambaugh, 2003), which gauges the liquidity risk. Another factor is the combination of the ESG (Environmental, Social, Government) and the sales divided by the producing emission, called the greenness factor (Lucia et al., 2019). This factor is suitable to compromise a new aspect for the Red (or Grey) stocks and how the sales of the Red companies are associated with the carbon emission. In addition, to create new factors protected by the high correlation between currencies and commodities return, the Principal Component Analysis (PCA) can be applied for dimensionality reduction and to reduce the correlation of the currency-specific factor and commodities-specific factor. One noteworthy issue that merits discussion is whether the green company is complying with green activities, as detailed in regulation policies to be characterize “Green”.

The factor models provide further insight and control into multi- or single-asset class investing, and therefore one key feature of finance theory is to retain several asset classes so they can generate a diversified portfolio. In other words, we can use the signals from the factors exposure and expect when one asset class has poor returns, and then another may have good returns (Markowitz, 1952). By employing these ideas of conventional philosophy, investors will develop vehicles to allocate investment within our 3-classes (Green, Grey, and Red), and create a cross-sectional equity strategy. Firms or investors can apply easier strategy and imply into a similar industry-specific class by using our classification and seeking to maintain optimal exposure to a diverse set of factors. For example, strategies such as momentum trading, factor tilting, or sector rotation can be used to exploit differences in factor exposures across and within these classes. This allows the investor to identify types of stocks or market conditions where one class may outperform others, enhancing return potential while managing risk.The factors develop new trading strategies for our specific asset group, seeking higher returns and understanding the risk exposure. Those elements drive the financial performance of the group securities, and the next step is the optimization framework. Our research reveals the characteristics of every asset class, which we can identify the investment process is suitable to perform for our risk tolerance and also, we can benefit from using an appropriate mix of investments and strategies between the asset class.

Chapter 3: Performance of Green vis-à-vis Red EU Securities

Abstract

The research compares the performance of Green (eco-friendly) versus Red (eco-enemy) returns for EU securities. Green securities are the stocks of companies whose primary business activities focuses on being relatively beneficial to the environment, while Red stocks are associated with business activities that are harmful to the environment. The study investigates their performance over time from 1/2000 till 12/2019, before and after the Global financial crisis in 2009. The methodology follows two parts in order to distinguish the financial performance between Green and Red stocks. The first part is to apply the asset pricing models from the Fama-French, the Carhart and their extensions for every security and estimate the alpha performance, and secondly continues with a cross-sectional regression to compare the asset classes. This chapter tests for potential market inefficiencies by assessing whether Green assets consistently outperform or underperform relative to Red asset. That strategy can shape investor preferences in their portfolio selection. The findings indicate that there is no statistically significant difference in financial performance between Red and Green securities and investor can balance a diversified portfolio without focusing of losing a superior alpha return.

Keywords: Asset Pricing Models, European Stock Market, Factor Analysis, Green Securities, Financial Performance

JEL classification: G11, G12, C5

3.1 Introduction

Green companies are known for their climate-friendly practices, prioritizing efforts to combat climate change and minimize harm to the environment. Investors are becoming conscious of incorporating green assets into their investing decisions (Alessi et al., 2021; Fatica et al., 2021; Oehmke & Opp, 2025; MacAskill et al., 2021; Heinkel et al., 2001). The real question is whether this has influenced the EU financial market and affected investing in Red securities.

As noted by professional investor McKeough (2009, 2021), caution is advised with green stocks as they may not offer the low risk and high rewards investors typically expect in terms of the risk-return tradeoff. The report emphasizes that for investors, this group of stocks may initially appear to be a safer investment option, thus attracting more investments due to its social contribution aspect. However, there is a nuanced understanding suggesting that these stocks have limited profit potential. This arises from high costs and the number of government policies/endorsements provided for the green companies. Thus, transitioning to environmentally friendly practices often involves significant upfront costs as companies need to invest in new technologies, equipment, and processes. Despite these initial challenges, green initiatives are seen as crucial for long-term environmental benefits and can lead to cost savings over time. Additionally, governments worldwide have recognized the importance of addressing environmental issues and have implemented policies and regulations to incentivize or mandate sustainable practices. These governmental actions may include tax incentives for green initiatives, emissions standards, renewable energy targets, and environmental certifications. Moreover, governments endorse and promote environmentally friendly practices through public campaigns and certifications, further encouraging businesses to embrace sustainability as a core value. Consequently, more and more companies are integrating eco-friendly practices into their strategies to meet consumer demand, improve reputation, and ensure long-term business success in an increasingly sustainability-conscious world. The EU commission, through the Renewable Energy Directive (2009/28/EC) initially established national targets for EU member countries, setting a precedent worldwide and decreasing the dependencies on coal, gas and nuclear energies and increasing green energy.

According to Roy (2015), companies change the traditional approach of the profit maximization problem; but they also try, simultaneously, to maximize their social responsibilities. One of the company's crucial issues is to be responsible for continuous beneficial improvements to the environment and society.

In prior literature, many researchers argue that better environmental performance means better financial and economic performance in their profits for these type of companies (Porter & Van der Linde, 1995; Hu & Zhao, 2024; Yu et al., 2023). However, other research paper (e.g. Ambec & Lanoie, 2008) appear to identify where is the optimal with environmental acts in their companies (partial or pseudo Green acts) to increase the profit of the companies, that can improve the firm's performance in an economic and financial level. Another crucial factor influencing a company's financial performance is the government's political commitment to implementing policies that support environmentally sustainable practices. When governments endorse and enact pro-"green" policies, such as tax incentives for eco-friendly initiatives (Hu et al., 2024), emissions regulations, and renewable energy support, it creates a conducive environment for businesses to embrace sustainability. This political backing not only encourages companies to adopt environmentally responsible measures but also fosters a positive reputation among consumers and investors, driving financial success in a world increasingly focused on sustainability. For instance, Eccles et al. (2014) find that companies with high sustainability profiles significantly outperform their counterparts in stock market and accounting performance. Futhermore Friede et al. (2015) observed there is a positive relationship between environmental, social, and governance (ESG) criteria and corporate financial performance.

As highlighted in the works of Ardia et al. (2022) and Pastor et al. (2022) Green stocks returns surpass those of Brown stocks, when the climate concern expands. This divergence can be attributed to unforeseen shifts in risk perceptions or preferences, further expounding on this concept, presenting a theoretical framework that elucidates such deviations through the escalating demand for green assets. Other studies (Garvey et al., 2018; In et al., 2019; Huij et al., 2021; Pastor et al., 2022; Bolton and Kacperczyk, 2021; Bolton et al., 2022; Görgen et al., 2020; Hsu et al. , 2022; Aswani et al., 2021) have empirically tested the returns associated with green investments, particularly for portfolios that take long positions in Green stocks while shorting Brown stocks. The overall of these findings suggest that investing in environmentally-friendly securities and simultaneously divesting from carbon-intensive assets has been associated with favorable financial performance.

My study focuses on the European securities, where I assess the performance of risk-adjusted alpha returns by applying well-established asset pricing models (e.g. Fama-French , Carhart and their extension multi-factor models). By applying established models to capture the Green and Red assets alpha returns, seeking to apply an effective investment strategy tailored to the unique characteristics of the European financial market. Unlike the previous research (e.g. Ardia et al., 2022; Pastor et al., 2022; Bolton and Kacperczyk, 2021; Bolton et al., 2022; Görgen et al., 2020; Hsu et al. , 2022; Aswani et al., 2021), which have focused broadly on carbon emission or other regions (mostly in US market). This analysis explores their performance over time, ex-crisis and post-crisis by splitting the sample in two periods. The critical element is the comparison of the performance between Green and Red/Brown securities. The classification of the assets into two categories, outlined in our prior chapter, following reports from financial institutions (refer to Table 2.1). The next step is the regressions with the asset pricing models for every security and the results from the adjusted abnormal returns from the markets signals. Lastly, we examine whether there is a relationship between the financial performance of Green and Red stocks. Our empirical results show that neither Red nor Green securities exhibited superior risk-adjusted alpha performance within these two asset classes and challenges the assumption of Green investment providing better financial benefits over Red. Thus, making this study a critical addition to the current literature.

This research aims to compare the performance of Green and Red assets using established models and their extensions by assessing the risk-adjusted alpha. The second section focuses on data collection and the methodology of the two-pass regression. Empirical results are presented in section three. The final part comprises evidence collection and discussions of potential improvements.

3.2 Asset Class, Factor Models and Two-Step Regression

In our research, we utilize Table 2.1 (from Chapter 2) to classify stocks as Green or Red. For more detailed insights into the evolution of asset pricing models and the incorporation of multi-factor frameworks, please refer to Chapter 2. This chapter builds on the seminal works of Fama & French (1992, 1993, 1995, 1996, 1998), Carhart (1997), and subsequent advancements in the field. It discusses the foundational three-factor model proposed by Fama and French, as well as extensions such as the four-factor and five-factor models. Furthermore, it explores recent contributions by Asness et al. (2019) and Frazzini & Pedersen (2014), introducing additional factors like quality and betting-against-beta, which have enhanced our understanding of asset performance. Additionally, alternative factors such as the Semi-factor structure and momentum factor are discussed, reflecting the continuous search for factors influencing returns and how to incorporate Green, Grey and Red assets. The general equation of factor models can be expressed as follows:

$$r - r_f = b * F_t + e \tag{3.1}$$

Here, r represents the vector of asset returns, b is the vector of factor loadings, F_t is the vector of factor returns, and e is the vector of idiosyncratic (or specific) asset returns. This equation encapsulates how asset returns can be modeled as a linear combination of factor exposures and idiosyncratic components.

This research paper makes a novel contribution to the existing literature by conducting an empirical investigation into the comparison of Green and Red security returns. It addresses a notable change from prior studies (Badia, 2019; Brammer et al., 2009; Climent & Soriano, 2011; Ibikunle & Steffen, 2017; Ilhan et al., 2020; Gimeno & Gonzalez, 2022, Garvey et al., 2018; In et al., 2019; Huij et al., 2021; Pastor et al., 2021a, 2022; Statman & Glushkov, 2016), where the focus predominantly revolved around the performance of portfolios or funds within specific subsets or supersets of Green or Red assets, or employed diverse approaches to compare the assets either as methodology or also as classification. Furthermore, the majority of these studies primarily utilized securities from the US financial market. Hence, this research aims to bridge a new aspect by exploring the connection between Green and Red security returns in the EU financial market and in a broader and more comprehensive context.

The primary question of interest is if the average returns are statistically different between Green and Red assets. Black et al. (1972) and Fama & MacBeth (1973) answer that the expected returns should be high if the asset has high exposure to the factors that carry large risk premia. For simplicity reason, we assume the case with the single factor in which the excess returns are linear in the betas (3.2):

$$E(r_{i,t}) - r_f = \beta_i E(F_t) \Rightarrow E(r_{i,t}) - r_f = \beta_i \lambda, \text{ i is the security index} \tag{3.2}$$

Since the factor, F_t , is also an excess return, the model applies to the factor as well $E(F_t) = 1 \times \lambda$, where λ is the price of risk (risk premium) associated with the factor (Cooper et al., 2022).

To estimate the model, we first apply a time series regression for each security to obtain the factor loadings, denoted as β_i. The d_i represents a dummy factor that indicates the presence (1) or absence (0) of a Green asset category. In this context, i refers to the individual security, while t denotes the time period. The second-pass regression is ready to estimate the factor risk premium λ and Green premium *D* from a cross-sectional regression of average returns on the obtained β_i and d_i values. Here, the time series allow for a free intercept for each asset, which effectively are ascribing to error any deviation from the risk-free rate intercept in the cross-section. The regression equation is (3.3):

$$E_T(r_{i,t}) - r_f = a_i + d_i * D + \beta_i \lambda + e_i \tag{3.3}$$

The cross-sectional regression residuals e_i from equation (3.3) are the pricing errors. We extend Fama and MacBeth Model by adding the Green dummy, which identifies the Green risk exposure that detects a shift on the average returns. This coefficient (d_i) and the alpha term (α_i) provides the average returns between the two classes and an alpha risk factor that cannot be explained by those factors(which they interpreted as risk factors). The dummy allows direct estimation of a discrete Green asset premium by separating assets abnormal returns to Red and Green, which can be more intuitive and interpretable. Thus, facilitate identification of non-linear or threshold effects that not be captured by the common continuous characteristic factors. Moreover, this approach mitigates potential model misspecification risks that arise from relying solely on continuous factor characteristics, which may be noisy or subject to measurement error (Shanken, 1992) and allows for the estimation of alpha performance differences between the two asset classes after risk adjusting. Estimating separate alphas for each asset category also helps address the errors-in-variables problem by using more alpha assets or portfolios of alphas helps make the estimates more stable and less sensitive to errors in individual alphas. Prior studies (Heston & Rouwenhorst, 1994; Nayar et al., 2023) applied dummy variables to identify factor premiums or to capture discrete effects linked to specific asset characteristics.

For the equation (3.2), we can imply multiple factors F_t (such as HML, SMB etc.) , as well as additional risk premia on the model that gives insight for understanding the differentiation between Red and Green assets returns. However, the two-pass technique has a central problem with the beta's measurement error (β_i) and gauge beta using the estimation from the asset class portfolio beta (β_p) that way, the error of the portfolio beta (β_p) will be less affected due to aggregation (Bai & Zhou, 2015; Kan et al., 1999, 2013). Our methodology attempts to solve the central problem of beta measurement error (β_i) in the two-pass technique using the cross-sectional regression residuals that enhances the reliability of the results and contributes to a more comprehensive understanding of the risk-return relationship in Green and Red assets.

3.3 Methodology

Chapter 1 of our thesis provides a comprehensive overview of the classification of the assets plus the data collection for our study.

Our research performs a two-pass regression model with a discrete variable to distinguish the performance of Green over the Red securities returns. Our statistical models are based firstly in the time series model, which take into consideration the individual securities of the Green, and Red securities heterogeneity, and the second one is the combination of the time series model followed by the cross-sectional model of the alpha factor to capture the differentiation between the Green and Red assets.

In simple terms, the statistical model applied Ordinary Least Squares (OLS) regression for each security, as presented in the corresponding equations 3.4-3.6. The dependent variable derives from two sectors; Green, and Red. The returns of these sectors are evaluated using the regression equations 3.4-3.6, and their extensions are employed for analysis:

$$r_{i,t}^{j} - r_{f,t} = a_i + b_{1,i}^{j} MKTRF_t + b_{2,i}^{j} SMB_t + b_{3,i}^{j} HML_t + b_{4,i}^{j} BAB_t + b_{5,i}^{j} QML_t + e_{i,t}^{j}$$

(Asness model) (3.4)

$$r_{i,t}^{j} - r_{f,t} = a_i + b_{1,i}^{j} MKTRF_t + b_{2,i}^{j} SMB_t + b_{3,i}^{j} HML_t + b_{4,i}^{j} RMW_t + b_{5,i}^{j} CMA_t + b_{6,i}^{j} MOM_t + e_{i,t}^{j}$$

(Dirkx 6F model) (3.5)

$r_{i,t}^{j}$ - $r_{f,t}$ = $a_i + b_{1,i}^{j}MKTRF_t + b_{2,i}^{j}SMB_t + b_{3,i}^{j}HML_t + b_{4,i}^{j}RMW_t + b_{5,i}^{j}CMA_t + b_{6,i}^{j}FEAR_t +$ $e_{i,t}^{j}$ (Durand 6FM) (3.6)

with i = 1,…,n, the n is 150 for Green stocks, and 367 for Red stocks, and j is an index that groups the stock (Green and Red). The t is the time of the stock in monthly frequency. $r_{i,t}^{j}$ is the return of asset i at time t (within the period, 2000-2019); $r_{f,t}$ is the risk-free rate at time t; the $MKTRF_t$ is the excess return on a European region's (Stoxx Europe 600 Index)value-weighted market portfolio at time t; the SMB_t is Small Minus Big size companies; the HML_t is high minus low based on the value of the companies; the RMW_t is Robust Minus Weak based on the operating profitability of the companies at time t; the CMA_t is conservative minus aggressive and based on the investment of the companies at time t; the MOM_t is the monthly momentum; BAB_t is based on betting against beta portfolios; QMJ_t is quality minus junk companies (refer to Table A2.2 – Table A2.4). The a_i is the stock's alpha performance, and b_k is the coefficient from the specific k-factor (with k=1,..,5). As the $r_{i,t}^{j}$ - $r_{f,t}$ denotes the excess return of security i in the time t with the specific asset class j.

Notably, the first step is to estimate the firm-specific alphas from the Fama-French Model, the Carhart model and their extensions, capturing the excess returns relative to the chosen risk factors. Thereby, for each asset, there is a time-series regression with no cross-sectional restrictions. The results from these firm-specific alphas are called "Green alpha" from Green securities or "Red alpha" from Red securities. As a second step, we use a vector of estimated alphas as the dependent variable in a cross-sectional regression and regresses these estimated alphas on the Red/Green dummies. By incorporating this dummy variable, we can isolate and better understand the specific influence of Green assets on the overall returns of the portfolio, shedding light on their unique contribution to the investment landscape. The "Green premium" is estimated by coefficient b, indicating whether Green securities yield a higher or lower average value compared to their Red counterparts. The regression follows the steps below and posits the models for the performance returns:

<u>1st step regression (TS):</u> applied the equations 3.4-3.6 and their extensions.
Here,
<u>2nd step regression (CS):</u>

$a_i = c + b_1 D_i + u_i$,with $D_i = \begin{cases} 1, i = Green\ asset \\ 0, i = Red\ /\ Brown\ asset \end{cases}$ i=1,…,517 and t=1/2000,….,12/2019

(3.7)

The two-pass regression method (Black et al., 1972; Fama & MacBeth, 1973; Cooper et al., 2022; Bai & Zhou ,2015; Kan et al., 2013; Shanken & Zhou, 2007) serves as the foundation of this approach and has proven instrumental in guiding investment decisions, evaluating portfolio performance, and studying various aspects of asset pricing across different assets.

3.4 Performance of Green over Red

This section presents the results from the individual-stock (winsorized) returns regression alphas with the dummy variable. This step is to distinguish the adjusted performance of Green over Red. The analysis is not only in the 1/2000-12/2019 period but also in sub-periods. The time period is divided at the end of 2009, so it can consider the aftereffect of the financial crisis.

3.4.1 Summary statistics of Green, and Red risk-adjusted alpha

In Table 3.1, we present the alphas for both Green and Red securities across three distinct asset pricing models (3FFM, 4CM, and 5FFM) for the periods 2000-2009, 2010-2019, and the entire period spanning from 2000 to 2019. Across all models, the mean alpha for Green securities for the first period ranged from 0.34% to 0.36%, exhibiting a relatively narrow range, while Red securities showed a wider range of mean alpha values, spanning from 0.38% to 0.54%. The results suggest that risk-adjust abnormal returns from Red securities are greater in Green securities during this period across the models. For the second period, a reversal in alpha performance is observed in both Green and Red by experiencing negative mean alphas, with Green ranging between -0.51% to -0.45%, likewise, Red, though the range was slightly broader from -0.60% to -0.46%. Finally, the entire period for Green mean alpha is between -0.34% and -0.30%, although Red is from -0.46% to -0.39%. Over the second and entire periods, Green and Red securities display a worse performance than the first period, with Red securities displaying a lower mean alpha performance than Green securities. Through all models and periods, the variance of alpha for Green securities ranged from 2.91% to 6.26%, and for Red securities, it ranged from 1.45% to 17.92%. Notably, the variance tends to be higher during the 2000-2009 period compared to the subsequent decade (2010-2019) for both asset classes, with the 5FFM model exhibiting the highest variance. In the second and entire period, the higher variance in Green assets' alpha indicates more significant fluctuations in their alpha returns compared to the Red, possibly reflecting the volatile nature of environmentally sustainable investments. During the 2009-2019 and 2000-2019 periods, skewness is predominantly negative for both Green and Red securities, indicating a left-skewed distribution with a higher frequency of extreme positive returns for Green alphas. However, during the 2000-2009 period, skewness becomes positive for both asset classes, implying a right-skewed distribution characterized by a higher frequency of extreme negative alpha returns. Kurtosis values are generally higher during the 2000-2009 period, suggesting more extreme values in the distribution. Specifically, Red alphas tend to exhibit higher value-spikes in kurtosis, indicating a greater likelihood of extreme alpha returns compared to Green securities.

Table 3.1: Cross-sectional risk-adjusted alphas moments of monthly excess returns from three asset pricing models and for two asset classes, Green and Red

Asset Class		**Green Securities Risk Adjusted Alpha Returns**			**Red Securities Risk Adjusted Alpha Returns**		
Time	**Summary stats**	**3FFM**	**4CM**	**5FFM**	**3FFM**	**4CM**	**5FFM**
2000 - 2009	Mean	0.36	0.34	0.34	0.44	0.38	0.54
	Variance	5.54	4.41	6.26	7.67	7.98	17.92
	Skewness	1.53	0.17	2.62	7.19	8.44	11.40
	Kurtosis	8.88	2.99	16.72	90.92	115.78	168.84
	Min	-7.04	-7.72	-5.11	-8.62	-7.81	-8.48
	Max	13.76	7.84	17.44	35.47	38.44	63.16
	Median	0.01	-0.02	0.00	0.29	0.18	0.15
2010 - 2019	Mean	-0.51	-0.45	-0.47	-0.56	-0.46	-0.60
	Variance	2.91	3.15	2.67	1.95	1.87	1.96
	Skewness	-0.50	-0.79	-0.48	-0.49	-0.68	-0.22
	Kurtosis	2.77	4.01	1.78	4.63	4.11	4.87
	Min	-5.69	-7.97	-5.19	-7.03	-6.94	-6.67
	Max	6.13	5.77	4.65	5.81	4.94	6.53
	Median	-0.32	-0.15	-0.35	-0.36	-0.27	-0.45
2000 - 2019	Mean	-0.30	-0.34	-0.31	-0.39	-0.39	-0.46
	Variance	2.28	2.55	2.07	1.46	1.45	1.49
	Skewness	-0.20	-0.57	-0.13	-0.64	-0.72	-0.22
	Kurtosis	3.91	5.84	2.11	6.19	5.81	7.10
	Min	-5.36	-7.97	-5.06	-6.74	-6.94	-6.59
	Max	6.13	5.77	4.65	5.81	4.94	6.53
	Median	-0.16	-0.18	-0.22	-0.24	-0.26	-0.41

The table shows the first four moments of Green, and Red, alphas (in percentage, %) and the median, minimum and maximum values within the two subperiods, and the whole period (the observations time is between 1/2000 till 12/2019 and with separation in 12/2009). The table includes the results after winsorization at 99% and the number of cross-sectional (n) securities, and the months which include these securities (T). The alpha is the risk-adjusted abnormal return relative to the applied proxies from FFM and CM. We denote as 3F-FFM – 3 Factor Fama French Model; 4F-CM – 4 Factor Carhart Model; 5F-FFM – 5 Factor Fama French Model and using the Kenneth R. French data library.

Moving to Table 3.2, we present risk-adjusted alphas for both Green and Red securities across the same three asset pricing models, expanded to include BAB and QMJ factors, for the same periods. Across all models and periods, the mean alpha returns for Green securities ranged from -0.50% to 0.55%, while for Red securities, the range was broader from -0.60% to 1.36%. Notably, Green securities have higher risk-adjust alpha returns than Red securities in the second half and the entire period per model, albeit with differences in the first period. All through the second half and the entire period, the variance of alpha returns consistently remains higher for Green securities across all models, suggesting more significant fluctuations in their excess returns compared to Red securities. Both Green and Red securities exhibit negative skewness in the second half and entire period, indicating a higher frequency of extreme positive returns. Conversely, they display positive skewness in the first period for different models, suggesting a higher frequency of extreme negative returns. Kurtosis tends to be higher for Red adjusted alphas in the first period, while in subsequent periods, it is higher for Green alphas, implying heavier tails and a higher likelihood of extreme alpha returns. These empirical findings underscore the importance for investors to comprehend the implications of alpha returns, facilitating more informed portfolio decision-making in navigating the volatility and fluctuations observed across different periods and models.

Table 3.2: Cross-sectional adjusted alphas moments of monthly excess returns from the three asset pricing models and for the two asset classes Green and Red

Asset Class		**Green Securities Adjusted Alpha Returns**			**Red Securities Adjusted Alpha Returns**		
Time	**Summary stats**	**3FF +QMJ+BAB**	**4CM +QMJ+BAB**	**5FF +QMJ+BAB**	**3FF +QMJ+BAB**	**4CM +QMJ+BAB**	**5FF +QMJ+BAB**
2000 - 2009	Mean	0.55	0.38	0.22	0.69	1.36	0.52
	Variance	9.68	7.68	4.81	20.96	219.14	9.24
	Skewness	3.56	1.32	0.63	10.24	15.71	4.09
	Kurtosis	21.66	2.94	2.36	148.69	258.90	39.70
	Min	-4.63	-4.86	-6.46	-16.99	-19.78	-12.04
	Max	22.92	12.21	8.31	66.24	244.76	30.70
	Median	0.03	-0.05	-0.01	0.14	0.12	0.12

2010 - 2019	Mean	-0.47	-0.45	-0.50	-0.60	-0.55	-0.58
	Variance	3.15	3.21	3.36	2.25	2.25	2.26
	Skewness	-0.40	-0.47	-0.32	-0.23	-0.23	-0.38
	Kurtosis	2.33	2.55	4.17	4.10	3.96	4.55
	Min	-6.56	-6.68	-7.65	-7.94	-7.79	-8.44
	Max	5.49	5.49	7.18	5.24	5.07	5.69
	Median	-0.38	-0.36	-0.41	-0.58	-0.52	-0.57
2000 - 2019	Mean	-0.35	-0.35	-0.36	-0.47	-0.46	-0.48
	Variance	2.54	2.55	2.69	2.00	2.00	1.93
	Skewness	0.03	-0.15	-0.06	-0.40	-0.42	-0.58
	Kurtosis	3.16	3.20	5.61	4.47	4.49	4.91
	Min	-6.20	-6.68	-7.65	-7.94	-7.79	-8.44
	Max	5.49	5.49	7.18	5.14	4.56	4.05
	Median	-0.31	-0.29	-0.34	-0.49	-0.48	-0.51

The table shows the first four moments of Green, and Red, alphas (in percentage, %) and the median, minimum and maximum values within the two subperiods, and the whole period (the observations time is between 1/2000 till 12/2019 and with separation in 12/2009). The table includes the results after winsorization at 99% and the number of cross-sectional (n) securities, and the months which include these securities (T). The alpha is the risk-adjusted abnormal return relative to the applied proxies from FFM and CM and their extension models. The global factors are collected from the Kenneth R. French data library, DataStream and Asness & Frazzini library. The results report dependent variables as simple returns. We denote as 3F-FFM – 3 Factor Fama French Model; 4F-CM – 4 Factor Carhart Model; 5F-FFM – 5 Factor Fama French Model and using the Kenneth R. French data library; and for the BAB, and QML factor using the Asness & Frazzini library.

Table 3.3 examines the alphas for Green and Red securities which is using additional factors (Momentum, FEAR, QML, and BAB) in the asset pricing models for the same time periods. The mean adjusted alpha for Green securities ranged from -0.46% to 0.21%, and for Red securities, it ranged from -0.61% to 0.60% across all models and periods. The variance of alpha for Green securities ranged from 1.92% to 4.76%, and for Red securities, it ranged from 1.46% to 25.73%. The inclusion of these additional factors revealed variations in the alpha moments for both Green and Red securities. The observations regarding the moments, minimum, maximum, and median values during various periods remain consistent with those presented in the previous tables (3.1-3.3). This includes the presence of negative skewness for both categories and lower values of kurtosis compared to the previous tables.

Table 3.3: Cross-sectional adjusted alphas moments of monthly excess returns from the three asset pricing models and for the two asset classes Green and Red

Asset Class		Green Securities Adjusted Alpha Returns			Red Securities Adjusted Alpha Returns		
Time	**Summary stats**	**5FF** +MOM	**5FF** +FEAR	**5FF** +FEAR +MOM	**5FF** +MOM	**5FF** +FEAR	**5FF** +FEAR +MOM
2000 - 2009	Mean	0.01	0.21	0.05	0.60	0.39	0.35
	Variance	4.76	3.71	4.31	25.73	7.67	5.81
	Skewness	-0.30	0.35	-0.14	12.77	4.46	2.01
	Kurtosis	1.99	0.52	2.08	195.66	52.67	16.12
	Min	-7.08	-5.22	-7.04	-9.28	-10.86	-9.37
	Max	5.63	4.83	5.62	78.41	30.91	19.13
	Median	-0.05	-0.05	-0.09	0.11	0.18	0.11
2010 - 2019	Mean	-0.43	-0.46	-0.43	-0.50	-0.61	-0.51
	Variance	2.72	2.54	2.64	2.00	1.97	2.00
	Skewness	-0.50	-0.78	-0.69	-0.30	-0.27	-0.27
	Kurtosis	2.22	1.42	2.08	4.20	4.80	4.26
	Min	-5.73	-5.61	-6.01	-6.75	-7.26	-6.89
	Max	4.57	3.59	4.13	5.77	6.07	5.48
	Median	-0.23	-0.31	-0.20	-0.35	-0.44	-0.41
2000 - 2019	Mean	-0.34	-0.31	-0.34	-0.43	-0.45	-0.42
	Variance	2.16	1.92	2.04	1.55	1.46	1.53
	Skewness	-0.25	-0.49	-0.51	-0.26	-0.19	-0.19
	Kurtosis	2.58	1.34	2.28	6.17	6.81	6.20
	Min	-5.49	-4.78	-5.48	-6.75	-6.76	-6.89
	Max	4.57	3.59	4.13	5.77	6.07	5.48
	Median	-0.29	-0.21	-0.28	-0.38	-0.41	-0.39

The table shows the first four moments of Green, and Red, adjusted alphas (in percentage, %) and the median, minimum and maximum values within the two subperiods, and the whole period (the observations time is between 1/2000 till 12/2019 and with separation in 12/2009). The table includes the results after winsorization at 99% and the number of cross-sectional (n) securities, and the months which include these securities (T). The alpha is the risk-adjusted abnormal return relative to the applied proxies from FFM and CM and their extension models. The global factors are collected from the Kenneth R. French data library, DataStream and Asness & Frazzini library. The results report dependent variables as simple returns. We denote as 3F-FFM – 3 Factor Fama French Model; 4F-CM – 4 Factor Carhart Model; 5F-FFM – 5 Factor Fama French Model and using the Kenneth R. French data library; and for the FEAR factor (European Volatility Index) using the Datastream.

Table 3.4 presents results that are in concordance with the findings observed in the preceding Tables 3.1 through 3.3. In Table 3.4, the adjusted alphas for Green and Red securities are explored using Currency (UK/EUR) and Commodity (Gold) factors along with the previously used asset pricing models. The mean adjusted alpha for Green securities ranged from -0.50% to 0.22%, while for Red securities, it ranged from -1.17% to 0.46% across all models and periods. Except for the first period in some models, our results have similar results to the previous tables with negative skewness for both categories and high values on kurtosis.

Investors can utilize the information to assess the impact of Currency and Commodity factors on the performance of Green and Red securities.

Table 3.4: Cross-sectional adjusted alphas moments of monthly excess returns from the three asset pricing models and for the two asset classes Green and Red

Asset Class		Green Securities Adjusted Alpha Returns			Red Securities Adjusted Alpha Returns		
Time	**Summary stats**	**5FF** +UK/EUR	**5FF** +GOLD	**5FF** +UK/EUR + GOLD	**5FF** +UK/EUR	**5FF** +GOLD	**5FF** +UK/EUR +GOLD
2000 - 2009	Mean	0.22	0.19	0.16	-1.17	0.25	0.46
	Variance	4.28	5.43	6.38	653.23	4.64	8.58
	Skewness	0.70	0.04	0.76	-16.75	-0.60	5.77
	Kurtosis	1.00	1.30	1.86	282.33	6.70	67.27
	Min	-5.11	-7.47	-6.02	-430.52	-12.39	-9.46
	Max	7.11	6.60	8.84	7.99	7.81	34.88
	Median	-0.15	0.01	-0.13	0.25	0.12	0.18
2010 - 2019	Mean	-0.46	-0.50	-0.49	-0.60	-0.64	-0.64
	Variance	2.61	2.77	2.71	1.97	1.98	2.00
	Skewness	-0.52	-0.48	-0.53	-0.22	-0.32	-0.31
	Kurtosis	1.73	1.72	1.65	4.77	4.89	4.73
	Min	-5.13	-5.34	-5.28	-6.59	-6.75	-6.75
	Max	4.50	4.51	4.35	6.63	6.50	6.60
	Median	-0.34	-0.36	-0.35	-0.46	-0.48	-0.49
2000 - 2019	Mean	-0.31	-0.33	-0.34	-0.46	-0.51	-0.51
	Variance	2.03	2.11	2.08	1.48	1.52	1.51
	Skewness	-0.17	-0.15	-0.18	-0.19	-0.31	-0.28
	Kurtosis	2.08	2.02	1.98	7.13	7.25	7.28
	Min	-5.07	-4.93	-4.95	-6.59	-6.75	-6.75
	Max	4.50	4.51	4.35	6.63	6.50	6.60
	Median	-0.23	-0.25	-0.24	-0.42	-0.41	-0.40

The table shows the first four moments of Green, and Red, adjusted alphas(in percentage, %) and the median, minimum and maximum values within the two subperiods, and the whole period (the observations time is between 1/2000 till 12/2019 and with separation in 12/2009). The table includes the results after winsorization at 99% and the number of cross-sectional (n) securities, and the months which include these securities (T). The alpha is the risk-adjusted abnormal return relative to the applied proxies from FFM and CM and their extensions using Currency (UK/EUR) and commodity (Gold) factors. We denote as 3F-FFM – 3 Factor Fama French Model; 4F-CM – 4 Factor Carhart Model; 5F-FFM – 5 Factor Fama French Model

Across these tables, a consistent pattern emerges, affirming the robustness of our analyses. The alpha estimates, encompassing various asset pricing models and incorporating additional factors, exhibit similar trends in terms of mean, variance, skewness, kurtosis, and moments across different time periods. This consistency underscores the reliability and stability of the observed patterns within our dataset. Despite variations in model specifications and the inclusion of additional factors such as momentum, fear, quality, currency, commodity and other factors, the overarching characteristics of alpha returns for both Green and Red securities remain aligned with our prior analyses. Moreover, the replication of consistent patterns across multiple tables strengthens the generalizability of our findings and enhances the credibility of our research outcomes. By demonstrating robustness across diverse specifications and additional factors, our study contributes to a deeper understanding of the dynamics of asset pricing and the determinants of alpha returns in financial markets.

In addition to the summary statistics presented in Tables 3.1 through 3.4, we conducted further analysis on the distribution of adjusted alphas for Green and Red securities using density plots in Figures A3.1 through A3.12 (refer to the Appendix). These density plots depict the probability density function of risk-adjusted alphas for each asset class, providing insight into the concentration of data points at different alpha levels. Our examination revealed that the density of risk-adjusted alphas for Green securities tended to concentrate around positive values, indicating a higher prevalence of positive alphas compared to Red securities. In contrast, the density of adjusted alphas for Red securities displayed greater dispersion, encompassing a broader range of negative and positive alpha values. These density plots offer valuable insights into the distributional characteristics of alphas within both asset classes. However, it is essential to recognize that these observations are influenced by the specific asset pricing models and additional factors employed in our analysis. Different factors or subperiods may produce distinct distributional patterns. Moreover, these plots complement the tabulated results, enhancing our understanding of the financial performance of Green and Red securities. They contribute to a comprehensive analysis of empirical data, facilitating the interpretation of research findings and strengthening the overall robustness of our study.

3.4.2 Statistical Analysis of Alpha values

This section test alpha values by following a methodology similar to that of Clarke & Shahraki (2023). These tests contribute to understanding sustainable investing and the implications of considering eco-friendly or eco-enemy assets in their portfolios or shaping a strategy between Red and Green assets by seeking better portfolio returns. We employed rigorous statistical analyses to assess the differences in alpha values derived from asset pricing models across distinct categories within our dataset. Firstly, we conducted t-tests to compare alpha values between the 'Green' and 'Red'. The null hypothesis stated that there were no differences in the mean alpha values between these groups, while the alternative hypothesis suggested otherwise. The empirical results from table 3.5 show that there is no statistically significant difference between these groups across each period examined. Additionally, we performed one-sample t-tests to determine if the alpha values within each category significantly deviated from zero. These tests were essential to ascertain the significance of alpha values within each category. Here, the results indicated that the alpha values for the 'Red' category consistently differed from zero across all periods examined. For the 'Green' category, alpha values were predominantly statistically different from zero during the second half of the period and throughout the entire observation period. This finding underscores the varying performance and significance of alpha values within each category over time. Furthermore, we utilized Analysis of Variance (ANOVA) tests to examine similar test with the first one whether there were statistically significant differences in alpha means across the 'Green' and 'Red' groups The results of this test reaffirm the findings of the previous analysis, underscoring that our study reveals no statistically significant difference (at 5%) between Green and Red alphas. Through the rigorous testing of these hypotheses, investors gained valuable insights into the no-statistical differences in alpha values between the categories, this strategy revealing that exposing only Green or Red assets does not provide any portfolio advantage. However, the alpha values within each category are mostly statistically significant, meaning the alpha's returns are different from zero, and the investor can seek an opportunity by the potential for obtaining risk-adjusted abnormal returns within the categories.

Table 3.5: Statistical Analysis of Alpha Values Across Categories and models

Test		**T-Test against Zero for each Category**				**T-Test between Green & Red Alphas**		**ANOVA Test**	
T	**Model**	**Green**		**Red**		**Green Vs Red**		**Green Vs Red**	
		t-value	**p-value**	**t-value**	**p-value**	**t-value**	**p-value**	**F-value**	**p-value**
2000 - 2009	3FM	1.69	0.09	2.7	0.00	-0.31	0.76	0.09	0.76
	4FM	1.80	0.07	2.29	0.00	-0.15	0.87	0.005	0.95
	5FM	1.54	0.13	2.16	0.03	-0.48	0.63	0.24	0.63
	3FM +QMJ+BAB	1.98	0.05	2.54	0.01	-0.31	0.76	0.09	0.76
	4FM+QMJ+BAB	1.53	0.13	1.56	0.12	-0.74	0.46	0.54	0.46
	5FM+QMJ+BAB	1.13	0.26	2.87	0.00	-0.98	0.33	0.95	0.33
	5FM + MOM	0.07	0.95	1.99	0.05	-1.23	0.22	1.53	0.22
	5FM +FEAR	1.20	0.23	2.36	0.02	-0.66	0.51	0.44	0.51
	5FM+MOM+FEAR	0.26	0.79	2.44	0.02	-1.21	0.23	1.46	0.23
	5FM + Cur	1.18	0.24	-7.60	0.00	0.61	0.54	0.37	0.54
	5FM + Com	0.89	0.38	1.92	0.06	-0.25	0.80	0.06	0.80

	5FM + Cur+ Com	0.69	0.49	2.67	0.00	-1.01	0.31	1.03	0.31
2010 - 2019	3FM	-4.12	0.00	-6.69	0.00	-0.28	0.78	0.08	0.78
	4FM	-3.11	0.00	-5.59	0.00	-0.06	0.95	0.005	0.95
	5FM	-4.02	0.00	-7.72	0.00	0.26	0.80	0.07	0.80
	3FM +QMJ+BAB	-3.14	0.00	-7.24	0.00	0.68	0.50	0.46	0.50
	4FM+QMJ+BAB	-2.90	0.00	-6.83	0.00	0.68	0.50	0.46	0.50
	5FM+QMJ+BAB	-2.36	0.02	-6.88	0.00	0.49	0.62	0.24	0.62
	5FM + MOM	-3.23	0.00	-6.39	0.00	0.30	0.77	0.09	0.77
	5FM +FEAR	-3.64	0.00	-7.85	0.00	0.72	0.47	0.51	0.47
	5FM+MOM+FEAR	-2.64	0.00	-6.59	0.00	0.62	0.54	0.38	0.54
	5FM + Cur	-3.94	0.00	-7.60	0.00	0.34	0.74	0.12	0.74
	5FM + Com	-4.16	0.00	-8.25	0.00	0.34	0.74	0.11	0.74
	5FM + Cur+ Com	-3.37	0.00	-8.12	0.00	0.42	0.67	0.18	0.67
2000 - 2019	3FM	2.7	0.00	-4.86	0.00	-0.07	0.95	0.005	0.95
	4FM	-2.57	0.00	-5.48	0.00	0.32	0.75	0.11	0.75
	5FM	-3.07	0.00	-6.81	0.00	0.47	0.64	0.22	0.64
	3FM +QMJ+BAB	-2.49	0.01	-5.75	0.00	0.69	0.49	0.48	0.49
	4FM+QMJ+BAB	-2.53	0.01	-5.91	0.00	0.78	0.44	0.60	0.44
	5FM+QMJ+BAB	2.87	0.00	-6.02	0.00	0.96	0.34	0.92	0.34
	5FM + MOM	-2.89	0.00	-6.73	0.00	0.63	0.53	0.39	0.53
	5FM +FEAR	-2.79	0.00	-6.66	0.00	0.65	0.52	0.42	0.52
	5FM+MOM+FEAR	-2.64	0.00	-6.62	0.00	0.79	0.43	0.63	0.43
	5FM + Cur	-3.10	0.00	-6.83	0.00	0.44	0.66	0.20	0.66
	5FM + Com	-4.08	0.00	-7.84	0.00	0.74	0.46	0.55	0.46
	5FM + Cur+ Com	-3.37	0.00	-7.88	0.00	0.71	0.48	0.51	0.48

The table presents the results of statistical analyses conducted to investigate differences in alpha values derived from asset pricing models across distinct categories within the dataset. Specifically, the table includes the outcomes of independent samples t-tests comparing alpha values between the 'Green' and 'Red' categories, one-sample t-tests examining deviations of alpha values within each category from zero, and Analysis of Variance (ANOVA) tests assessing differences in alpha means across the 'green' and 'red' groups. The table provides critical insights into the statistical significance of alpha values within and between categories, offering valuable information for understanding the dynamics of asset pricing models in different contexts.

Overall, the empirical analysis across the figures and the tables indicates variations in the adjusted alpha moments for Green and Red securities, as well as their sensitivity to different asset pricing models and additional factors. The presence of greater performance between Green and Red is not observed in any models and periods, suggesting the importance of considering additional various factors and different subperiods when evaluating the financial performance of environmentally (un)friendly investments. However, caution is advised in drawing definitive conclusions due to potential limitations and market-specific dynamics that may influence the observed results.

3.4.3 Green vis-à-vis Red risk-adjusted alpha performance

Assessing various multifactor asset pricing models entails comparing the statistical significance of their mean pricing errors (referred to as alphas). These alphas represent the excess returns of an asset after adjusting for its exposure to systematic risk factors. In our study, different asset pricing models incorporate distinct sets of factors, each aimed at capturing different aspects of market behavior and risk. As a result, the alphas generated by these models may vary due to the differing abilities of each model to explain and account for the complexities of asset returns. Therefore, the comparison of alphas across different models serves as a means to evaluate their effectiveness in pricing assets and capturing relevant sources of risk and return in the market. The previous section evaluates whether each asset class's alpha (Green and Red) is statistically significant from zero individually, as well as whether there is a statistically significant difference between the Green and Red alphas. In this section, the focus is on quantifying the magnitude of the difference between the risk-adjusted alphas of these two asset classes. This involves both testing the statistical significance of the difference and measuring its size.

The empirical results from Table 3.6 provide insights into the risk-adjusted alpha performance of Green securities compared to Red securities across three distinct periods: 2000–2009, 2009–2019, and the entire period from 2000–2019. These results are analyzed using both the Fama-French 3-factor and 5-factor models, as well as the Carhart 4-factor model. Alike, Table 3.7 presents the empirical results for extending the Fama-French and Carhart model.

In table 3.6, the Green factor does not exhibit statistically significant performance in any of the models. These findings suggest that there is no obvious outperformance or underperformance of Green securities compared to Red securities.

Table 3.6: Empirical results for comparing the Red versus Green returns (for the period 2000-2019 and the sub-periods)

Adjusted Alpha performance of Green VS Red securities									
Time	2000 – 2009			2010 – 2019			2000 – 2019		
Model	**3F -FFM**	**4F-CM**	**5F-FFM**	**3F -FFM**	**4FCM**	**5F-FFM**	**3F -FFM**	**4F-CM**	**5F-FFM**
Green Factor	-0.09	-0.04	-0.20	0.06	0.01	0.13	0.09	0.05	0.15

The table presents the adjusted alpha performance of Green securities compared to Red securities or Green Dummy premium. The row is the factor exposure from the cross-sectional (CS) regression, of the adjusted-alphas with the dummy variable. The alpha is the risk-adjusted abnormal return relative to the applied proxies from FFM and CM. We denote as 3F-FFM – 3 Factor Fama French Model; 4F-CM – 4 Factor Carhart Model; 5F-FFM – 5 Factor Fama French Model and using the Kenneth R. French data library. The table reports the results from equation [3.7]. Additionally, we note that beside the number with the star, the significant level (*, ** and *** corresponds to statistical significance at 10 %, 5 %, and 1 % levels, respectively).

Table 3.7 (Panel A) presents the results for the same time periods using an extended asset pricing model that includes factors such as QMJ and BAB (q-factor and betting against beta). Panel B provides the results when considering the asset pricing model that incorporates MOM (momentum) and FEAR (European Volatility Index) factors. Lastly, Panel C focuses on the asset pricing model that includes UK/EUR (currency factor) and Gold (commodity factor). Similar to Table 3.6, the Green factor exhibits a non-statistically significant negative alpha performance for the period from 2000 to 2009. However, for the second sub-period and the entire period, there is a positive non-statistically significant alpha. Both results indicate no distinguishable greater financial performance between Green and Red assets.

Table 3.7: Empirical results for comparing the Red versus Green returns using extension models (for the period 2000-2019 and the sub-periods)

Panel A									
Time	2000 – 2009			2010 – 2019			2000 – 2019		
Model	**3FF +QMJ+BAB**	**4CM +QMJ+BAB**	**5FF +QMJ+BAB**	**3FF +QMJ+BAB**	**4CM +QMJ +BAB**	**5FF +QMJ+BAB**	**3FF +QMJ+BAB**	**4CM +QMJ+BAB**	**5FF +QMJ+BAB**
Green Factor	-0.14	-0.98	-0.29	0.13	0.11	0.08	0.13	0.11	0.13
Panel B									
Model	**5FF +MOM**	**5FF +FEAR**	**5FF +FEAR +MOM**	**5FF +MOM**	**5FF +FEAR**	**5FF +FEAR +MOM**	**5FF +MOM**	**5FF +FEAR**	**5FF +FEAR +MOM**
Green Factor	-0.58	-0.18	-0.30	0.06	0.15	0.08	0.09	0.13	0.08
Panel C									
Model	**5FF +UK/EUR**	**5FF +Gold**	**5FF + UK /EUR + Gold**	**5FF + UK /EUR**	**5FF + Gold**	**5FF + UK/EUR +Gold**	**5FF + UK /EUR**	**5FF + Gold**	**5FF +UK/EUR + Gold**
Green Factor	1.39	-0.06	-0.31	0.14	0.14	0.15	0.15	0.18	0.17

The table presents the adjusted alpha performance of Green securities compared to Red securities or Green Dummy premium. The Green Factor is the factor exposure from the cross-sectional (CS) regression, of the alphas with the dummy variable. The alpha is the risk-adjusted abnormal return relative to the applied proxies from FFM, CM and their extension models. We denote as 3FF – 3 Factor Fama French Model; 4F-CM – 4 Factor Carhart Model; 5FFM – 5 Factor Fama French Model and using the Kenneth R. French data library; and for the BAB, and QML factor using the Asness & Frazzini library; and for the FEAR (European Volatility Index), Gold and Currency factor from the Datastream database. The table reports the results from equation [3.7] by using extension models. Additionally, we note that beside the number with the star, the significant level (*, ** and *** corresponds to statistical significance at 10 %, 5 %, and 1 % levels, respectively).

Throughout the analyzed periods (2000-2009, 2009-2019, and 2000-2019), we cannot draw conclusions regarding the superior or inferior performance between green and red assets. In Table 3.6-3.7, we do not observe statistically significant differences between the two categories of assets. Therefore, it remains inconclusive whether investors or firms should favor eco-friendly or eco-enemy investments to achieve better risk-adjusted returns. Despite the environmental benefits associated with green investments, such as transitioning to a "cleaner" market and reducing pollution, these factors alone do not guarantee superior performance. This suggests that increasing (or decreasing) the exposure to eco-friendly investments while decreasing (or increasing) the exposure to eco-enemy investments fails to yield financial gains.

Correspondingly, Ito et al. (2013) conducted research indicating that during periods of economic crisis, countries striving for rapid economic development may experience a trade-off between pursuing environmental initiatives and addressing liquidity concerns. In such circumstances, the benefits of environmental actions might be reduced, as governments prioritize immediate economic growth to stimulate economic activity. Bolton & Kacperczyk (2021) finds that firms with higher total carbon dioxide emissions, as well as changes in emissions, experience higher stock returns. This study finds a notable carbon premium in stock returns that suggests that investors may already be demanding compensation for their exposure to carbon emission risk in their investment decisions. Ito et al. (2013) perspective highlights the potential challenges faced by nations in striking a balance between environmental sustainability and economic development during times of crisis or boosting their economic activities. On the contrary, our findings indicate that Green securities did not outperform or underperform Red securities during our study periods. Other research papers from Bolton et al. (2022) show that returns are higher for Red companies than the other assets. Also, for Germany, Oestreich & Tsiakas (2015) found that Red companies outperformed those that did not harm the environment. The previous research conducted by Pástor et al.

(2021a) investigates a price premium associated with green assets, wherein investors are willing to pay a premium for environmentally sustainable investments while simultaneously accepting lower expected returns.

Overall, our empirical results across the different time periods and asset pricing models show non-statistically significant financial performance regarding the risk-adjusted alpha of Green versus Red securities. These results underscore the complexity of analyzing the performance of Green and Red securities and highlight the importance of considering multiple factors and multiple time frames in such studies. The relationship between environmental sustainability and financial performance provides investors with a better understanding, particularly those seeking a balanced approach to aligning their financial goals with their ethical and environmental values. As the world continues to address climate change challenges, incorporating Green securities into investment portfolios can play a vital role in shaping an environmental sustainable future.

3.5 Conclusion

This research examines the return performance of Green vis-à-vis Red securities. Red are those whose returns are associated with environmentally-unfriendly companies, and the Green returns are related to companies with environmentally-friendly activities.

This analysis aims to explore the financial implications and potential benefits of investing in environmentally sustainable options compared to those with higher carbon footprints. Our research suggests that neither a high nor low exposure to eco-friendly or eco-enemy unfriendly investments can guarantee sustainable gains or guarantee a strategy for consistent profitability. Our major empirical findings indicate non-statistically significant results across all the models and periods. These results underscore the potential benefits of increasing exposure to Green securities in investors' portfolios. As a result, investors should consider revisiting their investment strategies to incorporate a higher allocation towards Green over Red assets or the opposite strategy. This encapsulates a different view about the Green and Red asset class compared to the research papers from Bauer et al. (2022), Ito et al. (2013), Bolton et al. (2021; 2022) and Oestreich & Tsiakas (2015). These studies found different results to our study that Red or high carbon emission companies outperform the other companies (not just Green). The contradictory empirical results from Ardia et al. (2022) and

Pástor et al. (2022) show that low carbon emission (Green) companies are more attractive to investors when appears a suddenly increasing of the interests for the climate change. All these divergences in the research papers might be explained either by the differences in sample periods, market, or the factors applied or methods which tried to explain the performance of the low-high emission companies.

In the last part, we discuss extensions and applications of our methodology and offer ground for further research. The extension of the classical factor models can introduce new explanatory factors that will enhance the explanation of assets performance, offering new insights into Red and Green stocks, such as the liquidity (LIQ) factor (Pástor & Stambaugh, 2003), gauges the liquidity risk. The combination of factors may sharpen the view of the performance and explain better any class return dynamic. To comprehend what influences the returns and also what is the correct number of factors when the scenarios change as the economic environment changes and new risks appear on the horizon. However, the above factors are not exhaustive, as the exploration for the returns is unlimited. Our extension model offers enhanced insights into asset class returns and a deeper understanding of risk-adjusted alpha. Investors do not need to focus on applying or developing trading strategies by adjusting the portfolio positions between Green and Red securities, since there is no evidence of a statistical difference in their financial performance.

Chapter 4: European Green, Grey, Red Securities and crisis sentimental

Abstract

The research provides evidence of crisis sentimental indexes influencing the returns of Green (eco-friendly), Grey (eco-neutral) and Red (eco-enemy) securities in the EU. This study documents investors' crisis mood and economic uncertainty policy sentiment significantly impacting monthly returns on the Green, Grey and Red securities market. The monthly crisis factors are based on European countries' google query volumes during the period 1/2004 till 12/2019 and are created by following the adjusted Financial and Economic Attitudes Revealed by Search (FEARS) Index and the General Crisis Sentimental index (CSI). The research also applies the Global Economic Policy Uncertainty Index, another alternative sentimental index using sentiment from texts (Baker et al. 2016; Brand, 2021). The negative household mood during times of crisis and uncertainty decreases Grey and Red equity price returns, while the effect on Green equity returns are either insignificant or positive. The empirical data generally supports the preliminary conclusions on the potential effects of investor and economic sentiment on the Grey and Red equities markets (Baker & Wurgler, 2006; Da et al., 2015; Irresberger et al., 2015; Irresberger & Weiß, 2015). The analysis split the periods as follows: the ex-Global Crisis period (1/2004 till 08/2008), Global Crisis and after (9/2008 till 12/2019), and the entire period (1/2004 till 12/2019). The methodology compares the performance of the crisis sentimental indexes by using the extended Fama-French models (three and five-factor models). The implications drawn from these findings hold valuable insights for environmentally conscious investors aiming to (un)balance portfolios and make informed hedging decisions based on the level of investors' crisis sentiment. Additionally, policymakers can apply strategic measures for Green and Grey to mitigate contagion risks.

Keywords: Asset Pricing Models, European Stock Market, Financial crisis, Investor-Economic Sentiment

JEL classification: G21,G01,G02

4.1 Introduction

Investors are becoming aware of the importance of incorporating "green portfolios" into their investment decisions, reflecting their concern for the environment and their desire to align their investments with their values. Red securities refer to "old traditional" securities (such as the oil & petroleum companies) that may have negative impacts on the environment and Grey is a neutral environmental associate security (refer to Table 1.1). How do these types of assets react to investor fear in EU financial markets? The connection between asset class and sentiment remains unclear in the stock market. Our prior expectation is rooted in the premise that market sentimentality can exert a significant influence on stock returns, but does that equally influence all asset classes? Our study anticipates that crisis sentiment indexes, reflecting prevailing investor emotions during times of uncertainty or crisis, could potentially impact the trading behavior of any type of Green, Grey and Red securities. By investigating the relationship between these indexes and stock returns, we aim to uncover insights into how market sentiment interacts with investment decisions, offering a deeper understanding of the dynamics between emotional factors and financial outcomes. This is an important question for investors, as sentimental indexes can reveal the influence on the performance of the different types of securities and the general impact on the financial markets.

The potential channel through which sentimentality might influence stock returns is tied to investor behavior and decision-making. During periods of heightened uncertainty, market participants often make trading decisions based on emotions, rather than merely on fundamental or technical analysis signals. This emotional bias can lead to exaggerated price movements, as fear or optimism spreads across the financial market especially during the EU crisis events. This phenomenon is particularly evident during European Union (EU) crisis events that have fundamentally shaped the economic trajectory of member states (Appendix Table A4.1). Several financial crises illustrate how negative investor sentiment can exacerbate underlying economic vulnerabilities. For instance, the Icelandic banking crisis (2008–2009) and the Greek debt crisis (2009) show how heightened uncertainty and fear worsened market instability (Lapavitsas & Sergis, 2014; Kouretas & Vlamis, 2010). Similarly, the banking collapses in Ireland (2010), Portugal (2010–2014), and Spain (2012) demonstrate how crises initially rooted in economic issues were magnified by reducing investor confidence for the financial markets (McCann & McIndoe-Calder, 2014; Gentier, 2012).

Geopolitical shocks like Ukraine's crisis following the annexation of Crimea[11] (2014) and Brexit (2016–2019) further highlight how uncertainty increases financial volatility (e.g. Jones, 2021; Nivorozhkin & Castagneto-Gissey, 2016; Breinlich et al., 2018). Moreover, the global financial crisis following Lehman Brothers' collapse (2008) and the European sovereign debt crises underscore how rapidly shifting investor sentiment plays a critical role in escalating financial turmoil (Baker & Wurgler, 2006; Da et al., 2015).

Thus, the use of crisis sentiment indexes as proxies for measuring emotional shifts in investor behaviour may provide valuable insights into how collective investor psychology influences market outcomes during periods of financial distress. By capturing the prevailing mood of market participants, such indexes offer a quantifiable means of understanding the behavioral dimensions of financial crises, resulting changes in trading activity and how investor sentiment might contribute to stock price volatility and, ultimately, impact stock returns. While the underlying mechanisms of sentimentality affecting stock returns could apply broadly, there might be variations in the extent of the impact between Green, Grey and Red securities. Green securities, typically associated with environmentally responsible and sustainable companies, exhibit different sensitivities to market sentiment compared to Red and Grey securities, which might include industries with higher volatility or more traditional risk profiles. The specific market context, the nature of the crisis, and the prevailing investor sentiment could all play roles in shaping how Green, Grey and Red stocks respond to sentimentality. Therefore, it is essential to empirically examine these potential distinctions to provide a comprehensive view of how sentimentality indexes interact with different types of securities.

In the landscape of financial research, a collective body of work has sought to delve into the intricate relationship between market sentiment and its impact on various financial markets (Appendix Table A3.2). Notably, Baker & Wurgler (2006), Da et al. (2015), Irresberger et al. (2015), and Irresberger & Weiß (2015) have focused their studies on investigating the crisis sentimental index within the context of the US market. Their efforts encompass an array of approaches and methodologies, collectively shedding light on the role that investor sentiment plays in influencing market dynamics and price returns in times of crisis. Diverging from this line of inquiry, my research endeavours to extend the understanding of this phenomenon by shifting the geographical focus to the European Union's financial market. While Anastasiou & Drakos (2021)

[11] known as Russian-Ukraine war

contributed to the field by utilizing the crisis sentimental index for the EU market, with an emphasis on the country level, my study expanded to the continent level (EU). Specifically, I construct a comprehensive, aggregated index that encapsulates the collective sentiment of all EU member states. This approach aims to aggregate the sentiment index from local (country-specific) measures to a European-wide index, offering a broader perspective that captures sentiment-driven dynamics across the entire EU financial market. This study contributes to the literature by providing a more holistic and integrated view of investor sentiment across the distrinct EU environmental assets. Particularly, my research explores how crisis-driven emotions influence the returns of Green, Grey, and Red equities at a European level. This approach addresses the gap left by prior studies by not only extending the geographical scope but also analyzing sentiment impacts across distinct equity categories (Green, Grey and Red sectors), which have not been comprehensively studied in the existing literature. In order to measure sentiment, the study employs Google search volume data and constructed indexes from previous research studies (Baker & Wurgler, 2006; Baker et al., 2016; Brand, 2021; Da et al., 2015; Irresberger et al., 2015; Irresberger & Weiß, 2015; Anastasiou & Drakos, 2021).

The research focuses on the whole period of 16 years and ex-post crisis subperiods (collapse of Lehman brothers'), examining the relationship between crisis sentimental indexes and returns of Green, Grey & Red equities. The study's results suggest that an increasing of investors crisis-related emotion negatively impacts the returns of Grey, and Red equities. This finding contributes to our understanding of the behaviour of these equity returns and provides further explanation for the relationship between investor mood and economic outcomes.

The current study adds to the existing scholarly literature on the impact of investor mood on economic outcomes (Baker & Wurgler, 2006; Da et al., 2015; Irresberger et al., 2015) for the US market. The significant influence of these sentiment indexes on financial markets stems from the complex interplay between investor emotions and shifting market dynamics. When markets face crises, be it economic downturns, geopolitical turmoil, or unexpected global events, investors' emotional responses often translate into actual selling trading decisions (e.g., Shiller, 2003; Baker & Wurgler, 2007; Kaplanski & Levy, 2010). Fear-driven selling can lead to rapid price declines, while periods of heightened optimism may contribute to surges in buying activity. These emotional reactions augment the traditional supply-and-demand forces, resulting in increased market volatility and abrupt price fluctuations.

The rest of the study is organized as follows: Section 2 provides a comprehensive review of the existing literature on the topic, highlighting key findings and limitations, and identifying gaps in the knowledge this study aims to fill. Section 3 describes the variables used in the study, including a description of the dataset and an explanation of the variables utilized in the analysis. Section 4 outlines the empirical approach taken in the study, including a detailed explanation of the statistical techniques and models used. The empirical results are presented and discussed in Section 5, including descriptive statistics, the output of the statistical models, and an interpretation of the findings. The study concludes in the last section with a summary of the main results, a discussion of the limitations, and suggestions for future research.

4.2. Exploring Sentimental Indexes: Historical Insights and Cases for applying Sentimental Indexes

The role of sentiment in investment decision-making in financial markets was introduced by Keynes (1936) and, in later years, has gained significant attention from academic scholars. Keynes introduced the term "animal spirits," which was later extended by Akerlof & Shiller in 2009. This concept refers to the emotional and psychological factors, including confidence and optimism, that employ a significant influence on economic behavior. Akerlof & Shiller's (2009) extension delved deeper into the understanding of these animal spirits, emphasizing their role in shaping decision-making, market dynamics, and economic outcomes. Keynes emphasized the role of animal spirits as necessary for economic activity and investment decisions. According to Lopes (1987), fear and hope are the two primary emotions that shape investors' perception of risk when making investment decisions. Fear arises from the anticipation of potential losses, while hope stems from the expectation of gains. These emotions can influence investors' behavior and decisions, leading to both rational and irrational responses (e.g. Shleifer & Vishny, 1992). The role of fear and hope in financial markets has been widely discussed and studied, like Shefrin (2000) noted that greed and fear are the primary forces of driving market trends and movements. Greed can lead investors to take on excessive risks, while fear can cause them to sell assets immediately or avoid investing. Read's (2009) book in "The Fear Factor, What Happens When Fear Grips Wall Street", the sentiment of fear is considered to be balanced when it motivates people to take action against external factors that cause them concern, without focusing too much on minor threats. However, there have been many instances where panic has taken over the financial market, leading to huge losses. In other words, Read believes that while fear can be a useful motivator in making individuals take necessary precautions, too much fear can lead to irrational decision-making and potentially harmful outcomes. Barberis & Thaler (2003) argues that behavioural finance comprises two key components: limitations to arbitrage and psychology. Limitations to arbitrage suggest that rational traders may struggle to correct the imbalances created by less rational traders, at the same time, psychology focuses on the types of deviations from rationality that are expected. For example, imagine a stock's price is way off from its real value because of feelings in the market, not facts. Smart traders might want to fix this by trading smartly, but they could face problems like high costs or not having all the needed information. This makes it hard to fix the price difference quickly, which shows how limits to arbitrage affect how well markets work. At the same time, psychology looks into why people sometimes act strangely in finance. People can make decisions that aren't logical, and this can mess up how markets should work. Exploring these emotional and psychological aspects helps us understand why financial markets can behave in odd ways. So, understanding both limits to arbitrage and psychology in behavioral finance gives us insights into why financial markets sometimes don't act as expect. Barberis et al.(1998) defines investor sentiment as the way investors form their beliefs, a complex and qualitative trait influenced by various factors, making it difficult to identify. Therefore, numerous studies have utilized different techniques to understand, quantify, and measure sentiment (Brown & Cliff, 2004; Corredor et al., 2013; Sibley et al., 2016; Renault, 2017). Chau et al.(2016) investigated the impact of investor sentiment on trading behavior and found evidence of sentiment-driven buying and selling in the US stock market. Similarly, Yu & Yuan (2011) analyzed the influence of investor sentiment on the market's mean-variance tradeoff and concluded that sentiment traders can disrupt an otherwise positive mean-variance tradeoff during high-sentiment periods and Renault (2017) creates an index based on online investor sentiment that helped to predict the intraday stock index returns. Baker & Wurgler (2006) studied the potential impact of investor sentiment on the cross-section of stock returns and found that a surge in economic sentiment has an effect on securities. The growing availability of data has further fueled interest in sentiment analysis in finance, providing unprecedented opportunities for exploring its potential impact on financial market outcome.

The utilization of search volume data in predicting economic variables has gained significant attention in academia (e.g. Dzielinski, 2012). The studies cited offer intriguing insights into the nexus between internet search volume and financial market dynamics. The first indicator has gained significant attention in finance for its ability to provide an index by the direct and objective insights from individual sentiments created by Baker & Wurgler (2006). Baker utilized Google search volume data to construct the general crisis sentimental index, which directly measures the general economic mood of a crisis and quantifies the pessimistic market-wide sentiment of retail investors during the financial crisis (Irresberger et al., 2015, 2017; Irresberger & Weiß, 2015). Da et al. (2011) presented a pioneering notion, encouraging the utilization of search volume data to gauge investor attention. Subsequently, Vozlyublennaia (2014) operationalized this concept by applying an investor attention index derived from search volume data. The study explored the intricate relationship between this investor attention index and the performance of diverse security indexes spanning broad investment categories. Building upon this foundation, Da et al. (2015) and Bijl et al. (2016) delved into the domain of predictive analysis, demonstrating that Google search activity can serve as a valuable predictor of activity in the US stock market. Kostopoulos et al. (2020) extended this predictive power assessment to the German market. The implications suggest that shifts in investor sentiment, reflected in internet search behavior, hold potential predictive power for stock market movements in various global contexts. Furthermore, Bank et al. (2011) contribution underscored the broader implications of internet search volume. Their work established that search volume can function as a proxy for overall firm recognition, effectively capturing the attention of stock market investors. This recognition serves as a testament to the interplay between online search behavior and investor decision-making processes. Building on this foundation, subsequent researchers (e.g. Han & Li, 2021; Kaplanski & Levy, 2010) expanded their inquiries beyond individual securities, exploring these associations on a national scale. Moreover, Takeda (2014) study investigated the relationship between Japanese equities market and Google search volume. Building on this foundation, subsequent researchers expanded their inquiries beyond individual securities, exploring these associations on a national scale. These studies collectively underscore the importance of internet search volume and the growing relationship between investor attention and financial market performance. Their findings illuminate the potential predictive power of online search behavior, shaping our comprehension of market movements on both local and global scales (Appendix table A4.2).

In recent years, several studies have explored the potential of using search volume data to predict variations in stock returns and other economic variables. Among these studies are research works by Dimpfl & Jank (2016), Afkhami et al. (2017), and Perlin et al. (2017), who have investigated the relationship between investors' use of social internet-based information and their trading activity. The studies suggest that higher levels of information may lead to greater trading activity, which in turn can influence economic outcomes such as stock price volatility, market liquidity, and overall asset returns.

In addition to its use in predicting economic variables, search volume data derived from Google searches has also been applied to portfolio diversification and investment strategies. Preis et al. (2013) investigated the potential of search volume data as an information source for making informed investment decisions. The findings of the search volume data can provide valuable insights into the performance of individual stocks, allowing investors to make more informed decisions and potentially achieve better returns. Further research in this area could yield even more insights and help refine our understanding of how to use search volume data effectively in portfolio diversification and investment strategies.

Overall, the application of search volume data in economics has emerged as a promising area of research. The studies conducted thus far have shed light on the potential applications of search volume data and the ways in which it can be used to inform investment decisions. Further research in this area could yield even more insights and help refine our understanding of the relationship between internet information and economic performance outcomes.

4.3 Data Description and Methodology

4.3.1 Data Description

This study is built upon a comprehensive dataset spanning from January 2004 to December 2019, encompassing monthly data across twenty-eight (28) European Union countries. The dataset comprises a total of 2007 Grey, 150 Green, and 367 Red stocks, classified based on the criteria outlined in Table 1.1 (refer to Chapter 1). The dependent variable under examination is the monthly price returns, calculated as the quotient of the last observation of the month divided by the first observation of the month, with 1 subtracted, to signify the percentage change for each security.

The primary objective of this study is to investigate the evolving impact of crisis sentiment factors over discrete periods of time. The temporal framework includes a notable focus on the Global-European Union financial crises. In particular, the designated time period is divided into three distinct segments:

1. The ex-Global Crisis period (from January 2004 to August 2008): This phase represents the "calm" period before the lead-up to the global financial crisis, when investors feel optimistic about the financial markets.
2. The Global Crisis and Post-crisis period (from September 2008 to December 2019): This phase encompasses the period of the global financial crisis and after, which represents a period of high crisis intensity when investors feel pessimistic about the financial markets.
3. The entirety of the dataset period (from January 2004 to December 2019): The last phase contains the full period, including both periods.

This temporal division allows for a nuanced exploration of how crisis sentimentality unfolds across various stages, each characterized by unique financial dynamics and crisis-driven influences.

The risk factors and stock prices utilized in this study are sourced using the same method as in Chapter 2 and undergo similar transformations. The primary independent variable used in the analysis model is a modified Financial and Economic Attitudes Revealed by Search Index (FEARS Index), which is constructed using internet search volume data (GSVI) from the Google Trends database and also the second explanatory variable, the general crisis sentimental index (CSI). The modified FEARS Index utilizes the approach suggested by Da et al. (2015) , Irresberger et al. (2015), and Anastatiou & Drakos (2021) to gauge the collective outlook of households regarding the economy by employing Google search terms associated with the general condition of the economy[12]. The modified CSI Index is designed to measure the overall crisis sentiment of the investor towards the economy. It draws upon the methodology proposed by Baker & Wurgler (2006), which involves the use of limited search terms that relate to the state of the financial economy and aims to serve as a proxy for gauging general crisis sentiment. The Global Economic Policy Uncertainty (GEPU) Index[13], an alternative sentiment index developed by Baker et al. (2016), offers valuable insights into prevailing uncertainties in global economic policies, providing a perspective on the uncertainty of the economic conditions. The GEPU index is accessible through the researchers' website. The indexes objective is to act as a proxy for crisis sentiment and capture the behavior of the asset class group.

This study examines the relationship between several risk factors, and the sentimental factors and their moments of skewness and kurtosis (Appendix Tables A4.5-A4.7). The

[12] The EU index utilize the English words based on Anastasiou et al. (2019) and also constitutes the official EU language and the most common between the EU countries.
[13] https://www.policyuncertainty.com/global_monthly.html

sentimental and the classical risk factors are observed monthly, and the sample period spans from January 2004 to December 2019, that happens because the market factor reflects the overall performance and sentiment of the financial market. The indexes US and EU CSI are strongly correlated and exhibit similar moments by construction. Additionally, the PCA and average FEARS index exhibit strong correlation and divergent moments indicating a similar pattern but capture different behaviors. That means the first method captures the most important variation in the variables, whereas the average method combines the average effect of the variables, which may overlook some of the unique information each variable carries. In addition, the correlation matrix revealed that returns were negatively correlated with all the indexes. By incorporating sentiment indexes into our asset class portfolios and other combinations of market portfolios, investors can create more informed positions by using the increase of the sentimental indicators as a short signal to the market portfolio (similarly, for the opposite, a long position). Specifically, sentiment indexes serve as a proxy for market mood, which can influence investor behavior and price movements. These sentiment indicators can help to better understand a shifts in portfolio risk and return, providing a more comprehensive approach to investment strategy. These findings shed lights to understand the proxies portfolios and the sentimental factors movements when making investment decisions.

4.3.2 Crisis Indexes: Methodologies and Construction

I. FEARS Index

Da et al. (2015) studied 118 search terms to create the FEARS Index. These terms included both positive and negative sentiments. Interestingly, their analysis found that negative terms had a bigger effect on returns, then the study picked the most influential 30 terms out of the original 118. According to Da et al. (2015) research, the FEARS Index's integrated GSVIs (Google Search Volume Indices[14]) to capture investor sentiment regarding crises before it is fully incorporated into the market. Panel A of Table 4.1 lists the search terms used in Da et al. (2015) and Irresberger et al. (2015) analyses.

[14] The value of the terms represent the search interest relative to the highest point on the chart for the selected region and time. A value of 100 is the peak popularity of the term, whilst a value of 50 means that the term is half as popular and zero means the words it isn't popular at all or missing.

Table 4.1: FEARS Google Search terms

Panel A: This panel presents the thirty search terms to compute the US FEARS Index as proposed by Da et al., (2015).

GOLD PRICES	BANKRUPTCY	ECONOMY
FRUGAL	SOCIAL SECURITY CARD	PRICE OF GOLD
EXPENSE	GREAT DEPRESSION	THE GREAT DEPRESSION
RECESSION	UNEMPLOYMENT	UNEMPLOYED
GDP	THE CRISIS	POVERTY
DONATION	GOLD	**CAR DONATE**
GOLD PRICE	INFLATION RATE	**THE DEPRESSION**
CHARITY	DEFAULT	CRISIS
SAVINGS	BENEFITS	CAPITALIZATION
DEPRESSION	BANKRUPT	**SOCIAL SECURITY OFFICE**

Panel B: This panel presents the thirty-four search terms used to compute the adjusted-FEARS indices for the EU countries as extension and modified index by Anastasiou & Drakos (2021).

GOLD PRICES	BANKRUPTCY	ECONOMY
FRUGAL	SOCIAL SECURITY CARD	PRICE OF GOLD
EXPENSE	GREAT DEPRESSION	THE GREAT DEPRESSION
RECESSION	UNEMPLOYMENT	UNEMPLOYED
GDP	THE CRISIS	POVERTY
DONATION	GOLD	**CAR DONATION**
GOLD PRICE	INFLATION RATE	**ESM**
CHARITY	DEFAULT	**FINANCIAL CRISIS**
SAVINGS	BENEFITS	CAPITALIZATION
DEPRESSION	BANKRUPT	**SOCIAL SECURITY**
EUROPEAN FINANCIAL STABILITY FACILITY	**EUROPEAN DEBT CRISIS**	**GOVERNMENT DEBT**
-	-	CRISIS

Our study differs from previous research by constructing a modified FEARS Index designed explicitly for European Union countries, rather than the US market. In order to achieve this, we utilized core search terms recommended by Da et al., (2015) while substituting those with strong US associations with European Union associations to ensure the capture of the economic and investor behavior in the European Union[15]. The selection of relevant search terms was informed by Anastasiou & Drakos (2021) work, which focused on identifying EU-specific words plus other relevant popular words. The list of thirty-four search terms used in constructing the modified FEARS Index for this analysis can be found in Table 4.1(Panel B).

[15] Anastasiou (2021) added (i.e. the new GSVIs) specific keywords to the updated EU table. The words relevant to the European aspect of the data are DEBT CRISIS, ESM, FINANCIAL CRISIS, SOCIAL SECURITY, and EFSF and removed the specific keywords related to the US economy are THE GREAT DEPRESSION, THE DEPRESSION, CRISIS, and SOCIAL SECURITY OFFICE. The substitution based on the time-value of the term if it has zero value that means that the term isn't popular at all or missing and we should change it with EU related term.

The database provides monthly data on the Google Search Volume Index (GSVI) for any given search term. The index is defined on Google Trends' official website as follows:

$$\text{GSVI} = \frac{number\ of\ queries\ f\ or\ each\ keyword}{total\ Google\ search\ queries} \tag{4.1}$$

The first step to creating a modified FEARS Index is adjusting the previous research from Da et al., (2015) and Anastatisou & Drakos (2021) for European Union data at the country level. The methodology adopts a slightly different approach by aggregating the words for every European country as a single-word entity applying the average GSVI to reflect the unique word for the character of the European Union. The aggregation is as follows:

$$GSVI_{i,t}^{EU} = \frac{GSVI_{i,t}^{AU} + \cdots + GSVI_{i,t}^{UK}}{28} \tag{4.2}$$

,with i= the word and t= the time period

Following that, we compute the monthly log changes for each search term as follows:

$$\Delta GSVI_{\mathrm{i,t}} = \ln\,(\mathrm{GSVI_{i,t}}\,) - \ln(\mathrm{GSVI_{i,t-1}}) \tag{4.3}$$

As per the procedures described by Da et al. (2015) and Irresberger et al. (2015), this step involves removing potential outliers by applying the winsorization method for each original ΔGSVI time series at the 5% level (i.e. 2.5% in each tail). Next transformation in our data is the deseasonality, that step removed the seasonality effect to identify the true behavior of the data by regressing ΔGSVI on monthly dummies and obtaining the residual. Each deseasonalized time series is then scaled by its corresponding standard deviation to reduce heteroscedasticity; This step follows the approach adopted by Baker & Wurgler (2006), which applied the maximum value as a scalar method (refer to next subsection for the calculation details).

The adjusted FEARS INDEX is defined as the deseasonalized, winsorized, and standardized monthly change for each search phrase, while ΔAGSV is defined as the corresponding deseasonalized, winsorized, and standardized monthly change for each search word. The AVG FEARS index is expressed as follows:

$$\text{FEARS INDEX}_t = \frac{1}{34}\sum_{i=1}^{34} \Delta AGVI_t^i \quad (4.4)$$

In order to avoid giving equal weight to all search items in an ad hoc manner, we apply the second version of the FEARS index by computing the first principal component of the ΔAGSV items. The second version of the FEARS INDEX is employed by calculating the first primary component of all the ΔAGSV items. The second index is outlined by Anastasiou & Drakos (2021) by using PCA FEARS index as a means to capture the multifaceted variations inherent in the ΔAGSV variables. The PCA FEARS index is as follows:

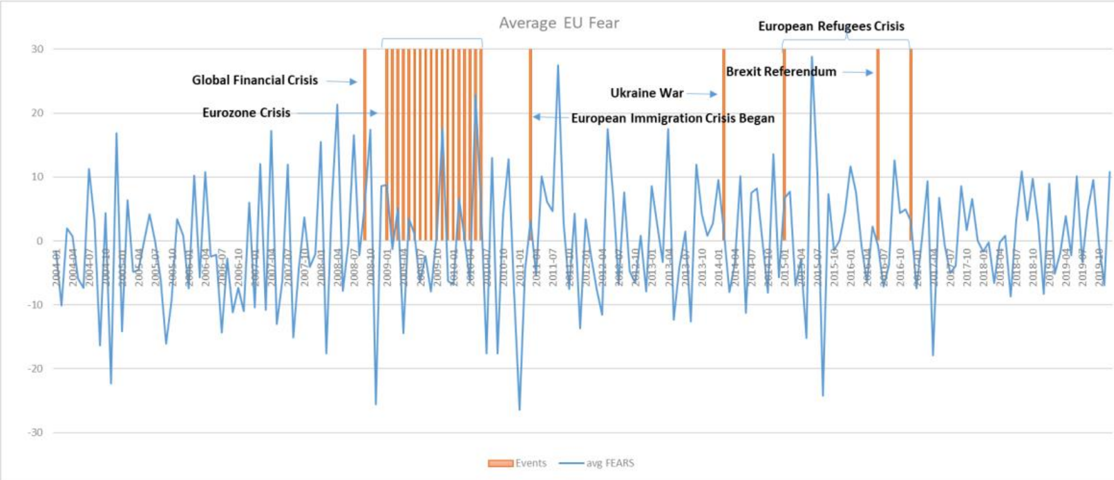
$$\text{PCA FEARS INDEX}_t = \sum_{i=1}^{34} w_t^i * \Delta AGVI_t^i \;, \quad (4.5)$$

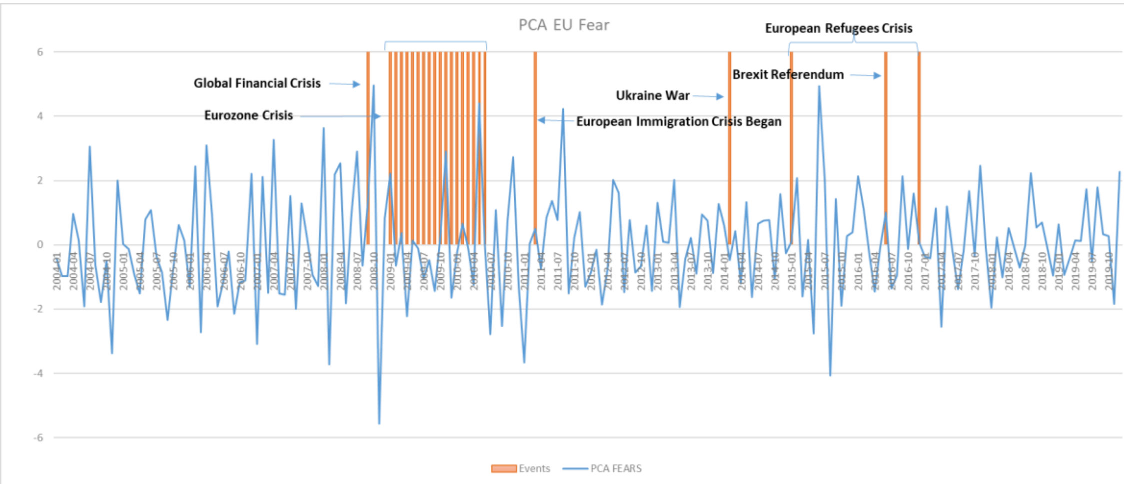
where w_t^1, w_t^2, ..., an are the weights of the linear combination of the ΔAGSV variables

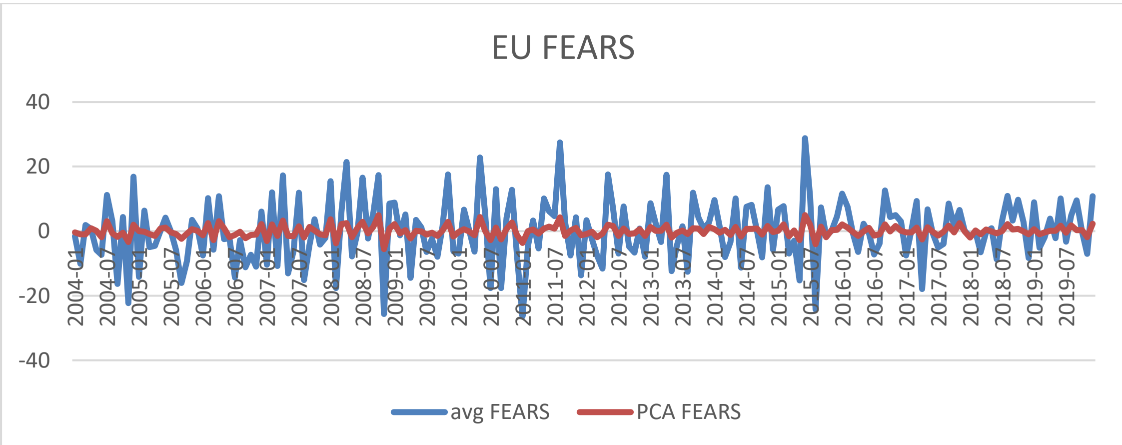
The PCA FEARS index$_t$ represents the linear combination of ΔAGSV variables that explains the largest possible amount of variation in the data for the whole period. Our rationale for emphasizing the first principal component is founded on the principle of maximizing the variance explained by a single linear combination of terms. This decision aligns with the broader objective of capturing the dominant underlying patterns driving the overall variation in the words. By harnessing the inherent power of the first PCA component, we aim to reveal the primary sources of variation that contribute most significantly to the data and align with Anastasiou & Drakos (2021) EU country index.

In our research, we develop two regional-level sentiment indexes for the European Union region to serve as proxies for crisis sentiment. The modified Financial and Economic Attitudes Revealed by Search (FEARS) indexes, follows either the Equal Weight FEARS Index or the PCA FEARS Index (Figure 4.1); both indices aim to capture investor's mood for 28 EU nation by relying on household internet search activity data sourced from the Google Trends Database.

Figure 4.1: Fears Indexes







Plot the FEARS index over the period January 2004 – December 2019 and significant events/periods in European Union. The pca and average FEARS indexes approach show similar patterns. The figure shows the time evolution of the FEARS crisis sentiment index measured as the first principal component of the search terms and the average of the search terms. The time evolution of both indexes is for the time period from January 2004 to December 2019.

In conclusion both plots, providing a comprehensive perspective on its ability to encapsulate major European crisis events (Iceland, Greece, Spain, Cyprus, immigration crisis periods). Notably, the FEARS indexes adeptly capture a range of pivotal events that defined the European crisis landscape, confirming its efficacy in reflecting market sentiment during tumultuous periods. The alignment of index spikes or before spikes with these events suggests that the FEARS index effectively captures heightened investor anxiety during periods of economic and geopolitical crisis. It is worth noting, however, that while the FEARS indexes adeptly captures the majority of major European crisis events or the lagged crisis effect, there are specific exceptions. Notably absent are the Brexit referendum and the Ukraine-Crimea annexation (refer as *Russo-Ukrainian War*), two significant events that appeared throughout the region. The unique characteristics of these events, which potentially introduced distinct sentiment dynamics, resulted in comparatively subdued signals within the FEARS indexes. Incorporating these insights, our analysis underscores the nuanced nature of the FEARS index in interpreting market sentiment during times of crisis, while also recognizing its selective response to distinct crisis events. This nuanced approach enables a more refined understanding of sentiment dynamics throughout the European crisis landscape.

II. CSI index

To gauge the negative market-wide sentiment of investing mood during the financial crisis, Baker & Wurgler's (2006) developed a General Crisis Sentiment Index as a direct measure of this sentiment. The index was calculated using Google Search Volume Indices (GSVIs) for variations of the search term "financial crisis," specifically "credit crisis," "bank crisis," and "subprime crisis"(Panel A, Table 4.2). In our analysis, the research doesn’t limit ourselves to these four terms and also recreates European associated index with 5-word terms (Panel B). However, both of them excluded words that were too similar to our chosen terms, such as "banking crisis," as they were highly correlated with our selected terms. We also restricted our analysis to English words as a proxy for worldwide crisis sentiment, although non-English speaking countries may use their native language when searching the internet. Baker observed that the GSVIs for all combinations of the four English crisis-related search terms and their respective translations were highly correlated. However, the EU crisis index based on the crisis related search volumes word, that means U.S.-centric terms yielded null results or exhibited very low search frequencies, limiting their relevance and effectiveness in capturing European sentiment. To address this issue, the original U.S.-based keywords were systematically substituted with EU-relevant equivalents—

terms that carry related meanings but are more contextually and linguistically appropriate for Europeans. This substitution process ensures that the resulting EU crisis index reflects search behavior and sentiment more accurately within the European context, while maintaining methodological consistency with prior study (Anastasiou & Drakos 2021).

Table 4.2: CSI Google Search terms

Panel A: This panel presents the four search terms to compute the US CSI Index as proposed by Baker & Wurgler (2006).

FINANCIAL CRISIS	BANK CRISIS	CREDIT CRISIS
SUBPRIME CRISIS	-	**-**

Panel B: This panel presents the five search terms used to compute the adjusted-CSI indices for the EU countries

FINANCIAL CRISIS	BANK CRISIS	CREDIT CRISIS
SUBPRIME MORTGAGE CRISIS	**EUROPEAN DEBT CRISIS**	**-**

The present study adopts Baker & Wurgler's (2006) approach and also modifies the method to construct a factor that captures the EU economy's crisis mood. Both indexes use only information from European countries, and the methodology follows a slightly different approach, aggregating the words for each European country as a single-word entity by using the average GSVI to represent the European Union's distinctive nature. The grouping is stated as follows:

$$GSVI_{i,t}^{EU} = \frac{GSVI_{i,t}^{AU} + \cdots + GSVI_{i,t}^{UK}}{28} \tag{4.6}$$

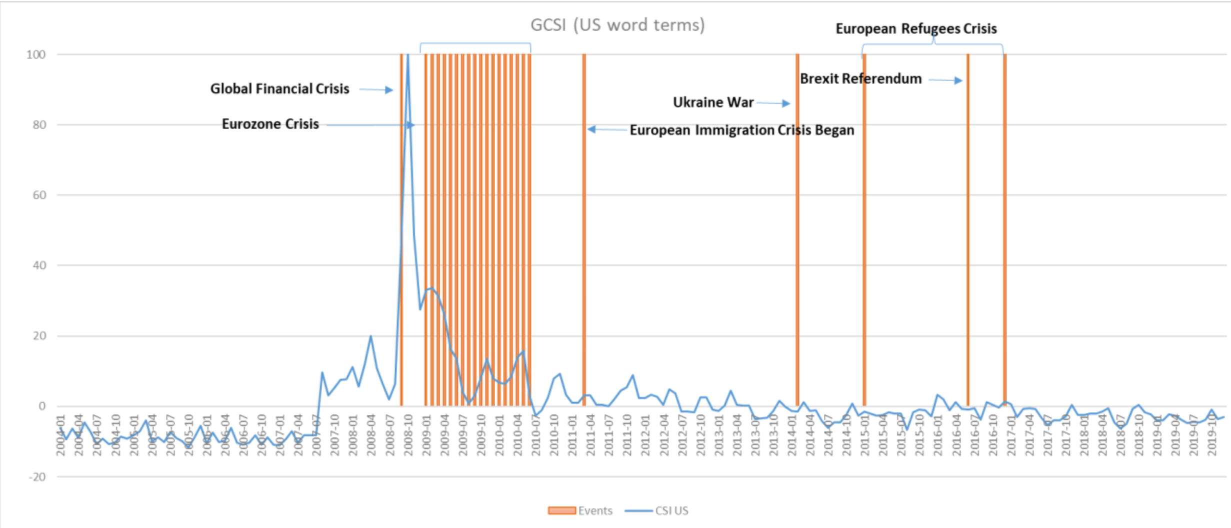
Specifically, the method first estimates the first principal component for 2004 by utilizing the GSVI values (as stated in equation 4.6) from each of the four-time (or five-time) series. Subsequently and independently run the analysis for each month for the remaining period, expanding the considered time span by one month after each estimation. This involves computing the first fundamental component in month t, using data from month one to month t. After calculating the first principal component for each month, the next step is scaling the time series that aligns with Google Trends by dividing all values with the maximum value of the time series and multiplying them by 100. The second index (Panel B) adopts slightly different words associated with EU countries. This methodology represents the development of the economic mood from the GSVIs of four and five crisis-related search keywords. The CSI at time t is then defined as:

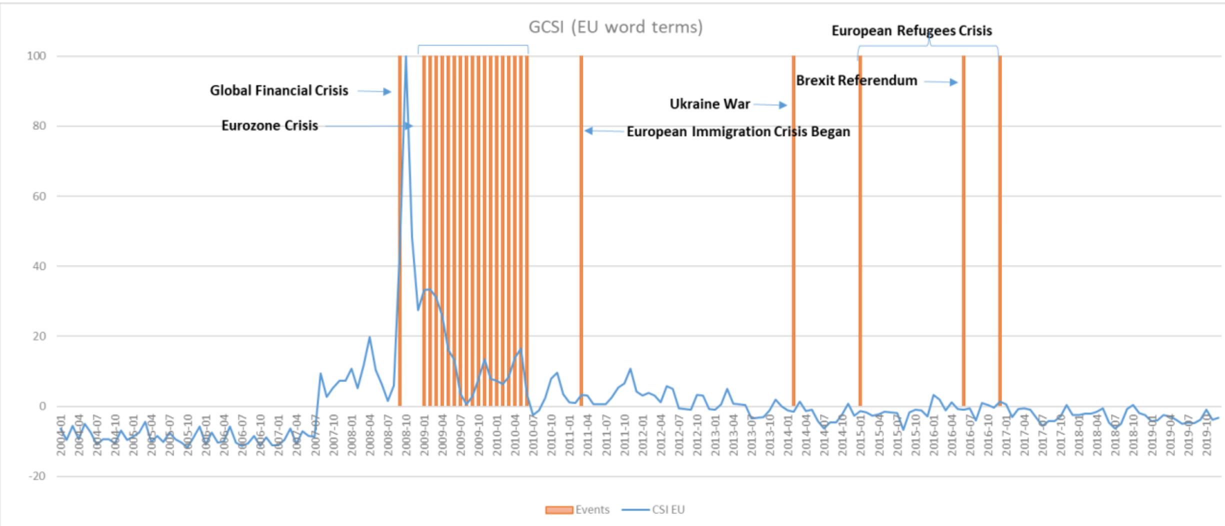
$$\text{General CSI INDEX}_t = \frac{\sum_{i=1}^{k} w_t^i * GSVI_t^i}{\max\left(\sum_{i=1}^{k} w_t^i * GSVI_t^i\right)} * 100 \,, \qquad (4.7)$$

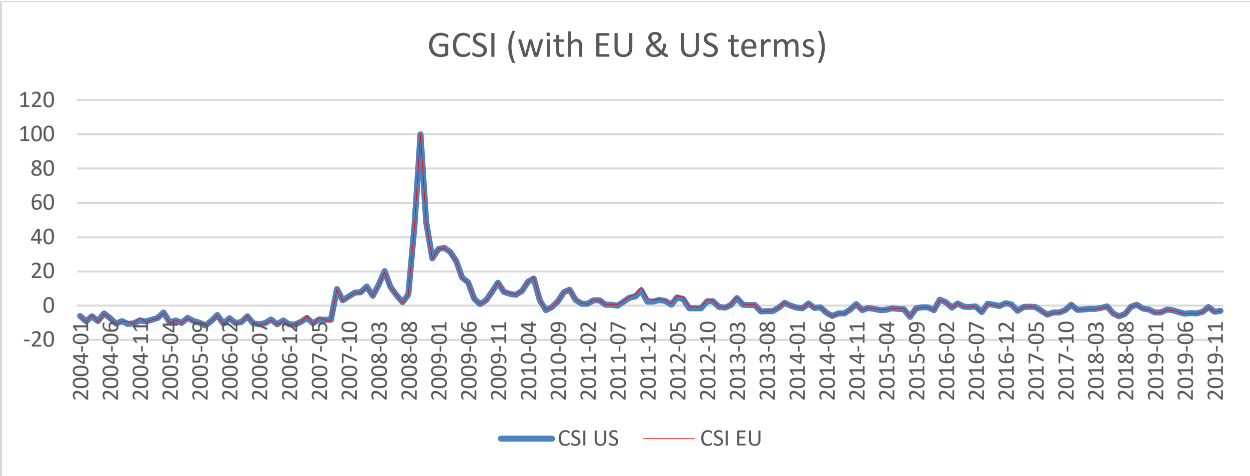
where $w_t^1, w_t^2, \ldots,$ are the weights of the GSVI variables k = 4 or 5

The PCA General CSI index represents the linear combination of GSVI variables that attempt to capture the majority of information from the data.

Figure 4.2: US & EU General CSI Indexes



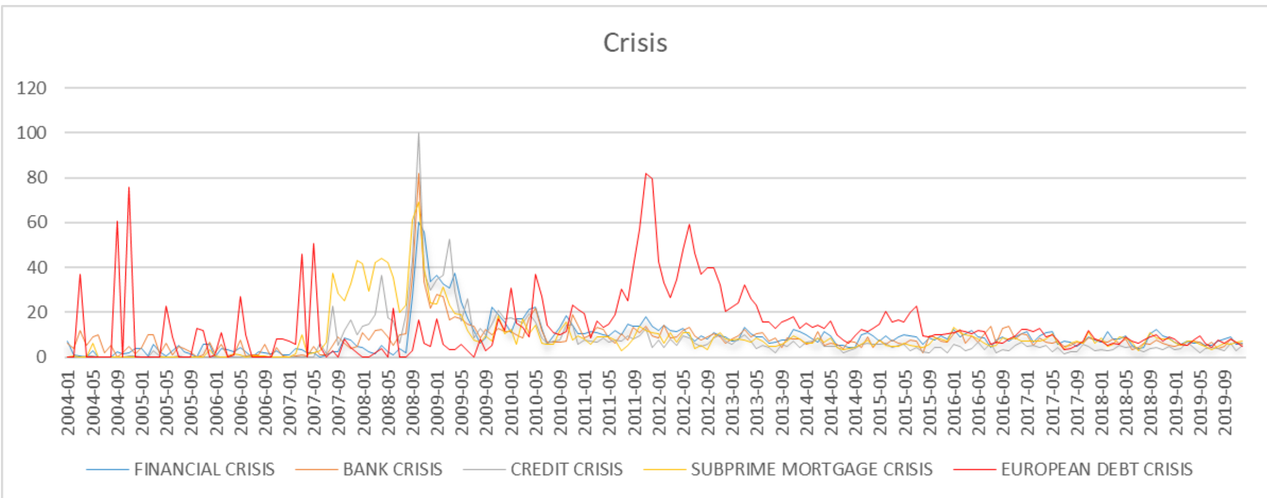




Plot two (2) CSI index over the period January 2004 – December 2019 and significant events/periods in European Union. The US and EU index approach shows similar behavior. The figure shows the time evolution of the General crisis sentiment index measured as the first principal component of the four search terms “financial crisis”, “credit crisis”, “bank crisis”, and “subprime crisis”, and five search terms plus “European dept crisis” and the time evolution for the time period from January 2004 to December 2019.

As anticipated, the degree of crisis sentiment rose around after the 3rd quarter of 2008 (Figure 4.2) and reached its peak in conjunction with the Lehman Brothers' collapse in 2008 and the contagion financial crisis from US to Europe in 2008 to 2012 (OECD, 2012). Although there was a gradual reduction in crisis sentiment at the end of 2009, but then the European debt crisis started to gain importance relative to the other crisis terms, which is supported by Nelson et al. (2012). Notably, during the crisis period, the "European debt crisis" search term should play a primary role in amplifying the crisis sentiment curve. This outcome does not appear in the index because the data has been normalized, and the "European debt crisis" term isn’t revealed any impact in the general crisis index (Figure 4.2-4.3)

Figure 4.3: Google Search Volume Indices for crisis-related search terms



Plot five (5) crisis terms from CSI indexes over the period January 2004– December 2019. The crisis terms show similar behavior pattern, except the European debt crisis. The time evolution of the GSVIs for the five search terms “financial crisis”, “credit crisis”, “bank crisis”, “subprime crisis”, and the “European dept crisis” search terms for the time period from January 2004 to December 2019.

For the General Crisis Sentiment indexes, it's important to recognize that the sentimental words are closely tied to the crisis, which means the construction of the index is most effective at capturing the essence of specific crisis periods, but its sensitivity can decline in post-crisis periods when crisis-related words become less widespread. This highlights the strong connection between sentiment and crisis events, and it's something to keep in mind when interpreting the index across different time periods. In short, our crisis index is best at reflecting the link between sentiment and market dynamics during major global and European crises, but its impact may fade afterward due to the reduced use of crisis-related terms.

III. GPEU index

The Global Economic Policy Uncertainty (GEPU) Index is an alternative sentimental index by Baker et al. (2016). This index measures the level of economic policy uncertainty worldwide and provides valuable insights into the prevailing uncertainties in economic policies across the globe, offering a nuanced perspective on economic conditions. The GEPU Index is generated using weighted aggregation of the Economic Policy Uncertainty (EPU) indices from the 21 countries: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, Russia, South Korea, Spain, Sweden, United Kingdom, and United States.[16] The methodology Baker et al. (2016) follows to construct the GEPU Index is:

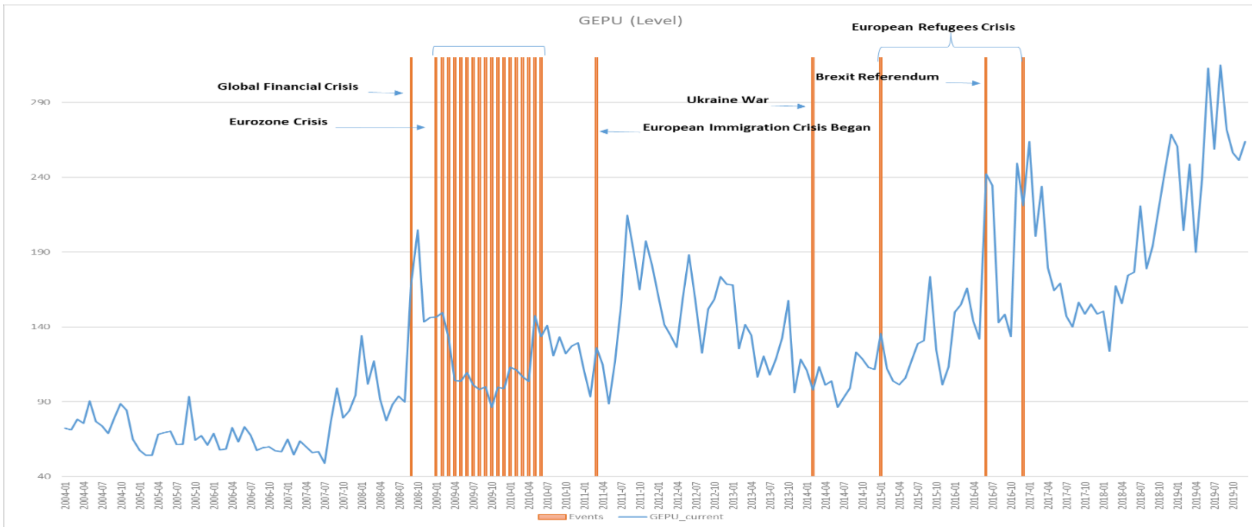
1. **Initial Normalization:** To create a consistent foundation, each national EPU index is normalized to an average value of 100 during the period from 1997 (or the initial year) to 2019. This step ensures that the indices are harmonized and comparable across different timeframes.
2. **Missing Data Handling:** For countries with missing data, a regression-based imputation technique is employed to estimate the absent values. This process results in a unified dataset comprising monthly EPU index values for all 21 countries, starting from January 1997.
3. **Calculation of GEPU Index:** The GEPU Index value for each month is then computed by calculating the GDP-weighted average of the 21 national EPU index values. This involves assigning weights to each country's EPU index based on their respective Gross Domestic

[16] Based on Baker et al (2016), the selection of the 21 countries for inclusion in the GEPU Index is significant sample to represent the substantial portion of the global economy.

Product (GDP) contributions. The GDP data is sourced from the International Monetary Fund's World Economic Outlook Database.

The GEPU Index is based on **Current-Price GDP Variant**, this means the index utilizes the GDP figures based on current market prices.[17] The figure 4.4 present the GEPU Index in levels:

Figure 4.4: Global Economic Policy Uncertainty (GEPU) Index - Level

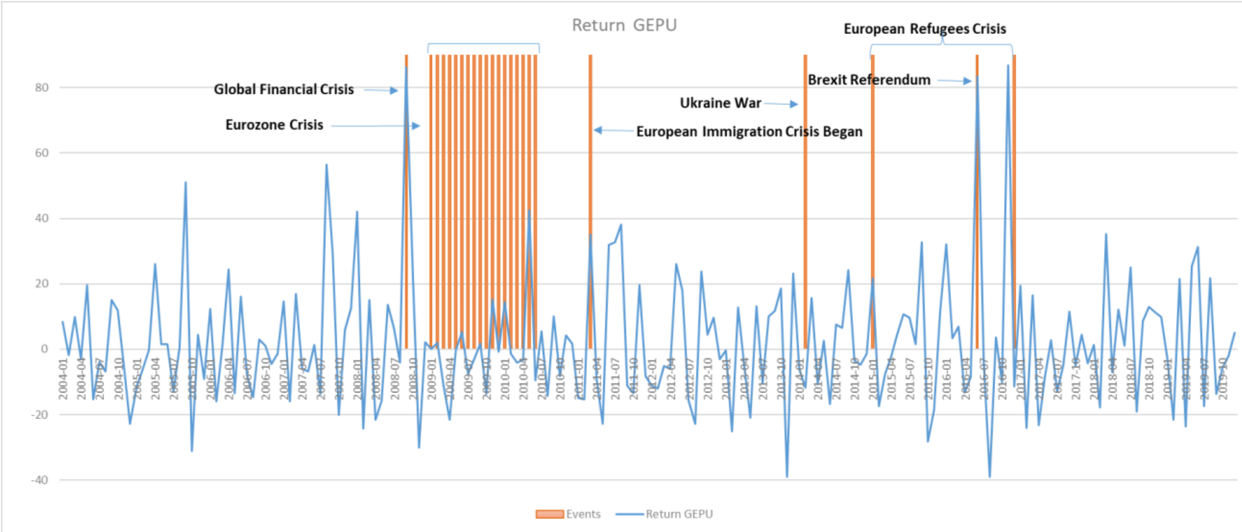


Plot presents the values of Global Economic Policy Uncertainty (GEPU) index over the period January 2004 – December 2019 and significant events/periods in European Union. The index captures the global events and does not capture the European crisis pattern, but only a limited pattern.

For a more comprehensive understanding of the GEPU Index, we transform the index applying the returns. The visual representation of various crisis events with the GEPU index returns provides a comparative measure regarding the sensitivity of the Index. The returns GEPU index has the unique capability to effectively capture and, at times, accurately represent the sudden surges or spikes corresponding to these notable events. The data drawn from the table of crisis events has been translated into this graphical form, allowing us to observe the shifts and fluctuations of the index that coincide with critical junctures in each crisis.

[17] The GEPU Index is presented in two variations: 1. Current-Price GDP Variant: This version utilizes GDP figures based on current market prices. 2.PPP-Adjusted GDP Variant: This version employs GDP figures adjusted for purchasing power parity (PPP).

Figure 4.5: Global Economic Policy Uncertainty (GEPU) Index – Return (%)



Plot presents the return of Global Economic Policy Uncertainty (GEPU) index over the period January 2004 – December 2019 and significant events/periods in European Union. The index captures the global events and does not capture the European crisis pattern, but only a limited pattern.

The GEPU Index, in both figures in levels and returns, serves as a perceptive gauge of global events, exhibiting an ability to encapsulate noteworthy occurrences on a worldwide scale. However, its efficacy in mirroring the trajectory of the European crisis pattern is somewhat limited. While the GEPU Index adeptly captures certain aspects of this pattern (Brexit voting, Global crisis and European Immigration Crisis), its representation remains constrained. Notably, the Ukraine war, a pivotal event with far-reaching implications, does not find resonance within the captured pattern of the GEPU Index. Its absence points to the intricacies of this index's responsiveness, suggesting that some critical regional crises may not align seamlessly with its signal. Conversely, the GEPU Index does manage to encapsulate a distinctive aspect of the European crisis narrative—the Brexit referendum. This inclusion underscores the index's capacity to resonate with specific pivotal events within the European context.

In essence, while the GEPU Index does a good job of capturing global events, its ability to fully reflect the European crisis pattern is limited. The way it selectively picks up certain events highlights the complex relationship between sentiment, market dynamics, and geopolitical changes.

IV. Crisis Sentiment indexes

The Global Crisis Sentiment Index (GCSI) adeptly captures the period after the global crisis and throughout the European crisis, offering insights into market sentiment during these pivotal economic upheavals. The FEARS Index exhibits a broader spectrum of sensitivity, encapsulating additional events such as the immigration period and the Brexit period (for PCA FEARS). However, it is important to note that some significant events, such as the Ukraine war, do not find resonance within the FEARS Index pattern. Meanwhile, the GEPU Index reveals its proficiency in capturing the Brexit period and other global events, including the immigration period. However, it is selective in its responsiveness, as it does not encapsulate certain events such as the Ukraine war.

In summary, each index offers a distinct lens through which to observe sentiment's influence on market dynamics during critical periods. While the GCSI concentrates on global and European crises, the FEARS Index encompasses broader events like immigration and Brexit, and the GEPU Index captures both global events and specific periods like Brexit, showcasing the complex interplay between sentiment and events across various contexts. In figures 4.1-4.5 can glimpse the temporal patterns and magnitudes of these crises more intuitively. The index acts as a lens through which we can better comprehend the impact and intensity of each crisis, translating complex timelines into a visual narrative that highlights pivotal moments. This approach not only facilitates a clearer understanding of the crisis events themselves but also enables us to detect potential patterns or correlations between Global and EU events. With our study gain insights into the interconnectedness of these crises, shedding light on the broader economic, social, and political dynamics that shaped those tumultuous years.

V. Crisis Sentiment indexes and Factor Models

There is an increasing trend in academic and financial institution circles towards extending equity factor models. Asset pricing models establish clear associations between multiple factors and ensuing returns. According to Cochrane (2001) and Feng et al (2020), adding factors in the asset pricing models aim to capture the random fluctuations affecting the returns. This subsection utilizes multivariate asset pricing regression models to address the issue of potential unobserved heterogeneity, revealing the importance of incorporating crisis sentiment into the models. Therefore, the multivariate regression includes the FEARS and CSI Index as the main explanatory variable and additional determinants stated at the end of this section.

The multi-factor model applied in our analysis is based on the 3-factor model of Fama & French (1992) and 5-factor model (Fama & French, 1996). Furthermore, the extension model are based on using the FEAR factor (Durand et al., 2011) which is the EU volatility index[18] that measure investors' anticipation regarding financial market uncertainty. This factor, supported by previous research, significantly influences stock performance. Besides that, our models incorporate the commodity (gold) factor (Baur & Lucey, 2010; Baur & McDermott, 2010), which encompasses gold prices. Gold prices are known to respond to macroeconomic factors like inflation, geopolitical tensions, and currency devaluations, thereby offering insights into market sentiment and risk aversion. By integrating gold prices as a factor, we account for market uncertainty and investor behavior, enhancing the resilience of asset pricing models. Another crucial factor is the currency factor, derived from UK/EUR exchange rates, reflecting the influence of regional economic conditions on financial markets. Fluctuations observed in exchange rates between the UK and the Eurozone signify alterations in trade balances, interest rate differentials, and economic growth prospects. By incorporating these exchange rates into the analysis, we effectively capture the influence of regional economic dynamics on asset returns, thereby augmenting the model's capacity to reveal variations in asset prices within EU markets. The analysis investigates the relationship between the specific asset class returns and crisis sentiment by employing the extension of multivariate asset pricing models. The models can be represented as follows:

$$r_{i,t}^{j} - r_{f,t} = a_i + b_{1,i}^{j} FEARS_t + b_{2,i}^{j} CSI_t + b_{3,i}^{j} RGEPU_t + e_{i,t}^{j} \quad (4.8)$$

$$r_{i,t}^{j} - r_{f,t} = a_i + b_{1,i}^{j} MKTRF_t + b_{2,i}^{j} SMB_t + b_{3,i}^{j} HML_t + b_{4,i}^{j} FEARS_t + b_{5,i}^{j} EUCSI_t + b_{6,i}^{j} RGEPU_t + e_{i,t}^{j} \text{ (ext. 3-factor model)} \quad (4.9)$$

$$r_{i,t}^{j} - r_{f,t} = a_i + b_{1,i}^{j} MKTRF_t + b_{2,i}^{j} SMB_t + b_{3,i}^{j} HML_t + b_{4,i}^{j} RMW_t + b_{5,i}^{j} CMA_t + b_{6,i}^{j} Gold_t + b_{7,i}^{j} EUCSI_t + e_{i,t}^{j} \text{ (ext. 5-factor model)} \quad (4.10)$$

[18] known as the "investor fear gauge"

$$r_{i,t}^{j} - r_{f,t} = a_i + b_{1,i}^{j}MKTRF_t + b_{2,i}^{j}SMB_t + b_{3,i}^{j}HML_t + b_{4,i}^{j}RMW_t + b_{5,i}^{j}CMA_t + b_{6,i}^{j}Gold_t + b_{7,i}^{j}FEARS_t + b_{8,i}^{j}RGEPU_t + b_{9,i}^{j}EUCSI_t + b_{10,i}^{j}RGEPU_t + b_{11,i}^{j}EUCSI_t + b_{12,i}^{j}Currency_t + e_{i,t}^{j} \text{(full ext. model)} \tag{4.11}$$

where i = 1,…,n, is the number of stocks: 2007 for Grey stocks, 150 for Green stocks, and 367 for Red stocks. The j is an index that groups the stock (0-Green, 1-Grey and 2-Red) and t is the time of the observation in monthly frequency.

$r_{i,t}^{j}$ is the return of asset i at time t (within the period, 2004-2019); $r_{f,t}$ is the risk-free rate at time t; the $MKTRF_t$ is the return on a European region's (Stoxx Europe 600 Index)value-weighted market portfolio at time t; the SMB_t is Small Minus Big size companies; the HML_t is high minus low based on the value of the companies; the RMW_t is Robust Minus Weak based on the operating profitability of the companies at time t; the CMA_t is conservative minus aggressive and based on the investment of the companies at time t; $FEAR_t$ is the change of the implied volatility (VSTOXX index); $Gold_t$ is the change of the Gold prices; $Currency_t$ is the change of the UK/EUR exchange rates (refer to Appendix Table A2.2-A2.5); the $FEARS_t$ is the investor crisis sentimental index; the CSI_t is the economic crisis sentimental index; $RGEPU_t$ is the return from the Global Economic Policy Uncertainty (GEPU) Index. a_i is the stock's alpha performance, and b_k is the coefficient from the specific k-factor (with k=1,..,5). $r_{i,t}^{j}$ - $r_{f,t}$ denotes the excess return of security i at time t within the specific asset class j. All the variables are transformed to percentage values.

The present research is to investigate the extent to which crisis indexes can contribute as a predictor (or explanatory variable) of Green, Grey and Red asset returns. To achieve this objective, we employ panel data regressions with random effects[19]. In our models, we utilize a lagged version of the crisis sentiment variable to explore whether past values can provide valuable insights into the relationship between crisis indexes and the returns of Green, Grey and Red stocks. The research examines the relationships among these different financial factors to gain insights into the overall health and trends of the grouped securities.

[19] Hausman test recommends in the majority of cases random effect

4.4. Empirical Results and Findings

In this section, we delve into the empirical analysis to provide investors with a comprehensive quantitative understanding of the relationships and dynamics among various factors with our asset class returns across different time periods. The following subsections present a detailed examination of the findings.

4.4.1. Analysis of Time-Series Factors

In order to understand the dynamics of market factors and their behavior during crisis periods, we conducted an empirical analysis on a dataset spanning the years 2004 to 2019. The factors under investigation were categorized into two groups: Classical Factors and Crisis-Related Factors.

The Classical Factors mean returns varied, from -0.22% to 1.69%, indicating diverse investment opportunities for the proxy portfolios during the different spanning periods. On the other hand, the Crisis-Related Factors, which included the Average Fear factor (AVG FEARS), Principal Component Analysis Fear factor (PCA FEARS), US Crisis factor, EU Crisis factor, and Global Economic Policy Uncertainty relative change factor (RGEPU), shed light on market behaviour during crisis periods. These factors exhibited varying mean returns and distribution characteristics, indicating their sensitivity to market uncertainties. Refer to Table A4.4 (Appendix) for a comprehensive overview of these factors' statistics. Further information for the shape of the distribution of the factors can be found in Appendix Table A4.4, which provides the first 4^{th} moments and gives an insight to the dispersion of the data.

Exploring the relationships among factors is pivotal for effective portfolio construction and risk management. The correlation coefficients tables (Appendix Tables A4.5-A4.6) provide insights into the co-movement and diversification potential of various factors. During the pre-crisis period (2004-8/2008), the Fama-French Market factor (MKTRF) shows a significant negative correlation of -44.55% with the implied volatility factor (FEAR). This suggests that heightened market uncertainty corresponds to lower market returns. The Small Minus Big factor (SMB) displays a positive correlation of 32.74% with the High Minus Low factor (HML) during the same period. This alignment indicates that smaller companies tend to outperform larger companies when value stocks outperform growth stocks. In the crisis period (9/2008-12/2019), the average Fear factor (AVG FEARS) and Principal Component Analysis Fear factor (PCA FEARS) exhibit a strong positive correlation of 90.78%, that can be explained by the construction of these two indexes. This implies that these two factors move closely together in response to market sentiment shifts.

Analyzing the correlations between sentiment-related crisis factors and other factors sheds light on how market sentiment interlinks with broader financial trends. The following correlations highlight significant relationships. The Global Economic Policy Uncertainty return factor (RGEPU) correlates positively with the implied volatility factor (FEAR) at 43.56% during the pre-crisis period. This suggests that increased global economic uncertainty aligns with higher implied market volatility, which is explained as the level of financial market uncertainty. This underscores the parallel movements of these sentiment-related factors and market factor during times of market turbulence. Before the crisis period, the AVG FEARS and PCA FEARS factors show correlations of -12.9% and -18.1% with the excess market factor, indicating a moderate negative association. On the other hand, the Crisis Sentiment Index (CSI) exhibits a more pronounced negative correlation of -33.0% with the market, while the Global Economic Policy Uncertainty index (GEPU) return shows a correlation of -18.9%, underlining their potential roles in capturing sentiment dynamics during this phase.

Interestingly, the Crisis Sentiment Index (CSI) exhibits a more pronounced and strong negative correlation of -33.0% with the market. This indicates that during times of potential distress or uncertainty, the sentiment captured by the CSI tends to be more divergent from the overall market trend. Similarly, the Global Economic Policy Uncertainty index (GEPU) shows a correlation of -18.9%, suggesting that economic policy uncertainties might have a relatively smaller impact on market before the crisis. Similarly, a comparable approach can be observed for the FEARS indexes. During and after the crisis period, the negative correlations increase between sentiment indices and market factors. The avg and pca FEARS index demonstrate correlations of -26.0% and -30.5% with the excess market factor, revealing a noteworthy negative relationship. This suggests that periods characterized by heightened feelings of uncertainty and crisis mood are associated with specific adverse market movements. Likewise, the US & EU CSI index portrays even more pronounced negative correlations of -36.9% and -37.2% with the market factor, indicating a robust inverse connection between crisis sentiment and market performance. Additionally, the RGEPU index showcases a substantial negative correlation of -34.6% with the market factor, further signifying the potential influence of global economic policy uncertainty on market dynamics. From an investment standpoint, these findings underscore the importance of considering sentiment indices as potential indicators for market movements, particularly in post-crisis scenarios where sentiment shifts can significantly impact investment strategies.

These insights highlight the nuanced interplay between sentiment indices and market factors, shedding light on the potential influences of different sentiment dimensions on market dynamics before and after the crisis period. It also underlines the value of incorporating sentiment indicators into financial models to capture shifts in investor sentiment and their potential impact on financial market performance.

Lastly, this analysis provides deeper insights into the interplay and co-movement between sentiment and investment factors. Interestingly, the Fears factors (AVG FEARS and PCA FEARS) display a low correlation with both the Crisis Sentiment Index (CSI) and the Global Economic Policy Uncertainty index (GEPU), suggesting that these sentiment indicators may offer unique insights that could potentially enhance the predictive power of our forthcoming modelling efforts.

4.4.2. Model Results

The primary aim is to investigate whether FEARS, economic crisis and policy uncertainty sentiment influence the asset class price Green, Grey and Red returns. The estimation results are presented in the tables below, in which the asset class returns (Green, Grey or Red) serves as the dependent variable. The Tables are divided per asset category into 3 tables based on the three distinct time periods: 2004-8/2009 (pre-global crisis), 9/2009-2019 (global crisis and post-ante EU crisis), and the entire period 2004-2019. The tables contain the coefficient values and the model performance; all of them are presented in tables 4.3-4.11. For every table, the first four columns present the relationship between crisis sentimental indexes and asset class returns, the next two (5-6) the extension of 3-factor model plus sentimental indexes, the 7-8 the 5-factor model plus the sentimental indexes and the rest columns are extension models (5 factor models plus FEAR, Gold and Currency factor) with sentimental indexes (and the lagged indexes).

In Tables 4.3-4.5, we observe that the sentiment-related factors negatively influence the Red assets returns. The (avg & pca) FEARS factor's coefficients (Avg is between -0.09 and -0.02 & PCA is between -0.64 and -0.10) show strong negative values across models and periods (Table 4.3-4.5), and during the periods, the other sentimental indexes have a reverse sign or insignificant results (at 5%) that did not play an essential role in shaping Red returns. Turning to Tables 4.4 and 4.5, covering the post-Global crisis and the entire period, we don't observe a intricate relationship between RGEPU sentiment factor and Red assets returns. The coefficients of this sentiment factor remain steady, statistically insignificant. Notably, in all study periods, the other global market factors, including MktRf, SMB, HML, RMW, CMA, FEAR, Gold, and Currency also exhibit varied relationships with returns. However, the coefficients generally show positive MktRf, SMB, RMW and Gold values and negative values for FEAR factor (for the second half and the entire period) and HML (for the first half period).

Table 4.3: Empirical results of the sentimental factors for Red excess returns for the period 2004-8/2009 (ex-Global crisis)

Red Returns Factors	**2004-8/2009 Ex-Global crisis**												
alpha	**0.62**	**0.65**	**0.59**	**0.63**	**0.25**	**0.27**	**0.65**	**0.66**	**0.47**	**0.51**	**0.44**	**0.49**	-0.06
MktRf					**1.03**	**1.03**	**1.07**	**1.07**	**1.06**	**1.07**	**1.09**	**1.09**	**1.05**
SMB							**0.63**	**0.64**	**0.56**	**0.56**	**0.51**	**0.53**	**0.52**
HML							**-0.75**	**-0.76**	**-0.62**	**-0.63**	**-0.55**	**-0.59**	0.06
RMW													**1.07**
CMA													-0.20
FEAR											**0.01**	0.01	**0.02**
$PCAFEARS_T$		**-0.50**		**-0.51**		**-0.19**		**-0.15**		**-0.14**			
$PCAFEARS_{T-1}$												**-0.15**	
$AvgFEARS_T$	**-0.09**		**-0.09**		**-0.05**		**-0.04**		**-0.04**				**-0.06**
$AvgFEARS_{T-1}$											**-0.05**		
US CSI_T	**-0.13**	**-0.14**											
EU CSI_T			**-0.13**	**-0.13**	0.008	0.003	0.02	0.02	0.02	0.02	**0.03**	0.02	0.03
$RGEPU_T$	**-0.05**	**-0.04**	**-0.04**	**-0.04**	**-0.02**	**-0.02**	0.006	0.009	-0.01	-0.00	-0.01	-0.00	0.002
Gold					**0.21**	**0.20**			**0.13**	**0.12**	**0.12**	**0.12**	**0.12**
Currency									0.06	0.04	0.05	0.02	**0.17**

R^2-within	2.7%	2.8%	2.7%	2.8%	14.4%	14.3%	14.8%	14.8%	15%	14.9%	15%	14.9%	15.7%
R^2-between	13.7%	13.2%	13.6%	13%	29%	29.2%	28%	28.2%	29%	29.2%	29.3%	29.4%	27.9%
R^2-overall	2.9%	3%	2.9%	2.9%	14.2%	14.1%	14.7%	14.6%	14.9%	14.8%	14.9%	14.8%	15.5%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentimentals index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

Table 4.4: Empirical results of the sentimental factors for Red excess returns for the period 9/2009-20019 (Global crisis and Post-ante EU crisis)

Red Returns Factors	**9/2009-2019 Global crisis and Post-ante EU crisis**												
alpha	**0.51**	**0.46**	**0.52**	**0.47**	**-0.50**	**-0.52**	**-0.57**	**-0.59**	**-0.61**	**-0.62**	**-0.56**	**-0.58**	**-0.57**
MktRf					**0.93**	**0.93**	**0.90**	**0.90**	**0.91**	**0.91**	**0.85**	**0.86**	**0.86**
SMB							**0.68**	**0.69**	**0.66**	**0.67**	**0.69**	**0.70**	**0.70**
HML							**0.27**	**0.27**	**0.31**	**0.31**	**0.34**	**0.33**	**0.32**
RMW													0.02
CMA													0.09
FEAR											**-0.03**	**-0.02**	**-0.02**
$PCAFEARS_T$		**-0.64**		**-0.64**		**-0.21**		**-0.10**		**-0.10**			
$PCAFEARS_{T-1}$												**-0.12**	
$AvgFEARS_T$	**-0.11**		**-0.11**		**-0.04**		**-0.02**		**-0.02**				**-0.03**
$AvgFEARS_{T-1}$											**-0.03**		
US CSI_T	**-0.11**	**-0.11**											
EU CSI_T			**-0.11**	**-0.11**	**0.02**	**0.02**	**0.04**	**0.04**	**0.04**	**0.04**	**0.03**	**0.04**	**0.03**
$RGEPU_T$	**-0.07**	**-0.06**	**-0.07**	**-0.06**	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gold					**0.06**	**0.06**			**0.08**	**0.07**	**0.08**	**0.08**	**0.08**
Currency									**-0.06**	**-0.06**	**-0.05**	**-0.05**	**-0.06**

R^2-within	3.2%	3.1%	3.2%	3.1%	12.9%	12.9%	13.7%	13.7%	13.8%	13.8%	13.8%	13.8%	13.8%
R^2-between	0.9%	0.9%	0.9%	1%	2.2%	2.2%	2.3%	2.3%	2.3%	2.3%	2%	2%	2.3%
R^2-overall	3.1%	3%	3.2%	3%	12.8%	12.8%	13.6%	13.6%	13.7%	13.7%	13.7%	13.7%	13.7%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentimentals index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

Table 4.5: Empirical results of the sentimental factors for Red excess returns for the period 2004-2019 (Entire period)

Red Returns Factors	**2004-2019 Entire Period**												
alpha	**0.55**	**0.52**	**0.55**	**0.53**	**-0.30**	**-0.31**	**-0.36**	**-0.37**	**-0.41**	**-0.42**	**-0.39**	**-0.40**	**-0.44**
MktRf					**0.94**	**0.94**	**0.91**	**0.91**	**0.92**	**0.92**	**0.89**	**0.89**	**0.89**
SMB							**0.63**	**0.65**	**0.62**	**0.63**	**0.64**	**0.64**	**0.65**
HML							**0.24**	**0.24**	**0.29**	**0.29**	**0.30**	**0.30**	**0.39**
RMW													**0.17**
CMA													0.02
FEAR											**-0.01**	**-0.01**	**-0.01**
$PCAFEARS_T$		**-0.62**		**-0.61**		**-0.21**		**-0.15**		**-0.14**			
$PCAFEARS_{T-1}$												**-0.15**	
$AvgFEARS_T$	**-0.11**		**-0.11**		**-0.05**		**-0.03**		**-0.03**				**-0.04**
$AvgFEARS_{T-1}$											**-0.03**		
US CSI_T	**-0.12**	**-0.11**											
EU CSI_T			**-0.12**	**-0.12**	0.01	0.01	**0.03**	**0.03**	**0.03**	**0.03**	**0.03**	**0.03**	0.03
$RGEPU_T$	**-0.07**	**-0.06**	**-0.07**	**-0.06**	-0.01	-0.00	0.01	**0.01**	0.00	0.00	0.00	0.00	0.00
Gold					**0.09**	**0.08**			**0.09**	**0.09**	**0.10**	**0.09**	**0.10**
Currency									-0.03	-0.03	-0.03	-0.03	-0.03

R^2-within	3.2%	3.1%	3.2%	3.1%	13%	13%	13.7%	13.7%	13.8%	13.8%	13.8%	13.8%	13.8%
R^2-between	1.7%	0.8%	1.6%	0.8%	12.2%	11.4%	11.9%	11.6%	12.6%	12.3%	12.3%	11.8%	12.8%
R^2-overall	3.2%	3.1%	3.2%	3.1%	13%	13%	13.7%	13.7%	13.8%	13.7%	13.7%	13.8%	13.8%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentimentals index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

Including additional variables in models supports analyzing the robustness of our sentiment indices like FEAR indexes, Gold and UKEUR factors, which can provide valuable insights for investment decisions. These models offer a more holistic understanding of market dynamics by accounting for a broader range of factors that influence market behaviour. This enhanced understanding can empower investors to make more informed decisions by identifying the underlying drivers of market sentiment changes. In Tables 4.3-4.5, the CSI generally is statistically significant in several models and periods but the sign is reserved for what we expected, such as the ex-post Global crisis and the entire period when other variables are considered; it suggests that sentiment alone might not be a reliable predictor of market movements during these periods and is correlated with other factors in the market. On the other hand, (both) FEARS remain significant for every period and has a steady sign, even in the presence of other variables, that it underscores the robustness of its influence on Red behaviour. Investors can consider monitoring FEARS sentiment indices as potential leading indicators of Red securities sentiment shifts. If these indices start showing an increase, it could indicate a potential reduction in Red market returns.

During the periods (Table 4.3-4.5), the CSI and RGEPU changes from negative to positive upon the inclusion of additional variables in a model, it signifies a noteworthy shift in the relationship between that sentiment index and the other factors under consideration. This change in sign indicates that the sentiment index's impact on the dependent variable has reversed direction due to the influence of the added variables. The increasing of the factors can simultaneously increase the correlation with the sentiment indexes, which can revert the sign of the sentiment. That suggests may be an optimal number of factors. The initial models showed a negative coefficient for these indexes, implying that higher levels of economic crisis or uncertainty were associated with lower Red securities performance, and the subsequent model with additional factors exhibits a positive coefficient for both sentiments, which suggests that might now be associated with higher Red asset performance when considered alongside the new factors. This change in sign can have several implications. It might indicate that the additional variables are interacting with both indexes in a way that counteracts its negative effect. Alternatively, it could highlight that the sentiment index is responding to broader market dynamics that have shifted over time. This observation underscores the importance of considering multiple variables when analyzing sentiment indices, as these indices often react to a complex interplay of factors. From an investment perspective, this sign reversal offers valuable insights. It suggests that the sentiment index's predictive power is contingent upon the context provided by the additional variables. Investors can use this information to recognize that crisis and uncertainty, in combination with other factors, might actually be a positive signal for Red performance during specific conditions. Consequently, the revised model guides investors in making more nuanced investment decisions by considering the broader context in which sentiment operates, thus enhancing their ability to respond to changing market dynamics effectively. The model selection depends on the preference of the investment strategy, so the investor allocation may be pursued between asset class and market portfolios. Additionally, more straightforward strategies help mitigate the issue of high correlation among proxy portfolios and sentimental indexes, making them more interpretable and reducing the risk of misleading the actual impact, which can alter the portfolio allocation.

Moreover, our three-, five- and six-factor models can help investors better assess risk and manage their portfolios. These models can provide a clearer picture of potential Red securities fluctuations and downside risks by capturing the interplay between sentiment, macroeconomic indicators, and other market factors. This information is crucial for developing risk management strategies such as hedging and optimizing asset allocation. Furthermore, understanding how different variables impact sentiment indices can guide investors in distinguishing between short-term market noise and long-term trends, aiding in crafting strategies that align with their investment goals.

In essence, the empirical analysis reveals the intricate relationships between sentiment factors and Red assets returns across various models and time periods. The results highlight the enduring impact of (Avg & PCA) FEARS sentiment factors (and also the lags on these) on Red assets behaviour, even in the presence of other market variables.

The investor may use these insights to tap into market psychology, providing a layer of insight that traditional performance models (e.g., CAPM, Fama-French) might overlook. For instance, when sentiment indicators suggest increased market optimism or pessimism, an investor could reduce exposure to risk in Red assets, respectively. By incorporating sentiment indices into their strategy, investors can better hedge against unpredictable market movements that classic asset pricing models might overlook.

Tables 4.6-4.8 present the empirical results that interplay between sentiment-related and Grey assets returns over the three periods, each period and model attempt to shed light on the relationship between these factors and Grey assets' performance. During Pre-Global Crisis Period (2004-8/2009), our investigation focuses on the coefficients of sentiment-related factors concerning Grey asset returns. Specifically in the first half, our attention is drawn to factors like AVG FEARS, PCA FEARS, US CSI, EU CSI, and RGEPU. Notably, these factors exhibit mostly negative betas values, suggesting a significant negative correlation with Grey asset returns. For instance, RGEPU is between 0.01 and -0.05, AVG FEARS is between -0.02 and -0.05, and PCA FEARS reveal negative coefficients ranging from -0.46 to -0.08, underscoring their potential influence on the downward trajectory of Grey asset returns during this period. Comparable, CSI coefficient have generally negative impact between -0.18 and -0.06. In the context of sentimental factors, our investigation uncovers intriguing patterns. While the CSI demonstrates statistical insignificance in certain models and time periods—such as the post-Global crisis and the entire duration when other variables are considered—it suggests that sentiment alone might not reliably predict market movements during these phases. In contrast, the RGEPU sentiment index maintains consistent when it is significance across the periods and models. Importantly, their coefficients retain a steady negative sign moving between the values of -0.05 and -0.001, even in the presence of other variables. This underscores the enduring impact of the economic policy uncertainty on Grey asset behavior. Investors can thus view RGEPU sentiment index as potential leading indicators of shifts in Grey securities sentiment. A rise in this index could signal a potential reduction in Grey market returns and a rebalancing in our portfolio away from these types of securities.

Table 4.6: Empirical results of the sentimental factors for Grey excess returns for the period 2004-8/2009 (ex-Global crisis)

Grey Returns Factors	**2004-8/2009 Ex-Global crisis**												
alpha	**-0.24**	**-0.21**	**-0.27**	**-0.25**	**-0.46**	**-0.45**	**-0.48**	**-0.48**	**-0.49**	**-0.47**	**-0.52**	**-0.50**	**-0.43**
MktRf					**0.90**	**0.90**	**0.88**	**0.88**	**0.88**	**0.88**	**0.92**	**0.91**	**0.94**
SMB							**0.66**	**0.66**	**0.68**	**0.68**	**0.63**	**0.63**	**0.63**
HML							**0.38**	**0.38**	**0.35**	**0.35**	**0.42**	**0.42**	**0.27**
RMW													**-0.22**
CMA													**0.15**
FEAR											**0.02**	**0.02**	**0.01**
PCAFEARS$_T$		**-0.35**		**-0.36**		**-0.10**		**-0.08**		**-0.09**			
PCAFEARS$_{T-1}$												**-0.11**	
AvgFEARS$_T$	**-0.05**		**-0.06**		**-0.02**		**-0.02**		**-0.02**				
AvgFEARS$_{T-1}$											**-0.02**		**-0.02**
US CSI$_T$	**-0.17**	**-0.17**											
EU CSI$_T$			**-0.18**	**-0.18**	**-0.06**	**-0.06**	0.00	-0.00	-0.00	-0.00	0.01	0.01	0.00
RGEPU$_T$	**-0.05**	**-0.04**	**-0.05**	**-0.04**	**-0.01**	**-0.01**	0.00	0.00	0.00	**0.01**	0.00	0.01	0.00
Gold					**0.03**	**0.03**			-0.02	**-0.03**	**-0.03**	**-0.04**	-0.02
Currency									0.04	0.03	0.03	0.02	0.01
R^2-within	2.6%	2.7%	2.6%	2.7%	10.3%	10.2%	11.3%	11.3%	11.3%	11.3%	11.3%	11.3%	11.4%
R^2-between	24.5%	24.5%	24.5%	24.4%	23.9%	23.9%	24.9%	24.9%	24.9%	24.9%	24.7%	24.7%	24.8%
R^2-overall	2.8%	2.9%	2.8%	3%	10.3%	10.3%	11.3%	11.3%	11.4%	11.4%	11.4%	11.4%	11.4%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentimentals index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

Table 4.7: Empirical results of the sentimental factors for Grey excess returns for the period 9/2009-20019 (Global crisis and Post-ante EU crisis)

Grey Returns Factors	**9/2009-2019 Global crisis and Post-ante EU crisis**												
alpha	**1.02**	**0.98**	**1.03**	**0.99**	**0.12**	**0.12**	**-0.06**	**-0.05**	-0.04	-0.03	-0.03	-0.02	-0.03
MktRf					**0.84**	**0.84**	**0.85**	**0.85**	**0.84**	**0.84**	**0.83**	**0.82**	**0.84**
SMB							**0.72**	**0.72**	**0.74**	**0.73**	**0.75**	**0.74**	**0.76**
HML							**0.15**	**0.15**	**0.12**	**0.12**	**0.13**	**0.13**	**0.07**
RMW													-0.03
CMA													**0.14**
FEAR											**-0.01**	**-0.01**	**-0.01**
$PCAFEARS_T$		**-0.49**		**-0.49**		**-0.08**		0.03		**0.04**			
$PCAFEARS_{T-1}$												0.03	
$AvgFEARS_T$	**-0.08**		**-0.08**		**-0.01**		**0.01**		**0.01**				**0.01**
$AvgFEARS_{T-1}$											**0.01**		
US CSI_T	**-0.12**	**-0.12**											
EU CSI_T			**-0.12**	**-0.12**	0.00	0.00	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**
$RGEPU_T$	**-0.07**	**-0.06**	**-0.07**	**-0.06**	**-0.01**	**-0.01**	-0.00	-0.00	**-0.00**	**-0.00**	**-0.00**	**-0.00**	**-0.01**
Gold					-0.01	-0.01			-0.01	-0.01	-0.01	-0.01	-0.01
Currency									**0.16**	**0.16**	**0.17**	**0.17**	**0.15**
R^2-within	3.96%	3.93%	4.00%	3.97%	15%	15%	16.1%	16.1%	16.2%	16.2%	16.2%	16.2%	16.2%
R^2-between	0.4%	0.4%	0.4%	0.4%	0.25%	0.26%	0.57%	0.57%	0.65%	0.65%	0.65%	0.65%	0.61%
R^2-overall	3.9%	3.9%	3.9%	3.9%	14.9%	14.9%	15.9%	15.9%	16%	16%	16.1%	16%	16.1%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentiment index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

Table 4.8: Empirical results of the sentimental factors for Grey excess returns for the period 2004-2019 (Entire period)

Grey Returns Factors	2004-2019 Entire Period												
alpha	**0.78**	**0.76**	**0.78**	**0.76**	**0.06**	**0.06**	**-0.10**	**-0.10**	**-0.10**	**-0.10**	**-0.10**	**-0.10**	**-0.09**
MktRf					**0.85**	**0.85**	**0.86**	**0.86**	**0.85**	**0.85**	**0.85**	**0.84**	**0.86**
SMB							**0.73**	**0.72**	**0.75**	**0.74**	**0.75**	**0.75**	**0.76**
HML							**0.15**	**0.15**	**0.12**	**0.12**	**0.12**	**0.12**	**0.04**
RMW													**-0.05**
CMA													**0.17**
FEAR											-0.00	-0.00	-0.00
$PCAFEARS_T$		**-0.46**		**-0.46**		**-0.09**		-0.01		-0.01			
$PCAFEARS_{T-1}$												-0.01	
$AvgFEARS_T$	**-0.08**		**-0.08**		**-0.01**		0.00		0.00				**0.004**
$AvgFEARS_{T-1}$											0.00		
US CSI_T	**-0.12**	**-0.11**											
EU CSI_T			**-0.12**	**-0.12**	-0.00	-0.00	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**
$RGEPU_T$	**-0.07**	**-0.06**	**-0.07**	**-0.06**	**-0.01**	**-0.01**	0.00	0.00	-0.00	-0.00	-0.00	-0.00	**-0.002**
Gold					0.00	0.00			-0.01	-0.01	-0.01	-0.01	-0.01
Currency									**0.14**	**0.14**	**0.14**	**0.14**	**0.12**
R^2-within	3.52%	3.55%	3.55%	3.57%	14%	14%	15.1%	15.1%	15.2%	15.2%	15.2%	15.2%	15.2%
R^2-between	0.23%	0.16%	0.22%	0.16%	1.6%	1.6%	1.9%	1.9%	2%	2%	2%	2%	2%
R^2-overall	3.5%	3.53%	3.53%	3.56%	13.9%	13.9%	15%	15%	15.1%	15.1%	15.1%	15.1%	15.1%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentiment index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

In table 4.7, both FEARS exhibit a shift from negative to positive coefficients upon the introduction of additional variables into the model and different time periods. This reversal signifies a significant transformation in the relationship between these sentiment indices and the other factors in consideration. The initial negative coefficients suggest that heightened investors' fears correlated with diminished Grey securities performance. Conversely, the subsequent model, enriched with additional variables, displays positive coefficients for both sentiments. This implies that these sentiment indices may now correlate with improved Grey asset performance, along with the newly incorporated factors. This change in sign carries multifaceted implications. It could indicate that the added variables are counteracting the negative effect of these sentiment indices. Alternatively, it might underscore the responsiveness of these sentiment indices to broader market dynamics that have evolved over time. This observation highlights the importance of considering multiple variables when interpreting sentiment indices, given their propensity to react to a complex interplay of factors. From an investment perspective, this reversal offers vital insights. It suggests that the predictive power of sentiment indices hinges on the contextual information provided by additional variables. This insight empowers investors to recognize that crisis and uncertainty, in conjunction with other factors, might actually signal improved Grey asset performance under specific conditions. Consequently, the revised model equips investors to make nuanced decisions by considering the comprehensive context in which sentiment operates, enhancing their ability to navigate their portfolio allocation effectively.

In closing, our empirical investigation uncovers the intricate relationships between sentiment factors and Grey asset returns across various models and time spans. The results underscore the enduring influence of FEARS and RGEPU sentiment factors on Grey asset returns, even in the presence of other market variables. Equipped investors with a better understanding of the index sentiments with the Grey assets, make informed investment choices by elevating their portfolio performance allocation based on the increasing or decreasing of the sentimental indexes.

The empirical results for our last asset category are included in Tables 4.9-4.11—the findings concerning the relationship between sentiment-related factors and the returns of Green assets for the same periods and models as the previous tables (4.3-4.8). Significantly, throughout all the analyzed time periods, the additional global market factors such as MktRf, SMB, HML, RMW, CMA, Gold and Currency showcase diverse connections with asset returns. However, the coefficients consistently reveal positive associations with MktRf, SMB, HML, Gold and Currency (respectively for the first and for the second half but both for entire period), while displaying negative associations with the FEAR (volatility) factor second half period. Spanning the entire analysis period, the negative coefficient values for sentiment factors remain consistent in the first four models as the previous asset class for every AVG FEARS, PCA FEARS, US CSI, EU CSI, and RGEPU consistently exhibit negative associations with Green assets returns. This prolonged trend reinforces the idea that these sentiment factors might impact Green asset's performance. In tables 4.9-4.11, the CSI shifts from negative to positive coefficients upon introducing additional variables into the model. This reversal signifies a significant transformation in the relationship between these sentiment indices and the other consideration factors. The reversal sign implies that CSI sentiment may now positively correlate with the Green asset returns, along with the newly incorporated factors, that results align with Grey and Red assets results (Table 4.3-4.11) that may explain a similar risk behaviour. During the entire period, the negative coefficients for CSI (between -0.22 and 0.03) and RGEPU (between -0.08 and -0.03) imply that increasing economic uncertainty and crisis were linked to diminished Green securities returns. While the FEARS after the first four models exhibits a lack of statistical significance, especially across the post-Global crisis and entire period, notably in the aftermath of the Global Crisis and throughout periods involving the consideration of other variables, this implies that solitary reliance on sentiment might not be a dependable predictor of Green securities trends during these junctures. Conversely, during the ex-Global period and after the first four models, the FEARS sentiment index sustains its significance with a consistently positive coefficient across the models (refer to Table 4.9).

Our research delves into the complex connections between sentiment factors and Green asset returns across different models and periods. The findings emphasize that there is no consistent evidence of the impact of sentiment factors on how Green assets behave, even when other portfolio proxy factors are considered. Although the goal is to avoid relying exclusively on sentiment, these indicators can still be valuable for timing tactical adjustments. The insignificance of the sentiment factor suggests that fluctuations in market sentiment do not have a systematic effect on the returns of your Green portfolio. This could imply that the portfolio's performance is more driven by macroeconomics and fundamental factors. In practice, it suggests that an investor should focus more on the traditional risk factors within the Green asset space, like market and growth portfolio, rather than sentiment fluctuations. The results deepen our understanding of Green assets and equip investors to navigate the market ups and downs confidently by enhancing the overall performance of their investment portfolios without relying on sentimental factors. Green assets share several resemblances with Grey and Red assets regarding CSI sentiment indexes, particularly in insignificance and few reverse signs from negative to positive in the multifactor models.

Table 4.9: Empirical results of the sentimental factors for Green excess returns for the period 2004-8/2009 (ex-Global crisis)

Green Returns Factors	**2004-8/2009 Ex-Global crisis**												
alpha	**1.02**	**1.02**	**0.98**	**0.97**	**0.65**	**0.61**	**0.98**	**0.95**	**0.78**	**0.71**	**0.81**	**0.74**	0.48
MktRf					**1.12**	**1.13**	**1.16**	**1.17**	**1.15**	**1.16**	**1.12**	**1.13**	**1.08**
SMB							**1.12**	**1.12**	**1.09**	**1.10**	**1.13**	**1.13**	**1.14**
HML							-0.38	-0.40	-0.30	-0.32	-0.36	-0.37	0.09
RMW													**0.72**
CMA													-0.28
FEAR											-0.01	-0.01	-0.01
PCAFEARS$_T$		-0.01		-0.01		**0.36**		**0.42**		**0.43**			
PCAFEARS$_{T-1}$												**0.46**	
AvgFEARS$_T$	0.01		0.01		**0.06**		**0.08**		**0.08**				**0.07**
AvgFEARS$_{T-1}$											**0.08**		
US CSI$_T$	**-0.22**	**-0.22**											
EU CSI$_T$			**-0.22**	**-0.22**	**-0.07**	**-0.07**	-0.01	-0.00	-0.02	-0.02	-0.02	-0.02	-0.02
RGEPU$_T$	**-0.06**	**-0.06**	**-0.06**	**-0.06**	-0.02	**-0.03**	0.02	0.01	0.01	0.00	0.01	0.00	0.02
Gold					**0.20**	**0.21**			0.09	0.10	0.10	**0.11**	0.09
Currency									0.15	0.19	0.15	0.19	0.23
R^2-within	2%	2%	2.1%	2%	10.2%	10.3%	11.6%	11.6%	11.6%	11.7%	11.6%	11.6%	11.8%
R^2-between	29.8%	30.1%	29.9%	30.2%	34.5%	34.1%	34.2%	33.8%	34%	33.6%	34.3%	33.8%	34.4%
R^2-overall	2.5%	2.5%	2.5%	2.5%	10.5%	10.6%	11.8%	11.8%	11.8%	11.9%	11.8%	11.8%	12.1%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentiment index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

Table 4.10: Empirical results of the sentimental factors for Green excess returns for the period 9/2009-20019 (Global crisis and Post-ante EU crisis)

Green Returns Factors	**9/2009-2019 Global crisis and Post-ante EU crisis**												
alpha	**0.67**	**0.62**	**0.69**	**0.64**	**-0.44**	**-0.44**	**-0.55**	**-0.54**	**-0.55**	**-0.54**	**-0.50**	**-0.49**	**-0.48**
MktRf					**1.04**	**1.03**	**1.01**	**1.01**	**1.00**	**1.00**	**0.96**	**0.95**	**0.97**
SMB							**0.71**	**0.69**	**0.72**	**0.71**	**0.73**	**0.72**	**0.73**
HML							**0.28**	**0.28**	**0.26**	**0.26**	**0.29**	**0.29**	**0.20**
RMW													-0.14
CMA													0.02
FEAR											**-0.02**	**-0.02**	**-0.01**
$PCAFEARS_T$		**-0.70**		**-0.69**		**-0.19**		-0.08		-0.07			
$PCAFEARS_{T-1}$												-0.09	
$AvgFEARS_T$	**-0.10**		**-0.10**		-0.01		0.01		0.01				
$AvgFEARS_{T-1}$											0.01		0.01
US CSI_T	**-0.14**	**-0.13**											
EU CSI_T			**-0.14**	**-0.14**	0.01	0.01	**0.03**	**0.03**	**0.03**	**0.03**	**0.03**	**0.03**	**0.03**
$RGEPU_T$	**-0.08**	**-0.07**	**-0.08**	**-0.07**	-0.01	-0.00	-0.00	0.00	-0.01	-0.00	-0.01	-0.00	-0.00
Gold					0.01	0.01			0.02	0.02	0.03	0.03	0.03
Currency									**0.20**	**0.20**	**0.21**	**0.20**	**0.20**
R^2-within	4.1%	4.2%	4.1%	4.2%	16.4%	16.4%	17.3%	17.3%	17.4%	17.4%	17.4%	17.4%	17.4%
R^2-between	0.00%	0.00%	0.00%	0.00%	0.4%	0.4%	1%	1%	2%	2%	3.9%	4%	2%
R^2-overall	4.1%	4.1%	4.1%	4.2%	16.2%	16.2%	17.1%	17.1%	17.2%	17.2%	17.2%	17.2%	17.2%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentiment index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level.

Table 4.11: Empirical results of the sentimental factors for Green excess returns for the period 2004-2019 (Entire period)

Green Returns Factors	**2004-2019 Entire Period**												
alpha	**0.77**	**0.75**	**0.77**	**0.75**	-0.16	-0.16	**-0.27**	**-0.26**	**-0.30**	**-0.29**	**-0.28**	**-0.27**	**-0.31**
MktRf					**1.04**	**1.04**	**1.02**	**1.01**	**1.01**	**1.01**	**0.98**	**0.98**	**0.98**
SMB							**0.76**	**0.76**	**0.78**	**0.77**	**0.79**	**0.79**	**0.80**
HML							**0.29**	**0.29**	**0.29**	**0.29**	**0.30**	**0.30**	**0.35**
RMW													0.08
CMA													-0.01
FEAR											-0.01	-0.01	-0.01
$PCAFEARS_T$		**-0.51**		**-0.51**		-0.04		0.04		0.05			
$PCAFEARS_{T-1}$												0.05	
$AvgFEARS_T$	**-0.08**		**-0.08**		-0.00		0.02		0.02				
$AvgFEARS_{T-1}$											0.02		0.02
US CSI_T	**-0.15**	**-0.15**											
EU CSI_T			**-0.15**	**-0.15**	-0.01	-0.01	0.14	0.01	0.01	0.01	0.01	0.01	0.01
$RGEPU_T$	**-0.08**	**-0.07**	**-0.08**	**-0.07**	**-0.01**	**-0.01**	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01
Gold					**0.04**	**0.04**			**0.05**	**0.05**	**0.05**	**0.06**	**0.05**
Currency									**0.21**	**0.21**	**0.21**	**0.21**	**0.21**
R^2-within	3.8%	3.9%	3.9%	3.9%	15.1%	15.1%	16%	16%	16.2%	16.2%	16.2%	16.1%	16.2%
R^2-between	1%	0.8%	1%	0.9%	3.4%	3.4%	5.1%	5.2%	6.4%	6.4%	6.2%	6.3%	6.5%
R^2-overall	3.80%	3.84%	3.84%	3.89%	15%	15%	15.9%	15.9%	16.1%	16.1%	16%	16%	16.1%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, Gold, Currency, FEAR, AVG FEARS, PCA FEARS, US CSI and EU CSI (for crisis sentiment index also their lags) and the RGEPU from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and google trend. The results report dependent variables as simple excess returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall.

In most cases, the coefficient of the (Avg & PCA) FEARS sentiment indexes retains its significance at a 95% confidence level, even after augmenting the regression with other control variables. The first four models results suggest that increasing the levels of crisis sentiment (as indicated by the modified FEARS Index, RGEPU and CSI Index), leads to lower price returns in the Grey and Red assets. This finding underscores the importance of monitoring and managing investor sentiment in the Grey and Red securities market, as it can significantly affect asset class outcomes. Furthermore, in several cases, the sign of the coefficient from the sentimental indexes reversed to negative, particularly noticeable with the CSI Index across all classes. Including additional factors in the model impacts the estimated coefficients, which can change due to the potential presence of correlated factors or cancel out effect between the factors. Understanding these changes provides valuable insights that can shape our investment strategy. By identifying how various factors interact with sentiment indexes, we can adjust our approach to investment decisions. That means building an investment strategy for our asset class involves not only recognizing the traditional factors, but also understanding how these interact with sentiment, particularly in times of crisis. By adjusting the strategy to account for shifts in investor mood either shorting for increasing in sentiment or long positioning in decreasing of sentiment, we can enhance the resilience and adaptability of the asset class portfolio, ensuring it remains well-positioned in both bullish and bearish market environments. In periods of crisis, where traditional signals may become less reliable due to heightened emotion and uncertainty, sentiment indexes offer a strong additional layer of insight for our Red and less strong in Grey asset class. Thus, by factoring in both quantitative and qualitative measures investors can develop a robust strategy that aligns both financial objectives and a commitment to environmental investment. This knowledge allows us to refine our strategies, enhance risk management techniques, and align our portfolio with changing market dynamics and irrational pricing in our assets class. For instance, we might reduce our reliance on economic indicators alone and incorporate a more comprehensive analysis of sentimental indicators and market volatility when making investment decisions related to assets. This approach enhances the accuracy of our predictions and enables us to make more informed and effective investment choices.

The study analyzed several control factors in the GLS regression model, including SMB, HML, RMW, CMA, FEAR, Gold and Currency. The results showed for statistically significant[20] factors that FEAR is negatively associated with Red, Grey or Green price returns, while the rest of the factors are mostly positively associated except for a few factors with Red, Grey or Green price returns.

[20] The statistical significance level is at 5%

Across all of the periods examined, our findings suggest that sentiment-related factors, particularly CSI, did not consistently play a significant role in determining returns for Red, Green and Grey assets. Instead, the impact of these factors appears to vary with changing market conditions, model and over different time segments. Investors should recognize that while sentiment factors can provide additional insights into market sentiment, they should not be the sole basis for making investment decisions. Combining sentiment indicators with broader global market factors provides a more comprehensive understanding of the factors driving asset returns.

Furthermore, our analysis underscores the importance of considering the interplay between sentiment factors and other market fundamentals. While sentimental factors may not directly determine returns, they could potentially interact with broader market dynamics to influence investment outcomes. Thus, investors are advised to adopt a holistic approach, integrating sentiment indicators into their investment strategies alongside traditional market factors.

Our empirical results indicate that while sentiment factors reverse impact returns assets, their significance can vary across market conditions, model structure and time periods. Investors are encouraged to consider sentiment indicators within the broader context of global market dynamics when making informed investment decisions. In overall, the study's findings validate the preliminary conjecture (Baker & Wurgler, 2006; Baker et al. 2016; Brand, 2021; Da et al., 2015; Irresberger et al., 2015; Gao et al., 2020; Kostopoulos et al., 2020) that investor crisis sentiment, economic crisis and economic policy uncertainty sentiment considerably impact asset class returns. In more straightforward terms, this implies that the asset class returns in a crisis tend to decrease when investors' awareness of the crisis-related search terms increases based on the construction of the RGEPU, FEARS and CSI Index. Our empirical results provide evidence for the connection between crisis sentiment and stock returns, which aligns with theoretical justifications of sentiment. In crisis periods of heightened sentimental indexes, the stock prices are below the equilibrium of the fundamental factors, resulting in decreased Grey and Red stock returns. However, Red stock returns increased as the crisis sentiment declined in our subsequent periods. According to Shahbaz et al. (2021), the response of green energy markets to crude oil and stock markets is asymmetrical, contingent upon prevailing market crisis, which can explain the reverse sign of positive effect in the Green assets. During economic downturns and in the aftermath (Davis & Taube, 2023), specific sectors in the stock market, such as Agri-food, Real estate, Forestry, Transport, and ICT, tend to exhibit stronger financial performance than other sectors.

That may explain the inverse direction of the FEARS coefficient with the Grey asset returns, indicating that investors opt for safer securities and sectors essential for the economy that type of companies provide protection against economic uncertainty and downturns. The relationship between sentiment and returns appears to be more pronounced for the current and lagged sentiments.

In summary, the findings of this study highlight the (in)significant impact of investor fear, economic policy uncertainty, general crisis, and household/investor sentiment, as reflected in the FEAR, RGEPU, modified FEARS Index and crisis-related search terms (CSI), on the price returns of Green, Grey and Red securities. Policymakers and investors should take note of these results and consider incorporating sentiment analysis into their decision-making processes.

4.5 Conclusion

In the landscape of financial markets, the interplay between investor sentimentality and stock returns remains a subject of enduring interest and ongoing exploration. This research endeavours to shed light on the impact of crisis sentimental indexes on stock performance, specifically focusing on the distinct categories of Green, Grey and Red securities. Our underlying assumption confirmed that market sentimentality, often driven by emotional reactions to crisis events, can substantially influence the behavior of investors and subsequently shape stock price dynamics.

The channel through which sentimentality exerts its potential impact is grounded in the realm of behavioral finance. Emotions, ranging from fear to optimism, have been shown to drive investment decisions, sometimes leading to deviating market movements that excel rational expectations (Keynes, 1936). Crisis and uncertainty sentimental indexes are poised to capture these emotions, acting as barometers of collective investor sentiment during times of upheaval. This sentiment-driven trading behaviour can introduce greater volatility and unpredictability into the market, potentially generating opportunities and risks for Green, Grey and Red securities.

While the fundamental mechanisms connecting sentimentality and stock returns might follow similar patterns, the nuanced characteristics of Green, Grey and Red securities could lead to divergent outcomes. Thus, an in-depth exploration of how crisis sentimentality interacts with these three categories of securities can yield insights into the intricate interplay between investor emotions, stock performance, and market dynamics.

This empirical study aims to contribute to the growing literature on Green, Grey and Red assets by studying and quantifying the influence of the GEPU returns index, EU-modified FEARS index and EU Crisis Sentimental Index on these asset class returns. This investigation was based on the methods provided by Baker & Wurgler (2006), Da et al. (2015) and Irresberger et al. (2015), and our research added an innovative method to these factors by extending from US associated crisis factor to EU associated crisis factor using Anastasiou & Drakos (2019) local EU FEARS index. The EU crisis indicator is an adjustment in the US search terms to reflect the terms on the European economy and is measured as a direct indicator of the sentiment using Google search volume data. The main research question is whether the economic crisis and policy uncertainty sentiment influences the Green, Grey or Red price returns.

According to the empirical evidence, the modified Financial and Economic Attitudes towards Revealed by Search (FEARS) Index, Global Economic Policy Uncertainty (GEPU) Index return and Crisis Sentimental Index (CSI) significantly impact the price returns of Grey and Red securities. These findings highlight the importance of adding sentiment analysis into investment decision-making processes, especially in crisis periods. The results confirm the initial conjecture that the sentiment indexes considerably influence asset class returns. The study findings on the crisis period suggest that asset class returns tend to decrease when investors' awareness of crisis-related search terms increases, as measured by the construction of the FEARS, RGEPU and Crisis Sentiment Index (CSI). In addition, for the post-Global crisis period and the entire period, the modified EU FEARS and CSI Index found generally the opposite results, that a higher internet search intensity of crisis-related search terms is associated with higher price returns in the Grey and Green (for the ex-crisis period) asset market. The outcome suggests that investors in the Green or Grey securities market pay close attention to social network sentiment and information related to crises when making investment decisions. That strengthens our assumptions of noise trading, which means the investors are buying and selling financial assets based on non-fundamental factors, such as rumours or emotions (Da et al., 2015; Irresberger et al., 2015; Gao et al., 2020; Kostopoulos et al., 2020). This can lead to market inefficiencies and mispricing. While noise trading can create short-term price bubbles, it can also provide liquidity to the market.

Understanding the crisis of sentimental indexes is essential for investors to appreciate the noise trading.

The study highlights the (Avg & PCA) FEARS and RGEPU sentiment factors consistently exhibit strong negative coefficients across models and time periods, indicating that higher levels of fear and economic policy uncertainty lead to lower Red asset returns. Likewise, the analysis indicates that Grey securities returns demonstrate consistently negative coefficients with (PCA) FEARS during both the ex-crisis period and the duration under consideration. This suggests that market participants' fear and uncertainty significantly impact the performance of riskier assets (Red assets). From Investor's perspective, one should closely monitor fear and economic policy uncertainty indicators, as an increase in these indicators might signal a potential decrease in eco-enemy securities. Moreover, If fear and uncertainty levels are rising, it could be a sign to consider reducing exposure to riskier assets or implementing risk mitigation strategies on this type of securities. Mainly, the Grey assets, typically considered moderate in terms of risk, the influence of sentiment factors suggests that during periods of fear and uncertainty, their returns might be adversely affected. Investors holding Grey assets might consider strategies to manage potential downside risks during such periods.

Additionally, the analysis demonstrates that sentiment factors, particularly (avg) FEARS, exhibit a shift from negative to positive coefficients upon introducing additional variables into the model for the Green and Grey asset returns. This suggests a complex interplay between sentiment and other factors influencing Green asset returns. The dynamic relationship between sentiment factors and Green asset returns highlights the need for a comprehensive approach to investment decision-making. Investors should consider sentiment factors in conjunction with other market dynamics to get a holistic view of potential Green asset performance.

The investigation identifies distinct patterns of sentiment impact on different asset classes. This differentiation is valuable for crafting tailored investment strategies for each asset class. Investors should recognize that sentiment factors affect asset classes differently. This awareness allows for better allocation of resources and more precise decision-making strategies. The analysis suggests that sentiment indices like FEARS and RGEPU could potentially serve as leading indicators for shifts in asset sentiment. An increase in these indices might indicate changing market conditions. Monitoring sentiment indices can provide insights into potential shifts in asset sentiment. This can help investors proactively adjust their portfolios in response to changing market dynamics. The final takeaway is that understanding the intricate relationships between sentiment factors and asset returns can equip investors with the knowledge needed to navigate market volatility, make informed decisions, and enhance portfolio performance over the long term. By applying sentiment analysis to their decision-making process, investors can enhance their ability to react effectively to changing market conditions and ultimately achieve better portfolio performance.

The inclusion of additional market factors like MktRf, SMB, HML, RMW, CMA, Gold and Currency reveals that these factors also play a role in influencing asset returns. Some factors show positive associations, while others show negative associations with different asset classes. Investors need to recognize that sentiment factors do not act in isolation; they interact with a multitude of other market variables. Understanding these interactions can help investors refine their investment strategies to capture a more accurate picture of potential returns.

The FEAR index or investor fear sentiment (Implied volatility index) reveals mostly statistically significant explanatory power for Green, Grey and Red securities returns and improvement in the contribution of the model performance. The empirical results confirm the previous literature (Whaley, 2009; Smales, 2016; Reis & Pinho, 2021) that the increase of the EU FEAR index is decreasing the securities returns and the subgroups such as in our case, the Green, Grey and Red securities (the first half period have deviations in particular asset classes). The study also incorporated various other control variables from Fama French in the GLS regression model: SMB, HML, RMW, and CMA. The inclusion of additional market factors like MktRf, SMB, HML, RMW, and CMA reveals that these factors also play a role in influencing asset returns. Some factors show positive associations, while others show negative associations with different asset classes. Investors need to recognize that sentiment factors do not act in isolation; they interact with a large number of other market variables. That means to avoid making decisions solely based on sentiment factors. Instead, they should incorporate sentiment indicators into a broader framework that includes various market fundamentals. Understanding these interactions can assist investors in fine-tuning their investment strategies, enabling them to gain a more precise understanding of potential returns, associated risks, and the possibility of diversifying their portfolios by employing portfolios aligned with these proxies.

Consequently, the research highlights how sentiment factors interact with macroeconomic indicators and other market factors across different periods. This understanding is crucial for developing risk management strategies and optimizing asset allocation within our portfolio.

Investors can use the insights gained from these analyses to create more effective risk management strategies, including hedging or (un)balancing their portfolio employing the proxy and our asset class portfolios. Investors typically need to consider their risk tolerance, investment goals, and time horizon when deciding whether to create a balanced or unbalanced portfolio. Balancing risk and potential reward is a fundamental principle in portfolio management, and the chosen approach should align with the investor's individual financial situation and objectives.

As mentioned in Chapter 1, alternative macroeconomic variables (e.g. LIQ factor) may be investigated with a combination of the sentimental crisis index to assess the asset class's performance. Another possible extension of my research would be to explore the global crisis sentimental factors that may influence securities stocks, such as Global FEARS or Global CSI. This would enable a deeper understanding of how the Google term trends can be tailored to the global financial market and contexts to maximize investment decisions.

Regarding potential avenues for future research, exploring the fundamental drivers behind internet searches would offer a captivating dimension. Additionally, there's an intriguing prospect to construct a localized index by incorporating translated search terms in respective local languages, culminating in the creation of an EU indexes. It is important to recognize that the market's dynamics are influenced not solely by fundamental and technical indicators, but also by the profound impact of social emotions. These insights hold immense potential in shaping trading strategies and tactics.

Chapter 5: Conclusion, Discussion and Future Research

In the evolving landscape of financial markets, this study significantly contributes to our understanding of the risks-returns associated with different environmental asset classes (e.g. Green, Grey, and Red), their financial performance and how market sentiment impacts upon these types of assets, particularly during times of crisis and no-crisis. The factor structure identifies the common variation of Green, Grey, and Red asset returns, additionally while considering sentiment factors, that can significantly enhance portfolio management of risk and return objectives. The key conclusion is drawn from the relationship with the diversified portfolios and the investor sentiment with the asset classes, especially as captured by crisis-related indexes like FEARS and Global Economic Policy Uncertainty (GEPU). These indexes and factors play a substantial role in shaping stock returns. This finding underlines the importance of incorporating tactics with diversified portfolios and behavioural finance principles into modern investment strategies, particularly when dealing with crisis-driven volatility.

The impact of these asset classes during the crisis and before the crisis is not uniform. **Green assets**—those associated with environmentally friendly companies—tend to offer more stable returns during crisis periods, while **Red assets**, tied to environmentally unfriendly companies, exhibit greater volatility. **Grey assets**, which fall between these two extremes, reflecting a moderate risk profile. The differentiation and the relation with the portfolio proxies are critical for investors, particularly those seeking to diversify their portfolios and mitigate risk during periods of market turmoil. In our investigation, we spotted the connections between asset class and proxy portfolios and how to shape our strategy based on these signals (e.g. Market, Size, Growth, Momentum and others).

The financial comparison between Green and Red securities highlights the challenges in **sustainable investing**. While Green assets provide a potentially lower-risk option during periods of economic instability, Red assets may offer higher returns under certain market conditions. In the end, alpha returns remain indifferent for these types of assets, meaning that whether you expose on eco-friendly or non-eco-friendly assets, consistent profits cannot be guaranteed over the other asset class.

Further insight is that **sentiment-driven trading behaviours**, often grounded in investor emotions such as the fear of financial crises. This leads to deviations in stock prices that go beyond rational market expectations. In our case, the empirical evidence shows that during periods of heightened economic uncertainty, investor crisis mood (as captured by the FEARS and GEPU indexes) leads to lower returns for riskier assets like Red and Grey securities, while Green assets may react more complexly depending on the economic environment and additional market variables. For instant, a portfolio manager tracking the FEARS index if notices a significant spike, that indicating rising market uncertainty. In practice, investors may decide to reduce exposure to Red and Grey securities when the feeling of crisis increases and instead allocate more resources to alternative investments like gold during this period.

This research underscores the complex and dynamic relationship between factor structure, sentiment and asset class returns, particularly in the context of crisis periods. Investors must recognize that while sentiment analysis offers powerful insights, it must be integrated within a broader framework of market fundamentals and macroeconomic indicators. Diversifying portfolios across Green, Grey, and Red assets, while actively monitoring sentiment factors, can significantly enhance risk management and return optimization strategies.

While this study provides robust insights into the relationship between alpha performance, asset class characteristics and crisis sentiment, it also opens up several avenues for future research. For instance, our research used a range of factors to explain the returns of Green, Grey, and Red securities, but there is scope for expanding these models further. Future studies could explore additional factors such as liquidity (LIQ) and quality (QML), or even develop new factors that better capture the nuances of environmentally focused investing. Another potential direction can involve the construction of localized sentiment indexes that reflect regional variations and append to the current sentiment. This would involve translating crisis-related search terms into local languages and tailoring sentiment measures to specific markets. The creation of localized EU sentiment indexes, for instance, could provide an additional layer and more informed assessments of how European investors react to crisis events, potentially leading to more regionally focused investment strategies. Furthermore, constructing a **global crisis sentiment** would offer valuable insights into how global investors react to crises. Incorporating a broader set of search terms across multiple languages and economies could deepen our understanding of how sentiment impacts global markets and allow for more sophisticated global portfolio strategies.

In conclusion, this study offers practical tools for investors and provides a foundation for future research that can further refine asset pricing models and investment strategies in an increasingly volatile and sentiment-driven financial environment. The integration of sentimental indexes into traditional financial models represents a step toward more sophisticated, adaptive investment approaches that align with both market conditions and investor expectations

References

Afkhami, M., Cormack, L., & Ghoddusi, H. (2017). Google search keywords that best predict energy price volatility. Energy Economics, 67, 17–27.

Akerlof, G. A., & Shiller, R. J. (2009). Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism. Princeton University Press.

Alessi, L., Ossola, E., & Panzica, R. (2021). What greenium matters in the stock market? The role of greenhouse gas emissions and environmental disclosures. Journal of Financial Stability, 54.

Ambec, S., & Lanoie, P. (2008). Does It Pay to Be Green? A Systematic Overview. Academy of Management Perspectives, 22(4), 45-62.

Anastasiou, D., & Drakos, K. (2021). European depositors' behavior and crisis sentiment. Journal of Economic Behavior & Organization, 184, 117–136.

Arellano, M., (2003). Panel Data Econometrics. Oxford University Press

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2022). Climate change concerns and the performance of green versus brown stocks. Management Science, 69 (12)

Asness, C. S., & Frazzini, A. (2013). The devil in HML's details. Journal of Portfolio Management, 39(3), 49–68.

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2019). Quality minus junk. Review of Accounting Studies, 24(1), 34–112.

Aswani, J., Raghunandan, A., & Rajgopal S. (2024). Are carbon emissions associated with stock returns?, Review of Finance, 28(1), 75–106

Badia, G., Ferruz, L., & Cortez, M.C., (2019). The performance of socially responsible stock portfolios: international evidence. EFMA European Financial Management Association 2019.

Bai, J., & Zhou, G. (2015). Fama-MacBeth Two-Pass Regressions: Improving Risk Premia Estimates. SSRN. https://ssrn.com/abstract=2591754 or http://dx.doi.org/10.2139/ssrn.2591754

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. The Journal of Finance, 61(4), 1645–1680.

Baker, S., Bloom, N., & Davis, S. (2016). Measuring Economic Policy Uncertainty. The Quarterly Journal of Economics, 131(4), 1593–1636.

Brandt, R. (2021). "Economic Policy Uncertainty Index: Extension and optimization of Scott R. Baker, Nicholas Bloom and Steven J. Davis's search term." DoCMA Working, Paper #5, Feb. 2021. doi: 10.17877/DE290R-21922

Bali, T. G., Cakici, N., & Fabozzi, F. J. (2012). Book-to-Market and the Cross-Section of Expected Returns in International Stock Markets. The Journal of Portfolio Management, 39(2), 101-115.

Baltagi, B. H., 2005. Econometric Analysis of Panel Data. Wiley

Bams, G., Blanchard, I., Honarvar, T., & Lehnert, T. (2017). Does oil and gold price uncertainty matter for the stock market?. Journal of Empirical Finance, 44, 270-285.

Bank, M., Larch, M., & Peter, G. (2011). Google search volume and its influence on liquidity and returns of German stocks. Financial Markets and Portfolio Management, 25(3), 239–264.

Barberis, N., Shleifer, A & Vishnya R. (1998). A model of investor sentiment. Journal of Financial Economics, 49(3), 307–343.

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In Handbook of the Economics of Finance, Financial Markets and Asset Pricing, Elsevier, 1053–1128

Bartram, S. M., & Bodnar, G. M. (2009). No place to hide: the global crisis in equity markets in 2008/2009. Journal of International Money and Finance, 28(8), 1246–1292.

Bartram, S. M., Lohre, H., Pope, P. F., & Ranganathan, A. (2021). Navigating the factor zoo around the world: an institutional investor perspective. Journal of Business Economics, 91(5), 655–703.

Bauer, M., Huber, D., Rudebusch, G. D., & Wilms, O. (2022). Where is the Carbon Premium? Global Performance of Green and Brown Stocks. Journal of Climate Finance, 1, 100006

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review, 45(2), 217-229.

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. Journal of Banking & Finance, 34(8), 1886-1898.

Bekaert, G. and Harvey, C. R., (1995). Time-Varying World Market Integration. Journal of Finance, 50(2), 403-444

Benediktsdóttir, S., Eggertsson, G.B. and Þórarinsson, E., 2017. The rise, the fall, and the resurrection of Iceland. Brookings Institution. Available at: https://www.brookings.edu/research/the-rise-the-fall-and-the-resurrection-of-iceland/ [Accessed 10 October 2024]

Begg, I., (2012). The EU's response to the global financial crisis and sovereign debt crisis. Asia Europe Journal, 9, 107-124

Bijl, L., Kringhaug, G., Molnár, P., & Sandvik, E. (2016). Google searches and stock returns. International Review of Financial Analysis, 45, 150–156.

Black, F., Jensen, M. C., & Scholes, M. (1972). The Capital Asset Pricing Model: Some Empirical Findings. In Jensen, M. C. (Ed.), Studies in the Theory of Capital Markets. Praeger, New York.

Blitz, D., & De Groot, W. (2014). Strategic allocation to commodity factor premiums. The Journal of Alternative Investments, 17(2), 103–115.

Bock, A. M., Henneberg, I., & Plank, F. (2015). "If you compress the spring, it will snap back hard": The Ukrainian crisis and the balance of threat theory. International Journal, 70(1), 101–109.

Bolton, P., & Kacperczyk M. (2021). Do investors care about carbon risk?. Journal of Financial Economics, 142(2), 517-549

Bolton, P., Zachery H., & Kacperczyk M. (2022) The Financial Cost of Carbon. Journal of Applied Corporate Finance, 34 (2), 17–29.

Bouvet, F. & King, S., (2013). Do national economic shocks influence european central bank interest-rate setting? The impact of the financial and sovereign debt crises. Journal of Common Market Studies, 51(2), 212–231.

Brammer, S., Brooks, C., & Pavelin, S., (2009). The Stock Performance of America's 100 Best Corporate Citizens. The Quarterly Review of Economics and Finance,49(3), 1065-1080

Breinlich, H., Leromain, E., Novy, D. and Sampson, T., (2018). The Economic Consequences of Brexit: Evidence from the Stock Market. Centre for Economic Policy Research (CEPR). Available at: https://cepr.org/voxeu/columns/economic-effects-brexit-evidence-stock-market

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. Journal of Empirical Finance, 11(1), 1–27.

Brunnermeier, M.K. (2009). Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic Perspectives, 23(1), 77-100.

Busch, T., Bauer, R. & Orlitzky, M. (2016). Sustainable development and financial markets: Old paths and new avenues. Business & Society, 55(3), 303-329.

Cakici, N. (2015). The five-factor Fama-French model: International evidence. Journal of Asset Management, 16(4), 211-223.

Cameron, C. A., & Trivedi, P. K. (2009). Microeconometrics Using STATA. Stata Press.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. The Journal of Finance, 52(1), 57-82.

Chau, F., Deesomsak, R., & Koutmos, D. (2016). Does investor sentiment really matter? International Review of Financial Analysis, 48, 221–232.

Cheema-Fox, A., LaPerla, B.R., Serafeim, G., Turkington, D. & Wang, H.S. (2021). Decarbonization factors. Journal of Impact and ESG Investing, 1(2), 36-56.

Choudhry, T. (2002). The Stochastic Structure of the Time Varying Beta: Evidence from UK Companies. The Manchester School, 70(6), 768–791.

Choudhry, T. (2004). Time-varying Beta and the Asian Financial Crisis: Evidence from Malaysian and Taiwanese Firms. Pacific-Basin Finance Journal, 13(1), 93–118.

Clark, G. L., Feiner, A., & Viehs, M. (2015) From the stockholder to the stakeholder: How sustainability can drive financial outperformance, Oxford: University of Oxford and Arabesque Partners.

Clarke, C., & Shahraki, M. (January 3, 2023). Testing Asset Pricing Models on Individual Stocks. Working Paper. Available at SSRN: https://ssrn.com/abstract=3805109 or http://dx.doi.org/10.2139/ssrn.3805109

Climate Bonds Initiative (2020) Green Bond Market Summary (2019), (5 February), Available at: www.climatebonds.net (Accessed: 2 October 2024).

Climate Bonds Initiative (2024) Quarterly Market Update (Q1 2024), (6 June), Available at: www.climatebonds.net (Accessed: 2 October 2024).

Claessens, S., Dell'Ariccia, G., Igan, D. & Laeven, L. (2010). Cross-country experiences and policy implications from the global financial crisis. Economic Policy, 25(62), 267-293.

Climent, F., & Soriano, P. (2011). Green and Good? The Investment Performance of US Environmental Mutual Funds. Journal of Business Ethics, 103, 275–287.

Cochrane, J. H. (2001). Asset Pricing. Princeton, NJ: Princeton University Press.

Cojoianu, T. F., Clark, G. L., Hoepner, A. G. F., Veneri, P., & Wójcik, D. (2020). Entrepreneurs for a low carbon world: How environmental knowledge and policy shape the creation and financing of green start-ups. Research Policy, 49(6).

Connor, G., & Korajczyk, R. (2022). Semi-strong Factors in Asset Returns. Journal of Financial Econometrics, 22(1), 1-26.

Cooper, I., Priestley, R., & Mitrache, A. (2022). A Global Macroeconomic Risk Model for Value, Momentum, and Other Asset Classes. Journal of Financial and Quantitative Analysis, 57(1), 1 - 30

Corredor, P., Ferrer, E., & Santamaria, R. (2013). Investor sentiment effect in stock markets: Stock characteristics or country-specific factors? International Review of Economics & Finance, 27, 572–591.

Da, Z., Engelberg, J., & Gao, P. (2015). The Sum of All FEARS Investor Sentiment and Asset Prices. The Review of Financial Studies, 28(1), 1–32.

Da, Z., Engelberg, J., & Gao, P. (2011). In Search of Attention. The Journal of Finance, 66(5), 1461–1499.

Davis, C., & Taube, S. (2023, May 11). What to Invest in During a Recession: 4 Ideas. NerdWallet. https://www.nerdwallet.com/article/investing/what-to-invest-in-during-recession

Shleifer, A. & Vishny R. (1992). Liquidation Values and Debt Capacity: A Market Equilibrium Approach. Journal of Finance, 47(4), 1343–1366.

Derwall, J., Koedijk, K., & Ter Horst, J. (2011) A tale of values-driven and profit-seeking social investors, Journal of Banking & Finance, 35(8), 2137-2147.

Dirkx, P., & Peter, F. J. (2020). The Fama-French Five-Factor Model Plus Momentum: Evidence for the German Market. Schmalenbach Bussiness Review, 72, 661–684.

Dimpfl, T., & Jank, S. (2016). Can Internet Search Queries Help to Predict Stock Market Volatility? European Financial Management, 22(1), 171–192.

Durand, R. B. B., Lim, D., & Zumwalt, J. K. (2011). Fear and the Fama-French factors. Financial Management, 40(2), 409–426.

Dorfleitner, G., Halbritter, G. & Nguyen, M. (2015). Measuring the level and risk of corporate responsibility–An empirical comparison of different ESG rating approaches. Journal of Asset Management, 16(7), 450-466.

Dhaliwal, D.S., Li, O.Z., Tsang, A. & Yang, Y.G. (2011). Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting. The Accounting Review, 86(1), 59-100.

Dyck, A., Lins, K. V., Roth, L., & Wagner, H. F. (2019), Do institutional investors drive corporate social responsibility? International evidence, Journal of Financial Economics, 131(3), 693-714.

Dzielinski, M. (2012). Measuring economic uncertainty and its impact on the stock market. Finance Research Letters, 9(3), 167–175.

Eccles, R.G., Ioannou, I. & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. Management Science, 60(11), 2835-2857

EU. (2010). Directive 2010/75/EU of the European Parliament and of the Council of 24 November 2010 on industrial emissions (integrated pollution prevention and control). OJ L 334, 17.12.2010, 17–119.

Erdinc, Y. (2018). Comparison of CAPM, Three-Factor Fama-French Model and Five-Factor Fama-French Model for the Turkish Stock Market. In: S. Gokten and G. Kucukkocaoglu, eds. Financial Management from an Emerging Market Perspective. London: IntechOpen. 69-99.

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. Journal of Political Economy, 81(3), 607-636.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. The Journal of Finance, 47(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3-56.

Fama, E. F., & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. The Journal of Finance, 50(1), 131-155.

Fama, E. F., & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. The Journal of Finance, 51(1), 55-84.

Fama, E. F., & French, K. R. (1998). Value versus Growth: The International Evidence. The Journal of Finance, 53(6), 1975-1999.

Fama, E. F., & French, K. R. (2008). Average Returns, B/M, and Share Issues. The Journal of Finance, 63(6), 2971-2995.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. Journal of Financial Economics, 105(3), 457-472.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1-22.

Fatemi, A., Fooladi, I. & Tehranian, H. (2015). Valuation effects of corporate social responsibility. Journal of Banking & Finance, 59, 182-192.

Fatica, S., Panzica, R., & Rancan, M. (2021). The pricing of green bonds: Are financial institutions special? Journal of Financial Stability, 54, 100873.

Feng, G., Giglio, S., & Xiu, D. (2020). Taming the Factor Zoo: A Test of New Factors. Journal of Finance, 75(3), 1327-1370.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. Journal of Financial Economics, 111(1), 1-25.

Friede, G., Busch, T. & Bassen, A. (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. Journal of Sustainable Finance & Investment, 5(4), 210-233.

Gao, Z., Ren, H., & Zhang, B. (2020). Googling investor sentiment around the world. Journal of Financial and Quantitative Analysis, 55(2), 549–580.

Garvey, G.T., Iyer, M., Nash, J., (2018). Carbon footprint and productivity: does the “E” in ESG capture efficiency as well as environment? Journal Investment Management 16 (1), 59–69.

Ibikunle, G., & Steffen, T., (2017). European Green Mutual Fund Performance: A Comparative Analysis with their Conventional and Black Peers. Journal of Business Ethics, 145, 337–355.

Gentier, A. (2012). Spanish Banks and the Housing Crisis: Worse than the Subprime Crisis? International Journal of Business, 17(4), 1-12.

Gimeno, R., & González, C. I. (2022). The Role of a Green Factor in Stock Prices. When Fama & French Go Green. BANCO DE ESPAÑA N.º 2207.

Greene, W. H., (2012). Econometric Analysis. Prentice Hall

Griffin, J.M. (2002). Are the Fama and French factors global or country specific? The Review of Financial Studies, 15(3), 783-803.

Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., Wilkens, M.,2020. Carbon risk. Unpublished working paper. University of Augs-burg. (August 10, 2020). Available at SSRN: https://ssrn.com/abstract=2930897 or http://dx.doi.org/10.2139/ssrn.2930897

Global Sustainable Investment Alliance (GSIA) (2022) Global Sustainable Investment Review 2022. Available at: http://www.gsi-alliance.org (Accessed: 2 October 2024).

Giese, G., Lee, L.E., Melas, D., Nagy, Z. & Nishikawa, L. (2019). Foundations of ESG investing: How ESG affects equity valuation, risk, and performance. The Journal of Portfolio Management, 45(5), 69-83.

Harvey, C. R., (1991). The World Price of Covariance Risk. Journal of Finance, 46(1), 111-157

Harvey, C.R., Liu, Y. & Zhu, H. (2016). ...and the cross-section of expected returns. The Review of Financial Studies, 29(1), 5-68.

Han, Y. & Li, Q., (2021). A dynamic analysis of the relationship between investor sentiment and stock market realized volatility: Evidence from China. PLOS One, 16(4), 1-22

Heidenreich, T., Lind, F., Eberl, J. M., & Boomgaarden, H. G. (2019). Media Framing Dynamics of the 'European Refugee Crisis': A Comparative Topic Modelling Approach. Journal of Refugee Studies, 32(1), i172–i182

Heinkel, R., Kraus, A., & Zechner, J. (2001). The effect of green investment on corporate behavior. Journal of Financial and Quantitative Analysis, 36, 431–449.

Heston, S.L. and Rouwenhorst, K.G., 1994. Does industrial structure explain the benefits of international diversification?. Journal of Financial Economics, 36(1), 3–27

Hu J. & Zhao Y., (2024) Improving corporate profitability from the inside out with environmental performance: an empirical analysis based on Chinese listed company data. Frontiers in Environmental Science, 12:1489896

Hu, G., Li, X., & Cao, Z. (2024). Do tax incentives make firms greener? Evidence from the accelerated depreciation policy in China. The British Accounting Review, 101517

Huij, J., Laurs, D., Stork, P., & Zwinkels, R. C. J. (2021). Carbon Beta: A Market-Based Measure of Climate Transition Risk Exposure. Working Paper. Available at SSRN: https://ssrn.com/abstract=3957900 or http://dx.doi.org/10.2139/ssrn.3957900

Hsiao, C., (2014). Analysis of Panel Data. Cambridge University Press

Hsu, P.H., Li, K. & Tsou, C.Y. (2023) The pollution premium, The Journal of Finance, 78(3), 1343–1392.

Hou, K., Xue, C. & Zhang, L. (2015). Digesting anomalies: An investment approach. The Review of Financial Studies, 28(3), 650-705.

Ilhan, E., Krueger, P., Sauter, Z., & Starks, S. T. (2023). Climate Risk Disclosure and Institutional Investors.The Review of Financial Studies 36(7), 2617–2650.

In, S. Y., Park, K. Y., & Monk, A. (2019). Is 'Being Green' Rewarded in the Market? An Empirical Investigation of Decarbonization and Stock Returns. Working paper, Stanford Global Project Center. https://www.sustainablefinance.ch/upload/cms/user/SSRN-id3020304.pdf

Ito, Y., Managi, S., & Matsuda, A. (2013). Performances of socially responsible investment and environmentally friendly funds. Journal of the Operational Research Society, 64(11), 1583–1594.

Irresberger, F., Mühlnickel, J., & Weiß, G. N. F. (2015). Explaining bank stock performance with crisis sentiment. Journal of Banking & Finance, 59, 311–329.

Irresberger, F., König, F. E., & Weiß, G. N. F. (2017). Crisis Sentiment in the U.S. Insurance Sector. Journal of Risk and Insurance, 84(4), 1295–1330.

Irresberger, F., & Weiß, G. (2015). Depositor Sentiment. Working Paper. SSRN. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2532870

Jensen, M., (1967) The Performance of Mutual Funds in the Period 1945-1964. Journal of Finance, 23(2), 389-416.

Jegadeesh, N., Noh, J., Pukthuanthong, K., Roll, R. W., & Wang, J. L. (2019). "Empirical Tests of Asset Pricing Models with Individual Assets: Resolving the Errors-in-Variables Bias in Risk Premium Estimation. Journal of Financial Economics, 133(2), 273-298

Jones, K. (2021). Brexit and the Crisis of European Integration. In Populism and Trade: The Challenge to the Global Trading System. Oxford University Press.

Kan, R., Robotti, C., & Shanken, J. (2013). Pricing model performance and the two-pass cross-sectional regression methodology. Journal of Finance, 68, 617–2649.

Kan, R., & Zhang, C. (1999). Two-Pass Tests of Asset Pricing Models with Useless Factors. The Journal of Finance, 54(1), 203-235.

Kanwal, M. (2022). Brexit and its Implications for the European Union. SSRN. http://dx.doi.org/10.2139/ssrn.4312258

Kaplanski, G. & Levy, H., (2010). Sentiment and Stock Prices: The Case of Aviation Disasters. Journal of Financial Economics, 95(2), 174-201.

Kepler Cheuvreux. (2015, November 23). Carbon Compass: Investor guide to carbon footprinting. Retrieved from https://iasj.org/wp-content/uploads/investor-guide-to-carbon-footprinting.pdf

Keynes, J. M. (1936). The General Theory of Employment, Interest and Money. London: Macmillan.

Kostopoulos, D., Meyer, S., & Uhr, C. (2020). Google search volume and individual investor trading. Journal of Financial Markets, 49, 100544.

Kouretas, G. P., & Vlamis, P. (2010). The Greek crisis: Causes and implications. Panoeconomicus, 57(4), 391–404.

Laeven, L. & Valencia, F. (2013). Systemic banking crises database. IMF Economic Review, 61(2), 225-270.

Lane, P.R. (2012). The European Sovereign Debt Crisis. Journal of Economic Perspectives, 26(3), 49-68.

Lapavitsas, C., & Sergis, N. T. Z. (2014). Review of Crisis in the Eurozone. Community Development Journal, 49(1), 167–170. Published by Oxford University Press.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. Review of Economics and Statistics, 47(1), 13–37.

Lins, K. V., Servaes, H., & Tamayo, A. (2017) Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis, The Journal of Finance, 72(4), 1785-1824.

Lopes, L. L. (1987). Between Hope and Fear: The Psychology of Risk. Advances in Experimental Social Psychology, 20, 255–295.

MacAskill, S., Roca, E., Liu, B., Stewart, R. A., & Sahin, O. (2021). Is there a green premium in the green bond market? Systematic literature review revealing premium determinants. Journal of Cleaner Production, 280, 124491.

Markowitz, H. M. (1952). Portfolio Selection. Journal of Finance. 7(1), 77-91.

Mawutor, J. K. M. (2014). The Failure of Lehman Brothers: Causes, Preventive Measures and Recommendations. Research Journal of Finance and Accounting, 5(4), 85–96.

McArdle, P. (2012). The Euro Crisis: Refinancing the Irish bailout – the options post the June 2012 Summit. Working Paper, The Institute of International and European Affairs, Dublin.

McCann, F., & McIndoe-Calder, T. (2014). Property debt overhang: The case of Irish SMEs. VoxEU Column, CEPR, 23 September.

McKeough, P. (2009, June 11). What are green stocks? TSI Wealth Daily Advice.

McKeough, P. (2021, January 24). Green chip stocks can be riskier investments than many investors realize. TSI Wealth Daily Advice.

Margolis, J.D., Elfenbein, H.A. & Walsh, J.P. (2009). Does it pay to be good...and does it matter? A meta-analysis of the relationship between corporate social and financial performance. SSRN Electronic Journal. Available at: https://ssrn.com/abstract=1866371 [Accessed 2 Oct. 2024].

Minteh, Binneh S. (2016). The European Migration Crisis (2011-2015): A Crisis of Failed and Fragile States. American Political Science Association, 2017 Annual Conference.

Miroshnychenko, I., Barontini, R. & Testa, F. (2017). Green practices and financial performance: A global outlook. Journal of Cleaner Production, 147, 340-351.

Mody, A. & Sandri, D. (2012). The Eurozone crisis: how banks and sovereigns came to be joined at the hip. Economic Policy, 27(70), 199-230.

Molina-Azorín, J., Claver-Cortés, E., López-Gamero, M. & Tarí, J. (2009). Green management and financial performance: a literature review. Management Decision, 47(7), 1080-1100.

McGuire, J., Sundgren, A. & Schneeweis, T. (1988). Corporate Social Responsibility and Firm Financial Performance. The Academy of Management Journal, 31(4), 854-872.

Nayar, N., Price, S. M., & Shen, K. (2023). Macroeconomic Uncertainty and Predictability of Real Estate Returns: The Impact of Asset Liquidity. Journal of Real Estate Research, 46(1), 82–113

Nelson, R. M., Belkin, P., Mix, D. E., & Weiss, W. A. (2012). The Eurozone Debt Crisis: Overview and Issue for the Congress. Congress Research Service.

Nivorozhkin, E. and Castagneto-Gissey, G., (2016). Russian stock market in the aftermath of the Ukrainian crisis. *Russian Journal of Economics*, 2(1), 23-40.

Nofsinger, J., & Varma, A. (2014). Socially responsible funds and market crises, Journal of Banking & Finance, 48, 180-193.

Oestreich, A. M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the EU Emissions Trading Scheme. *Journal of Banking and Finance, 58*, 294-308.

Oehmke, M., & Opp M. M. (2025). A theory of socially responsible investment. *The Review of Economic Studies*, 92(2), 1193–1225

Ólafsson, S. (2011). Iceland’s financial crisis and level of living consequences. *University of Iceland, Social Research Centre Working Paper 3:2011.*

OECD. (2012). Financial Contagion in the Era of Globalized Banking? *OECD Economics Department Policy Notes, No. 14, June.*

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111(3)*, 642-685.

Pástor, L., Stambaugh, R., & Taylor, L. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics, 142(2)*, 550-571.

Pástor, L., Stambaugh, R., & Taylor, L. (2022). Dissecting green returns. *Journal of Financial Economics, 146(2)*, 403–424.

Perelman, J., Felix, S., & Santana, R. (2015). The Great Recession in Portugal: Impact on hospital care use. *Health Policy, 119(3)*, 307–315.

Perlin, M. S., Caldeira, J. F., Santos, A. A. P., & Pontuschka, M. (2017). Can We Predict the Financial Markets Based on Google's Search Queries? *Journal of Forecasting, 36*, 454–467.

Pojarliev, M., & Levich, R. (2008). Do professional currency managers beat the benchmark?. Financial Analysts Journal, 64(5), 18–32.

Porter, M., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspective, 9(4)*, 97-118.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying Trading Behavior in Financial Markets Using Google Trends. *Scientific Reports, 3*, 1684.

Read, C. (2009). The Fear Factor: What Happens When Fear Grips Wall Street. *Palgrave Macmillan.*

Reis, P. M. N., & Pinho, C. (2021). A reappraisal of the causal relationship between sentiment proxies and stock returns. *Journal of Behavioral Finance, 22(4)*, 420–442.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the US stock market. *Journal of Banking & Finance, 84*, 25–40.

Romano, S. (2021). The 2011 Crisis in Italy: A Story of Deep-Rooted (and Still Unresolved) Economic and Political Weaknesses. *In Financial Crisis Management and Democracy.*

Roy, J. K. (2015, August 1). Green stocks: Green investment, Green return. *The Financial Express.*

Shahbaz, M., Trabelsi, N., Tiwari, A. K., Abakah, E. J. A., & Jiao, Z. (2021). Relationship between green investments, energy markets, and stock markets in the aftermath of the global financial crisis. *Energy Economics, 104*, 1-10.

Shanken (1992), On the Estimation of Beta-Pricing Models, The Review of Financial Studies, 5(1), 1–33

Shanken, J. A., & Zhou, G. (2007). Estimating and testing beta pricing models: alternative methods and their performance in simulations. Journal of Financial Economics, 84(1), 40-86.

Sharpe, W. F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance, 19*, 425-442.

Shefrin, H. (2000). Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing. *Oxford University Press.*

Sibley, S. E., Wang, Y., Xing, Y., & Zhang, X. (2016). The information content of the sentiment index. *Journal of Banking & Finance, 62*, 164–179.

Smales, L. A. (2016). Risk-On/Risk-Off: Financial Market Response to Investor Fear. *Finance Research Letters, 17*, 125–134.

Statman, M., & Glushkov, D. (2016). Classifying and Measuring the Performance of Socially Responsible Mutual Funds. *The Journal of Portfolio Management, 42*, 140-151.

Takeda, Y. (2014). Investigation into the association between Google search volume and stock returns in the Japanese equities market.

Tetlock, P. C. (2007) Giving content to investor sentiment: The role of media in the stock market, The Journal of Finance, 62(3), 1139-1168.

Vozlyublennaia, N. (2014). Investor attention, index performance, and return predictability. *Journal of Banking & Finance, 41*, 17–35.

Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management, 35*, 98–105.

Wooldridge, J. M., (2010). Econometric Analysis of Cross Section and Panel Data. MIT Press

Yu, B., Liu, L., & Chen, H. (2023). Can green finance improve the financial performance of green enterprises in China? International Review of Economics & Finance, 88, 1287–1300

Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean–variance relation. *Journal of Financial Economics, 100*, 367–381.

Zenios, S. A. (2013). The Cyprus Debt: Perfect Crisis and a Way Forward. *Cyprus Economic Policy Review, 7(1)*, 3–45.

Appendices

E1.0 Renewable & Alternative Energy	E2.0 Energy Efficiency	E3.0 Water Infrastructure & Technologies	E4. 0 Pollution Control	E 5.0 Waste Management & Technologies	E6.0 Environmental Support Services	E 7.0 Food, Agriculture & Forestry
E1.1 Wind Power Generation Equipment	E2.1 Power Network Efficiency	E3.1 Water Infrastructure	E4.1 Pollution Control Solutions	E5.1 Waste Technology Equipment	E6.1 Carbon and Other Environmental Assets Trading	E7.1 Sustainable and Efficient Agriculture
E1.2 Solar Energy Generation Equipment	E2.2 Industrial Energy Efficiency	E3.2 Water Treatment Equipment	E4.2 Environmental Testing and Gas Sensing	E5.2 Recycling and Value Added Waste Processing	E6.2 Environmental Consultancies	E7.2 Logistics, Food Safety and Packaging
E1.3 Other Renewables Equipment	E2.3 Buildings Energy Efficiency	E3.3 Water Utilities		E5.3 Hazardous Waste Management	E6.3 Diversified Environmental	E7.3 Sustainable Forestry and Plantations
E1.4 Renewable Energy Developers and IPPs	E2.4 Transport Energy Efficiency	E3.4 Diversified Water Infrastructure and Technology		E5.4 General Waste Management		
E1.5 Biofuels	E2.5 Consumer Energy Efficiency			E5.5 Diversified Waste and Technology		
E1.6 Diversified Renewable and Altemative Energy	E2.6 Diversified Energy Efficiency					

Appendix A

Table A2.1: FTSE environmental sectors and sub-sectors

Note: This table shows a classification within the Green sector — Source: FTSE and Kepler Cheuvreux

Table A2.2: Classical factors Variable names, definition and description

Variable name	Variable definition	Variable description
SMB (Small Minus Big)	1/3 ($SMB_{(B/M)}$ + $SMB_{(OP)}$ + $SMB_{(INV)}$) $SMB_{(B/M)}$ = 1/3 (Small Value + Small Neutral + Small Growth) - 1/3 (Big Value + Big Neutral + Big Growth) $SMB_{(OP)}$ = 1/3 (Small Robust + Small Neutral + Small Weak) - 1/3 (Big Robust + Big Neutral + Big Weak) $SMB_{(INV)}$ = 1/3 (Small Conservative + Small Neutral + Small Aggressive) - 1/3 (Big Conservative + Big Neutral + Big Aggressive)	the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios
HML (High Minus Low)	1/2 (Small Value + Big Value) – 1/2 (Small Growth + Big Growth)	the average return on the two value portfolios minus the average return on the two growth portfolios. Basically, the two high B/M portfolios for a region minus the average of the returns for the two low B/M portfolios.
RMW (Robust Minus Weak)	1/2 (Small Robust + Big Robust) - 1/2 (Small Weak + Big Weak)	the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios
CMA (Conservative Minus Aggressive)	1/2 (Small Conservative + Big Conservative) - 1/2 (Small Aggressive + Big Aggressive)	the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios
Rm–Rf (excess market)		the return on a region's value-weight market portfolio minus the one month Euro short-term interest rate (from ECB).
MOM (Monthly momentum)	1/2 (Small High + Big High) – 1/2 (Small Low + Big Low)	the equal-weight average of the returns for the two winner portfolios for a region minus the average of the returns for the two loser portfolios
Data is from 2000 – 2019, taken daily, monthly and annually frequency. Countries: Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Great Britain, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Sweden Source: Library Keneth Fama/French		

Table A2.3: Additional factors Variable names, definition and description

Variable name	Variable definition	Variable description
HML^{Devil} (High Minus Low) †	$\frac{1}{2}$ (Small Value + Big Value) – $\frac{1}{2}$ (Small Growth + Big Growth)	the average return on the two value portfolios minus the average return on the two growth portfolios. Basically, the two high B/M portfolios for a region minus the average of the returns for the two low B/M portfolios. The book equity and the current market value of equity are calculated at the end of each month that rebalancing frequently the weights for the portfolios.
BAB (Betting Against Beta) †	$\frac{1}{b_t^L}(r_{t+1}^L - r_f) - \frac{1}{b_t^H}(r_{t+1}^H - r_f)$	the weighted returns from the two (low-high) betas portfolios which is long low-beta and short the high beta portfolio.
QMJ (Quality Minus Junk) †	$\frac{1}{2}$ (Small Quality + Big Quality) - $\frac{1}{2}$ (Small Junk + Big Junk)	the average return on the two Quality investment portfolios minus the average return on the two Junk investment portfolios
FEAR INDEX (VSTOXX)‡	The VSTOXX index is calculated from the implied volatility from different expiration day(30,60,360) options on the Euro stoxx 50. The variable is the change of price of this index	The index constructed from the expected volatility (or implied volatility) from the Euro vstoxx 50 options bid/ask quotes. We apply the change of this index to measure the levels of uncertainty.
Data is from European countries the period of 2000 – 2019, taken daily, monthly and annually frequency. †Source: Asness and Frazzini database ‡Source: Data Stream		

Table A2.4: Commodities Variable names, definition and description

Commodities	Variable description
Oil	The prices are from the Europe Brent Oil Spot Price Free on Board (Dollars Per Barrel).
Gold (XAU)	The gold price change from the amount of supply, demand, and investor behavior for the economic environment.
Aluminium (LME)	The aluminum price change from the amount of supply, demand, and investor behavior. Notably, we use the London Metal Exchange-Aluminium 99.7% Cash U$/MT has the historical LME prices and other data for all contracts traded on the Exchange available on the market.
Lumber (LB1)	The price is from the random length lumber futures on the CME.
The time-series data are from 1/1/2000 – 31/12/2019, taken daily but converted to a monthly frequency. Each commodity is transformed in the percentage rate. The commodity shows how much of the quote cost in euro currency to buy one unit. The data are collected from data stream and investing historical data.	

Table A2.5: Currency Variable names, definition and description

Exchange Rate	Variable definition	Variable description
U.S. Dollar (EURUSD)	EURUSD	The base currency is EUR and quote currency is USD
British Pound (EURGBP)	EURGBP	The base currency is EUR and quote currency is GBP
Japanese Yen (EURJPY)	EURJPY	The base currency is EUR and quote currency is JPY
Korean Won (EURKRW)	EURKRW	The base currency is EUR and quote currency is KRW
Chinese Yuan(EURCNY)	EURCNY	The base currency is EUR and quote currency is CNY
The time-series data are from 1/1/2000 – 31/12/2019, taken daily but converted to monthly frequency. Each currency is compared by 1 unit of Euro currency. The exchange rate shows how much of the quote currency is needed to buy one base currency unit. The data are collected from Eikon data stream.		

Table A2.6: First four moments of time-series classical factors

Period	**4th moments**	MKTRF	SMB	HML	RMW	CMA	MOM
2000-2009	Mean	0.2157	0.2808	1.0369	0.2431	0.6456	0.583
	Variance	31.8938	5.8499	7.8006	3.1746	5.4433	28.8496
	Skewness	-0.7150	-0.2492	0.2890	-0.2521	0.3066	-1.2397
	Kurtosis	1.8174	1.3917	2.9661	1.2966	2.0848	4.8051
2009-2019	Mean	0.5723	0.1730	-0.2422	0.3903	-0.05	0.9543
	Variance	22.1077	2.5565	5.1270	2.3882	1.2670	7.8426
	Skewness	-0.2237	0.1131	0.4236	-0.2796	0.1413	0.0602
	Kurtosis	0.3276	0.0580	-0.0704	-0.3309	0.0256	1.3830
2000-2019	Mean	0.394	0.2269	0.3974	0.3167	0.2978	0.7686
	Variance	26.9197	4.1886	6.8475	2.7752	3.4626	18.3039
	Skewness	-0.5562	-0.1453	0.4528	-0.2813	0.6534	-1.12778
	Kurtosis	1.4715	1.7404	1.9745	0.7472	3.7802	7.0922

The table shows the first four moments of the six factors within each of the two subperiods and the whole period. MKTRF, SMB, HML, CMA and RMW are the Fama-French market, Size, value, profitability, and investment factors; and MOM is the Carhart momentum factor. The results are expressed as percentages (%).

Table A2.7: First four moments of time-series additional macro-factors

Period	4^{th} moments	HML^{Devil}	BAB	QMJ	FEAR
2000-2009	Mean	1.001	1.33	0.52	1.4928
	Variance	0.14	0.20	0.08	377.5288
	Skewness	0.2475	-0.1838	-0.3164	1.4734
	Kurtosis	8.3661	0.6383	4.2059	3.2561
2009-2019	Mean	-0.40	0.71	0.63	1.0243
	Variance	0.04	0.04	0.04	387.4558
	Skewness	0.1499	0.1783	0.1739	0.5694
	Kurtosis	-0.4825	-0.0889	0.2477	0.1491
2000-2019	Mean	0.30	1.02	0.58	1.2585
	Variance	0.09	0.12	0.06	382.5471
	Skewness	0.6163	0.0006	-0.2014	1.0055
	Kurtosis	10.0138	1.9711	3.8053	1.6235

The table shows the first four moments of the four additional macro factors within each of the two subperiods and the whole period. HML^{Devil}, BAB, QMJ and FEAR INDEX are the alternative value, betting beta, quality and volatility factors. The results are expressed as percentages (%).

Table A2.8: First four moments of time-series commodities factors

Period	4^{th} moments	Oil	XAU	LME	LB1
2000-2009	Mean	1.1578	0.9447	0.5198	-0.0156
	Variance	132.6818	18.5857	36.1586	99.4060
	Skewness	-0.2096	0.5134	0.2022	0.3958
	Kurtosis	0.9508	0.7592	0.3493	0.2335
2009-2019	Mean	0.2376	0.4965	-0.0958	0.7359
	Variance	67.5711	21.9274	29.7042	79.5892
	Skewness	0.0071	0.1023	0.2448	0.1462
	Kurtosis	0.8095	0.8291	-0.1237	0.8018
2000-2019	Mean	0.6977	0.7206	0.2120	0.3602
	Variance	100.3382	20.3068	33.0261	89.6388
	Skewness	-0.1114	0.2680	0.2347	0.2772
	Kurtosis	1.2559	0.8136	0.1623	0.4345

The table shows the first four moments of the four factors within each of the two subperiods and the whole period. Oil, XAU, LME, and LB1 are commodities factors. The results are expressed as percentages (%).

Table A2.9: First four moments of time-series currency factors

Period	**4th moments**	EURUSD	EURGBP	EURJPY	EURKRW	EURCNY
2000-2009	Mean	0.3492	0.2826	0.2481	0.1478	0.3264
	Variance	9.0223	5.7042	10.9481	8.9145	12.7521
	Skewness	0.0969	1.2768	-0.8892	0.0227	1.0489
	Kurtosis	1.3208	8.6531	4.4673	1.3000	3.8117
2009-2019	Mean	-0.1083	-0.0814	-0.0968	-0.1923	-0.1288
	Variance	6.4482	4.4550	11.4099	5.9280	4.7807
	Skewness	-0.2491	0.4509	-0.2722	-0.3836	-0.0879
	Kurtosis	0.5350	0.8711	0.6048	0.3687	-0.0213
2000-2019	Mean	0.1204	0.1006	0.0756	-0.0223	0.0988
	Variance	7.7876	5.1127	11.2087	7.4502	8.8182
	Skewness	0.0077	0.9594	-0.5686	-0.0828	0.9934
	Kurtosis	1.1561	5.8017	2.3094	1.1596	4.7773

The table shows the first four moments of the six factors within each of the two subperiods and the whole period. EURUSD, EURGBP, EURJPY, EURKRW, and EURCNY are curremcy factors. The results are expressed as percentages (%).

Table A2.10: Correlation of the six factors the period 2000-2009

Variables	*Mkt-RF*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
Mkt-RF	1					
SMB	-0.07	1				
HML	0.03	-0.07	1			
RMW	-0.38	0.11	-0.36	1		
CMA	-0.40	-0.15	0.62	-0.06	1	
MOM	-0.50	0.25	-0.20	0.49	0.21	1

The table shows the correlation of the six factors within the period 2000-2009. MKTRF, SMB, HML, CMA and RMW are the Fama-French market, Size, value, profitability, and investment factors; and MOM is the Carhart momentum factor.

Table A2.11: Correlation of the four commodities factors the period 2000-2009

Variables	Lumber	Oil	LME	Gold
Lumber	1			
Oil	0.21	1		
LME	0.14	0.27	1	
Gold	-0.01	0.13	-0.03	1

The table shows the correlation of the 4 factors within period 2000-2009. Oil, Gold, LME, and LB1 are the returns of the commodities price.

Table A2.12: Correlation of the five currency factors the period 2000-2009

Variables	US/EUR	JAP/EUR	UK/EUR	KR/EUR	CHN/EUR
US/EUR	1				
JAP/EUR	0.59	1			
UK/EUR	0.60	0.32	1		
KR/EUR	0.97	0.59	0.59	1	
CHN/EUR	0.39	0.31	0.28	0.40	1

The table shows the correlation of the five currency factors within period 2000-2009. EURUSD, EURGBP, EURJPY, EURKRW, and EURCNY are the change of the exchange rates based on euro currency.

Table A2.13: Correlation for all factors the period 2000-2009

Variables	*Mkt-RF*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	*BAB*	*ML DEVI*	*QMJ*	*VSTOXX*	*US/EUR*	*JAP/EUR*	*UK/EUR*	*KR/EUR*	*CHN/EUR*	*Lumber*	*Brent*	*Aluminium*	*Gold*
Mkt-RF	1.00																		
SMB	-0.07	1.00																	
HML	0.03	-0.07	1.00																
RMW	-0.39	0.11	-0.35	1.00															
CMA	-0.40	-0.16	0.62	-0.07	1.00														
MOM	-0.50	0.24	-0.20	0.50	0.20	1.00													
BAB	-0.12	0.43	0.19	0.28	0.25	0.46	1.00												
HML II	0.19	-0.16	0.71	-0.52	0.35	-0.66	-0.18	1.00											
QMJ	-0.73	0.03	-0.25	0.71	0.28	0.74	0.45	-0.55	1.00										
VSTOXX	-0.59	0.10	0.06	0.32	0.32	0.36	0.38	-0.18	0.53	1.00									
US/EUR	0.47	0.05	0.08	-0.08	0.01	0.00	0.50	-0.05	-0.03	0.01	1.00								
JAP/EUR	0.39	0.06	0.05	0.01	-0.18	-0.03	0.32	-0.01	-0.07	-0.25	0.59	1.00							
UK/EUR	0.26	-0.15	0.12	-0.23	0.15	-0.04	0.07	0.01	-0.01	-0.16	0.60	0.32	1.00						
KR/EUR	0.53	0.01	0.09	-0.11	0.00	-0.04	0.47	-0.01	-0.07	-0.03	0.97	0.59	0.59	1.00					
CHN/EUR	-0.08	-0.05	-0.07	0.13	0.21	0.24	0.35	-0.12	0.34	0.15	0.39	0.31	0.28	0.40	1.00				
Lumber	0.21	0.05	-0.07	0.17	-0.04	-0.12	0.03	0.05	-0.07	-0.28	0.09	0.11	-0.03	0.10	-0.06	1.00			
Brent	0.21	0.29	-0.11	0.12	-0.30	0.03	0.21	-0.08	-0.05	-0.15	0.12	0.10	-0.10	0.11	-0.01	0.21	1.00		
Aluminium	0.41	0.12	0.05	-0.22	-0.24	-0.16	0.05	0.10	-0.34	-0.21	0.23	0.28	0.06	0.24	-0.14	0.14	0.27	1.00	
Gold	-0.20	0.15	-0.15	0.08	-0.03	0.26	0.07	-0.18	0.16	0.14	-0.15	-0.22	-0.20	-0.13	0.01	-0.01	0.13	-0.03	1.00

Table A2.14: Correlation of the six factors the period 2010-2019

Variables	*Mkt-RF*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
Mkt-RF	1					
SMB	-0.12	1				
HML	0.47	-0.04	1			
RMW	-0.41	-0.05	-0.82	1		
CMA	0.03	-0.10	0.57	-0.47	1	
MOM	-0.34	0.05	-0.44	0.42	-0.05	1

The table shows the correlation of the six factors within period 2010-2019. MKTRF, SMB, HML, CMA and RMW are the Fama-French market, Size, value, profitability, and investment factors; and MOM is the Carhart momentum factor.

Table A2.15: Correlation of the four commodities factors the period 2009-2019

Variables	Lumber	Oil	LME	Gold
Lumber	1			
Oil	0.20	1		
LME	0.12	0.34	1	
Gold	0.00	-0.02	0.11	1

The table shows the correlation of the 4 factors within period 2009-2019. Oil, XAU, LME, and LB1 are the returns of the commodities price.

Table A2.17: Correlation of the five currency factors the period 2009-2019

Variables	US/EUR	JAP/EUR	UK/EUR	KR/EUR	CHN/EUR
US/EUR	1				
JAP/EUR	0.67	1			
UK/EUR	0.45	0.21	1		
KR/EUR	0.90	0.63	0.52	1	
CHN/EUR	0.44	0.38	0.35	0.50	1

The table shows the correlation of the five currency factors within period 2009-2019. EURUSD, EURGBP, EURJPY, EURKRW, and EURCNY are the change of the exchange rates based on euro currency.

Table A2.18: Correlation for all factors the period 2009-2019

Variables	*Mkt-RF*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	*BAB*	*ML DEVI*	*QMJ*	*VSTOXX*	*US/EUR*	*JAP/EUR*	*UK/EUR*	*KR/EUR*	*CHN/EUR*	*Lumber*	*Brent*	*Aluminium*	*Gold*
Mkt-RF	1.00																		
SMB	-0.12	1.00																	
HML	0.47	-0.04	1.00																
RMW	-0.41	-0.05	-0.83	1.00															
CMA	0.03	-0.10	0.57	-0.46	1.00														
MOM	-0.33	0.04	-0.44	0.42	-0.05	1.00													
BAB	-0.06	0.25	-0.02	-0.02	0.13	0.23	1.00												
HML II	0.49	0.02	0.80	-0.62	0.40	-0.59	-0.15	1.00											
QMJ	-0.71	-0.08	-0.80	0.82	-0.23	0.55	0.16	-0.72	1.00										
VSTOXX	-0.67	0.32	-0.27	0.20	0.00	0.31	0.25	-0.24	0.41	1.00									
US/EUR	0.69	0.10	0.42	-0.35	0.10	-0.25	0.44	0.37	-0.46	-0.30	1.00								
JAP/EUR	0.64	-0.04	0.49	-0.42	0.13	-0.31	0.11	0.32	-0.51	-0.44	0.67	1.00							
UK/EUR	0.11	-0.01	0.17	-0.12	0.21	0.10	0.20	0.06	0.01	0.00	0.45	0.21	1.00						
KR/EUR	0.56	0.07	0.41	-0.35	0.10	-0.20	0.42	0.35	-0.39	-0.19	0.90	0.63	0.52	1.00					
CHN/EUR	0.09	0.10	0.21	-0.32	0.26	-0.10	0.34	0.01	-0.14	0.01	0.44	0.38	0.35	0.50	1.00				
Lumber	0.30	0.21	0.03	0.09	-0.10	0.00	-0.10	0.16	-0.11	-0.19	0.17	0.10	-0.05	0.05	-0.27	1.00			
Brent	0.44	0.02	0.25	-0.24	0.01	-0.25	-0.05	0.43	-0.37	-0.30	0.30	0.25	-0.07	0.22	0.06	0.20	1.00		
Aluminium	0.41	-0.04	0.26	-0.23	0.08	-0.16	-0.02	0.35	-0.32	-0.22	0.37	0.22	0.31	0.32	0.00	0.12	0.34	1.00	
Gold	0.78	-0.37	0.31	-0.26	-0.05	-0.35	-0.47	0.33	-0.57	-0.77	0.14	0.39	-0.21	0.03	-0.20	0.16	0.26	0.15	1.00

Table A2.19: Correlation of the six factors the period 2000-2019

Variables	*Mkt-RF*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*
Mkt-RF	1					
SMB	-0.09	1				
HML	0.19	-0.05	1			
RMW	-0.39	0.05	-0.54	1		
CMA	-0.27	-0.13	0.61	-0.18	1	
MOM	-0.44	0.19	-0.27	0.46	0.14	1

The table shows the correlation of the six factors within period 2000-2019. MKTRF, SMB, HML, CMA and RMW are the Fama-French market, Size, value, profitability and investment factors; and MOM is the Carhart momentum factor.

Table A2.20: Correlation of the four commodities factors the period 2000-2019

Variables	Lumber	Oil	LME	Gold
Lumber	1			
Oil	0.20	1		
LME	0.13	0.30	1	
Gold	-0.01	0.06	0.04	1

The table shows the correlation of the 4 factors within period 2000-2019. Oil, XAU, LME, and LB1 are the returns of the commodities price.

Table A2.21: Correlation of the five currency factors the period 2000-2019

Variables	US/EUR	JAP/EUR	UK/EUR	KR/EUR	CHN/EUR
US/EUR	1				
JAP/EUR	0.63	1			
UK/EUR	0.54	0.27	1		
KR/EUR	0.94	0.60	0.56	1	
CHN/EUR	0.40	0.33	0.30	0.44	1

The table shows the correlation of the five currency factors within period 2000-2019. EURUSD, EURGBP, EURJPY, EURKRW, and EURCNY are the change of the exchange rates based on euro currency.

Table A2.22: Correlation for all factors the period 2000-2019

Variables	*Mkt-RF*	*SMB*	*HML*	*RMW*	*CMA*	*MOM*	*BAB*	*HML II*	*QMJ*	*VSTOXX*	*US/EUR*	*JAP/EUR*	*UK/EUR*	*KR/EUR*	*CHN/EUR*	*Lumber*	*Brent*	*Aluminium*	*Gold*
Mkt-RF	1.00																		
SMB	-0.09	1.00																	
HML	0.19	-0.05	1.00																
RMW	-0.40	0.05	-0.54	1.00															
CMA	-0.27	-0.14	0.61	-0.18	1.00														
MOM	-0.44	0.19	-0.27	0.46	0.14	1.00													
BAB	-0.10	0.39	0.15	0.19	0.24	0.41	1.00												
HML II	0.26	-0.11	0.74	-0.53	0.39	-0.64	-0.15	1.00											
QMJ	-0.72	-0.01	-0.44	0.75	0.14	0.68	0.37	-0.58	1.00										
VSTOXX	-0.62	0.19	-0.08	0.27	0.20	0.32	0.32	-0.18	0.47	1.00									
US/EUR	0.56	0.07	0.23	-0.20	0.05	-0.08	0.47	0.09	-0.19	-0.13	1.00								
JAP/EUR	0.50	0.02	0.25	-0.19	-0.06	-0.12	0.24	0.11	-0.25	-0.35	0.63	1.00							
UK/EUR	0.19	-0.10	0.16	-0.18	0.18	0.00	0.11	0.04	0.00	-0.08	0.54	0.27	1.00						
KR/EUR	0.54	0.03	0.23	-0.21	0.04	-0.09	0.45	0.11	-0.19	-0.10	0.94	0.60	0.56	1.00					
CHN/EUR	-0.02	0.00	0.04	-0.03	0.23	0.15	0.35	-0.07	0.19	0.09	0.40	0.33	0.30	0.44	1.00				
Lumber	0.25	0.11	-0.04	0.14	-0.07	-0.08	-0.01	0.07	-0.08	-0.24	0.12	0.10	-0.04	0.08	-0.14	1.00			
Brent	0.30	0.21	0.03	-0.02	-0.21	-0.05	0.14	0.07	-0.16	-0.21	0.19	0.16	-0.08	0.15	0.01	0.20	1.00		
Aluminium	0.41	0.06	0.15	-0.22	-0.13	-0.16	0.03	0.18	-0.33	-0.21	0.30	0.25	0.18	0.27	-0.08	0.13	0.30	1.00	
Gold	-0.22	0.09	-0.21	0.18	-0.06	0.19	0.01	-0.11	0.20	0.20	-0.21	-0.37	-0.12	-0.19	-0.11	-0.01	0.06	0.04	1.00

Table A2.23: Terminology and portfolio construction

Portfolio Construction to Determine Fama-French Factors		
Small	Book to market (**B/M**)	Small High (**SH**) Small Neutral (**SN**) Small Low (**SL**)
	Profitability (**OP**)	Small Robust (**SR**) Small Neutral (**SN**) Small Weak (**SW**)
	Investment (**INV**)	Small Conservatice (**SC**) Small Neutral (**SN**) Small Agresive (**SA**)
Big	Book to market (**B/M**)	Big High (**BH**) Big Neutral (**BN**) Big Low (**BL**)
	Profitability (**OP**)	Big Robust (**BR**) Big Neutral (**BN**) Big Weak (**BW**)
	Investment (**INV**)	Big Conservatice (**BC**) Big Neutral (**BN**) Big Agresive (**BA**)

Source: Library Keneth Fama/French[9] and Erdinç, Y. (2018). "Comparison of CAPM, Three-Factor Fama-French Model, and Five-Factor Fama-French Model for the Turkish Stock Market."

Equation A1.24: Relationship of simple returns.

The stock returns are derived by the aggregation from daily to a multi-period (monthly) performance return. The aggregation in monthly data for (simple) returns is defined as (1.8):

$$r_{i,t}^{j} = \left(\frac{P_{i,t_2} - P_{i,t_1}}{P_{i,t_1}} + 1\right) \ldots\ldots \left(\frac{P_{i,t_2} - P_{i,t_2}}{P_{i,t_2}} + 1\right) - 1 = \frac{P_{i,t_2}}{P_{i,t_1}} * \frac{P_{i,t_3}}{P_{i,t_2}} * \ldots\ldots * \frac{P_{i,t_k}}{P_{i,t_{k-1}}} - 1 = \frac{P_{i,t_k}}{P_{i,t_1}} - 1$$

(1.8)

Table A2.25: Empirical results of the extension models in the Green returns including the period 2000-2019 and the sub-periods ex and post EU crisis.

Green R. Factors	*2000-2009 Ex-ante EU crisis*				*2009-2019 Post-ante EU crisis*				*2000-2019 Full period*			
alpha	0.18	0.18	0.28	**0.45**	**-0.49**	**-0.44**	**-0.47**	-0.14	**-0.31**	**-0.31**	**-0.26**	**-0.10**
MktRf	**0.97**	**0.98**	**0.91**	**0.76**	**1.00**	**1.02**	**0.96**	**0.84**	**0.98**	**1.00**	**0.95**	**0.80**
SMB	**0.59**	**0.60**	**0.54**	**0.48**	**0.85**	**0.84**	**0.81**	**0.75**	**0.71**	**0.71**	**0.68**	**0.62**
HML	0.13	0.12	0.05		**0.36**	**0.31**	**0.32**		**0.27**	**0.25**	**0.23**	
MOM		-0.01		**0.15**		**-0.09**		-0.02		-0.03		**0.07**
RMW	0.12	0.12	**0.27**	**0.55**	-0.07	-0.04	-0.05	0.03	0.01	0.03	0.1	**0.3**
CMA	0.11	0.12	0.18	-0.02	-0.11	-0.05	-0.1	-0.05	0.08	0.1	0.13	0.14
BAB			0.05	0.11			0.09	0.01			0.03	0.02
HML ^{DEVIL}				0.12				0.2				0.13
QMJ			-0.25	**-0.76**			-0.17	**-0.4**			-0.15	**-0.55**
FEAR	-0.01		-0.01	0.01	-0.01		-0.01	**-0.02**	-0.01		-0.01	**-0.01**
US/EUR				**-0.79**				**0.32**				**0.21**
JAP/EUR				**0.12**				-0.07				0.03
UK/EUR				**0.44**				0.12				**0.17**
KR/EUR				**0.7**				-0.11				-0.05
CHN/EUR				-0.05				0.09				0.04
Lumber				0.02				-0.01				0.002
Brent				-0.001				-0.03				-0.01
Aluminium				**-0.06**				0.02				-0.01
Gold				0.02				0.05				**0.05**
R^2-within	17.6%	17.6%	17.6%	18.1%	14.5%	14.5%	14.5%	14.7%	15.5%	15.5%	15.5%	15.7%
R^2-between	1.81%	1.83%	1.91%	0.75%	1.41%	1.44%	1.46%	3.57%	2.77%	2.74%	2.78%	3.79%
R^2-overall	17.4%	17.4%	17.4%	17.9%	14.3%	14.4%	14.4%	14.6%	15.4%	15.4%	15.4%	15.6%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, MOM, HML(Devil), FEAR, BAB, QML, four commodities and five currencies factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and Asness & Frazzini library. The results report dependent variables as simple returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Table A2.26: Empirical results of the extension models in the Grey returns including the period 2000-2019 and the sub-periods ex and post EU crisis.

Grey R. Factors	*2000-2009 Ex-ante EU crisis*				*2009-2019 Post-ante EU crisis*				*2000-2019 Full period*			
alpha	**0.23**	**0.25**	**0.29**	**0.30**	**-0.06**	-0.01	-0.05	**0.16**	0.04	**0.07**	**0.11**	**0.22**
MktRf	**0.89**	**0.86**	**0.88**	**0.78**	**0.86**	**0.87**	**0.81**	**0.75**	**0.88**	**0.87**	**0.85**	**0.75**
SMB	**0.65**	**0.68**	**0.69**	**0.76**	**0.78**	**0.78**	**0.72**	**0.65**	**0.68**	**0.70**	**0.67**	**0.69**
HML	**-0.38**	**-0.42**	**-0.42**		**0.17**	**0.12**	**0.13**		**-0.22**	**-0.26**	**-0.27**	
MOM		**-0.07**		**-0.04**		**-0.08**		**-0.10**		**-0.08**		**-0.08**
RMW	**-0.53**	**-0.46**	**-0.38**	**-0.37**	**0.06**	**0.08**	**0.18**	**0.24**	**-0.41**	**-0.36**	**-0.28**	**-0.14**
CMA	**0.08**	**0.15**	**0.17**	**-0.18**	**0.08**	**0.14**	**0.08**	**0.14**	**0.06**	**0.13**	**0.13**	**-0.04**
BAB			**-0.05**	**-0.14**			**0.14**	**0.09**			-0.00	**-0.08**
HML ^{DEVIL}				**-0.13**				**-0.07**				**-0.17**
QMJ			**-0.14**	-0.04			**-0.19**	**-0.39**			**-0.17**	**-0.21**
FEAR	**0.01**		**0.01**	0.001	**-0.01**		**-0.01**	**-0.01**	-0.00		-0.00	**-0.01**
US/EUR				**0.25**				**0.22**				**0.32**
JAP/EUR				**-0.12**				-0.02				**-0.08**
UK/EUR				-0.01				**0.17**				**0.08**
KR/EUR				0.001				**-0.17**				**-0.11**
CHN/EUR				**0.04**				**0.09**				**0.04**
Lumber				**0.03**				**0.01**				**0.02**
Brent				**-0.02**				**-0.01**				**-0.01**
Aluminium				**-0.02**				**-0.02**				**-0.01**
Gold				**-0.02**				**0.02**				0.01
R^2-within	17.7%	17.7%	17.7%	17.8%	13.2%	13.2%	13.2%	13.4%	15.1%	15.1%	15.1%	15.3%
R^2-between	13.1%	12.5%	12.6%	12.2%	0.55%	0.53%	0.53%	0.68%	0.93%	0.91%	0.9%	1.09%
R^2-overall	17.6%	17.6%	17.6%	17.7%	13%	13.1%	13.1%	13.2%	15%	15%	15%	15.2%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, MOM, HML(Devil), FEAR, BAB, QML, four commodities and five currencies factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and Asness & Frazzini library. The results report dependent variables as simple returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

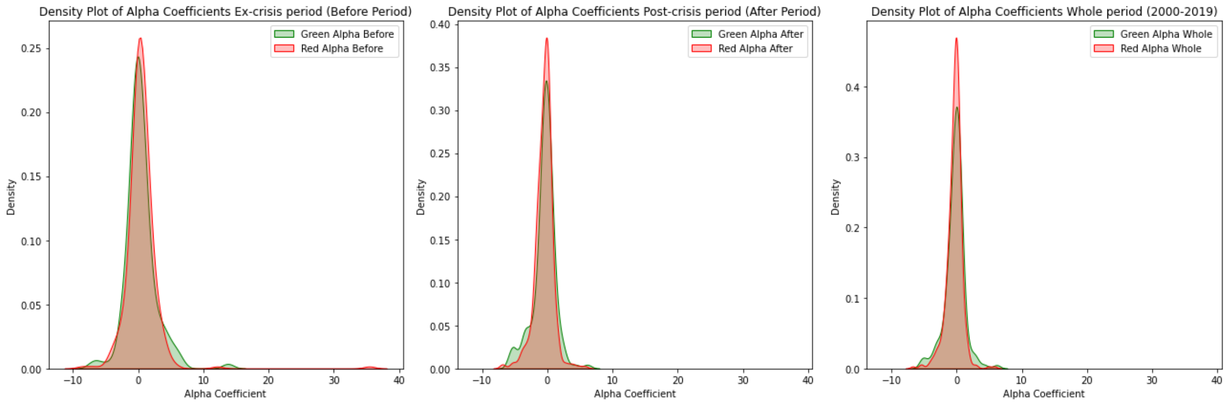
Table A2.27: Empirical results of the extension models in the Red returns including the period 2000-2019 and the sub-periods ex and post EU crisis.

Red R. Factors	*2000-2009 Ex-ante EU crisis*				*2009-2019 Post-ante EU crisis*				*2000-2019 Full period*			
alpha	0.12	0.11	**0.22**	-0.20	**-0.59**	**-0.48**	**-0.56**	**-0.27**	**-0.41**	**-0.42**	**-0.43**	**-0.44**
MktRf	**0.84**	**0.85**	**0.71**	**0.80**	**0.94**	**0.93**	**0.89**	**0.65**	**0.88**	**0.89**	**0.84**	**0.71**
SMB	**0.69**	**0.67**	**0.43**	**0.43**	**0.59**	**0.62**	**0.52**	**0.37**	**0.67**	**0.66**	**0.55**	**0.42**
HML	**0.21**	**0.24**	**0.14**		**0.41**	**0.33**	**0.36**		**0.37**	**0.37**	**0.34**	
MOM		**0.05**		**0.16**		**-0.14**		0.04		0.01		**0.13**
RMW	**0.33**	**0.29**	**0.23**	**0.16**	0.12	**0.15**	**0.27**	0.12	**0.23**	**0.22**	**0.16**	0.08
CMA	0.09	0.04	-0.05	**-0.17**	0.08	**0.18**	0.10	-0.02	**0.13**	**0.12**	0.05	0.03
BAB			**0.29**	**0.21**			**0.13**	**0.12**			**0.18**	**0.12**
HML ^{DEVIL}				**0.44**				**0.59**				**0.47**
QMJ			**-0.18**	0.04			**-0.23**	-0.19			-0.05	-0.08
FEAR	-0.00		**-0.02**	-0.01	0.00		0.00	**-0.01**	-0.00		**-0.01**	**-0.01**
US/EUR				-0.05				**0.38**				**0.32**
JAP/EUR				-0.04				-0.03				-0.01
UK/EUR				0.06				0.03				-0.01
KR/EUR				0.03				**-0.16**				**-0.16**
CHN/EUR				**0.05**				0.02				**0.06**
Lumber				-0.00				0.02				0.01
Brent				**0.5**				**0.10**				**0.09**
Aluminium				-0.02				0.02				0.01
Gold				-0.01				0.03				**0.03**
R^2-within	19.3%	19.4%	19.8%	20.4%	11.7%	11.8%	11.8%	12.7%	13.7%	13.7%	13.8%	14.6%
R^2-between	24.2%	22.9%	19.9%	20.4%	1.39%	1.11%	1.45%	1.74%	12.1%	12.1%	11.8%	13.5%
R^2-overall	19.2%	19.2%	19.7%	20.3%	11.6%	11.7%	11.7%	12.6%	13.7%	13.7%	13.8%	14.6%

The table shows the alpha and beta value of the MktRf, SMB, HML, MOM, RMW, CMA, MOM, HML(Devil), FEAR, BAB, QML, four commodities and five currencies factors from the random effect regression (after winsorization). The global factors are collected from the Kenneth R. French data library, DataStream and Asness & Frazzini library. The results report dependent variables as simple returns. The table reports the results from the extensions models and the last 3 rows are the R squared for within, between, and overall. Numbers in bold are significantly greater than zero with 95% confidence. The results are expressed as percentages (%) and round on 2nd decimal. The use of robust standard errors is not changing the significance level that we mentioned in our table (below and over 5%).

Figure A3.1: Density plot for the risk adjusted alphas of monthly excess returns from 3FFM for the Green & Red assets

(i) Alpha’s density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha’s density plots Ex-crisis, Post-crisis & Whole period for each Category

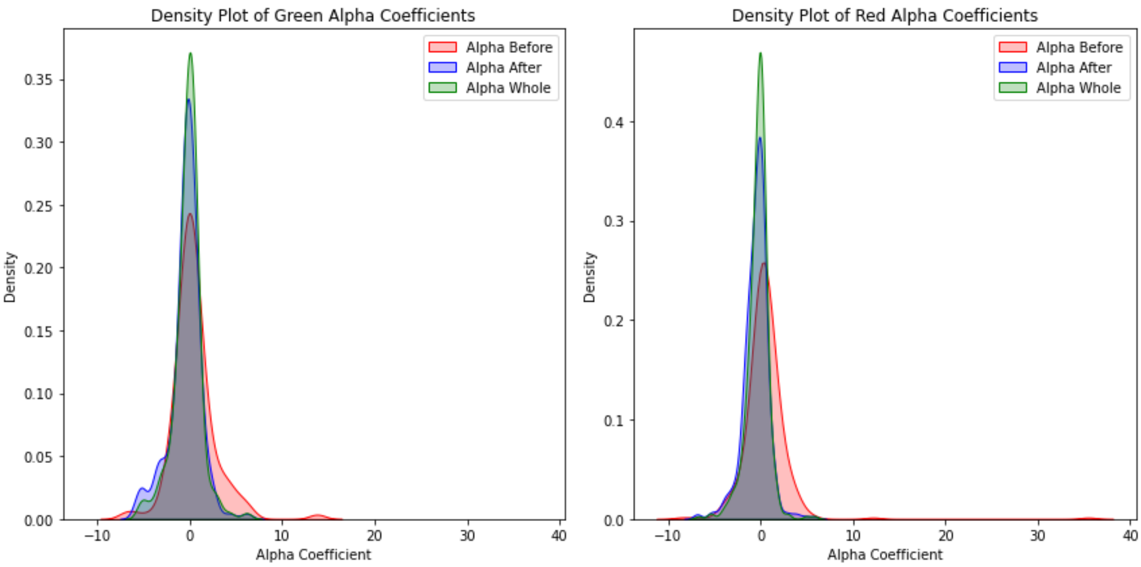
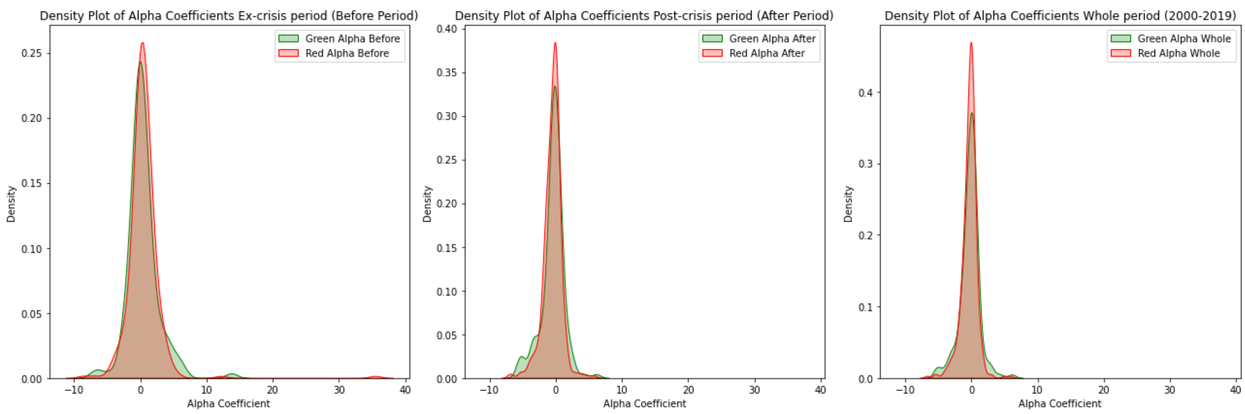


Figure A3.2: Density plot for the risk adjusted alphas of monthly excess returns from 4CM for the Green & Red assets

(i) Alpha’s density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha’s density plots Ex-crisis, Post-crisis & Whole period for each Category

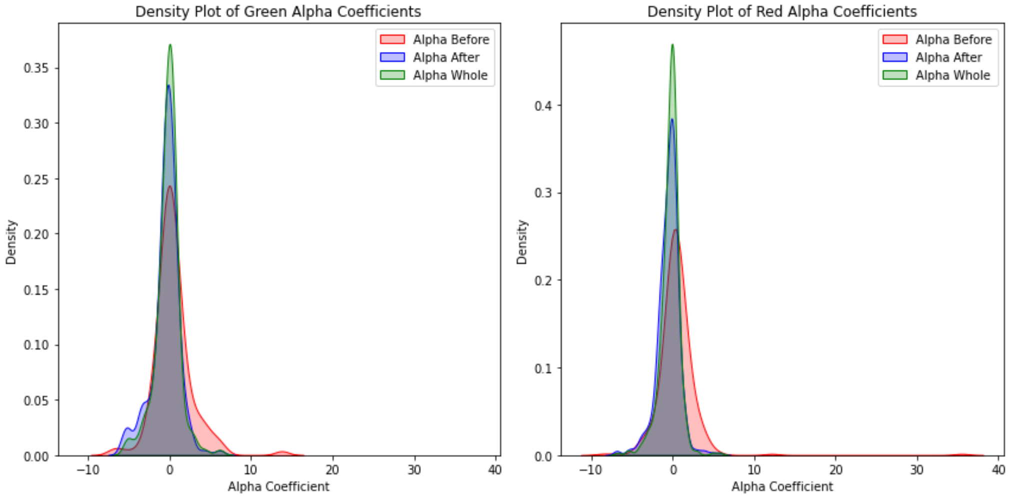
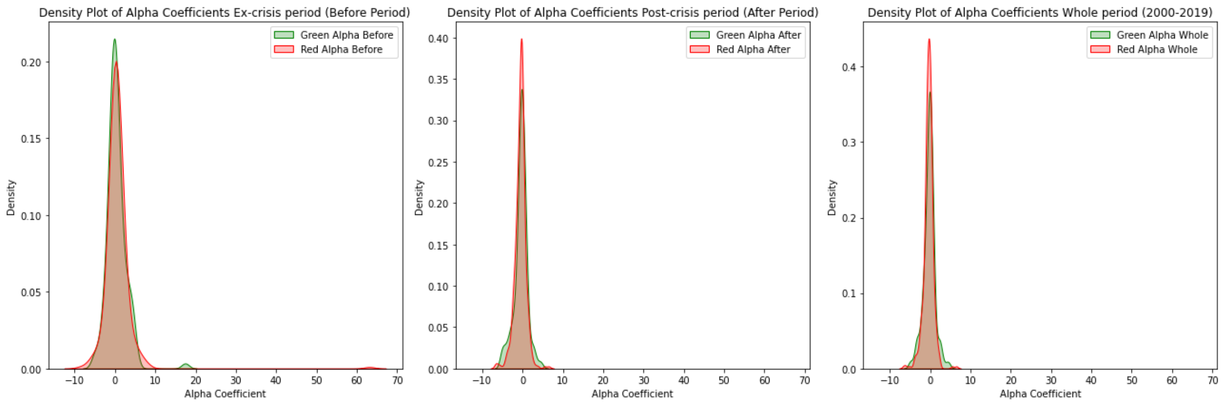


Figure A3.3: Histogram and Density plot for the adjusted alphas of monthly excess returns from 5FF for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

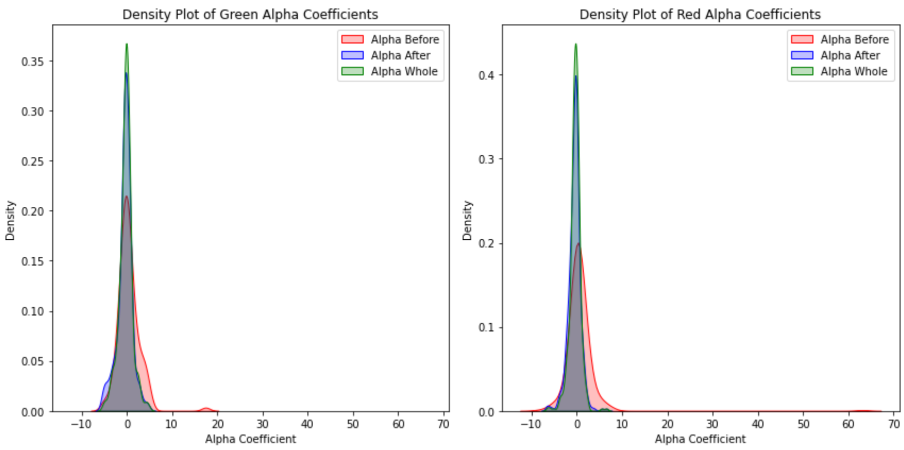
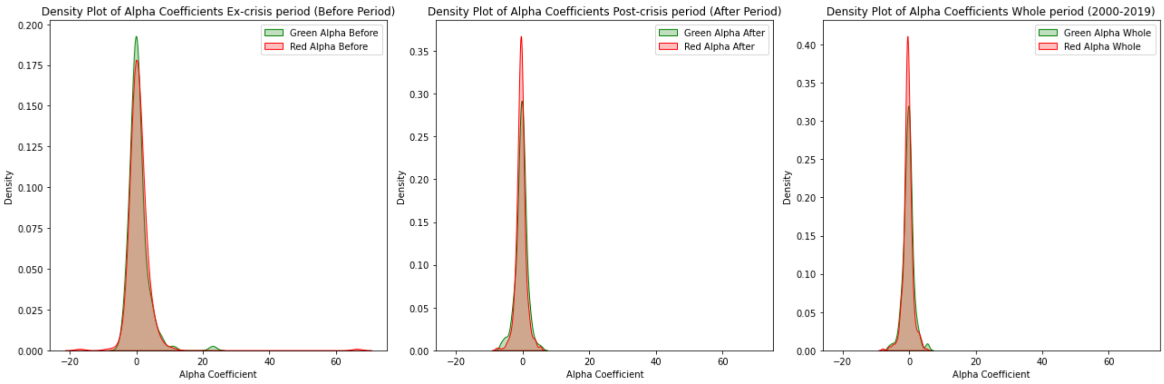


Figure A3.4: Density plot for the adjusted alphas of monthly excess returns from 3FF +QMJ+BAB for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

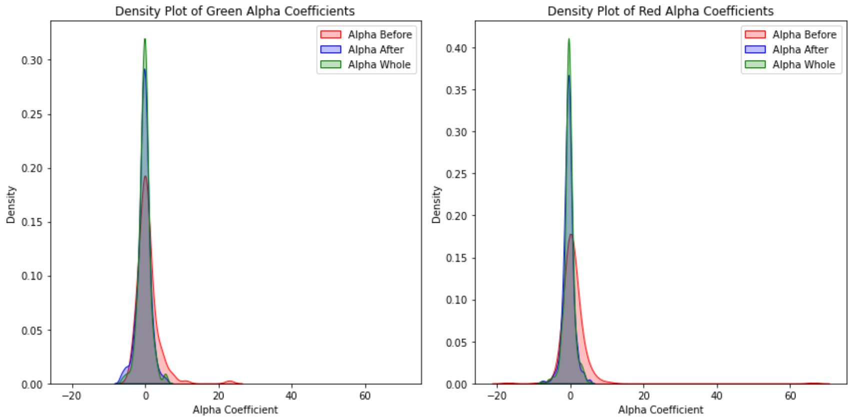
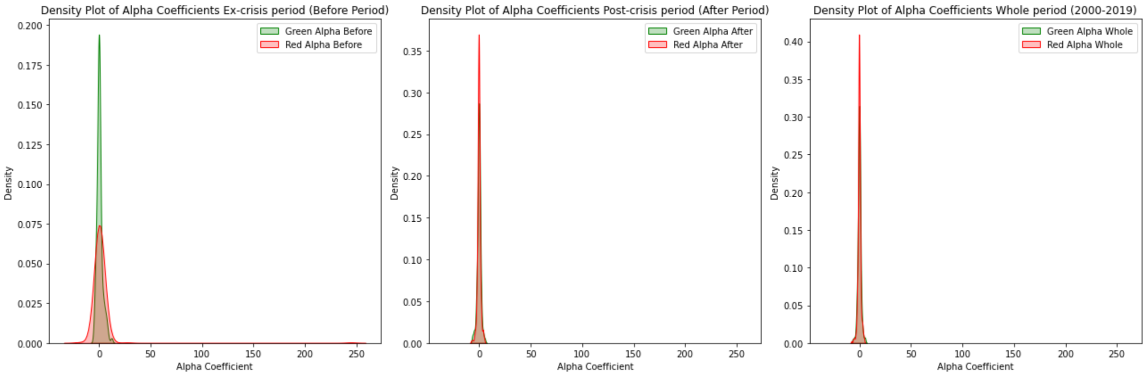


Figure A3.5: Density plot for the adjusted alphas of monthly excess returns from 4CM +QMJ+BAB for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

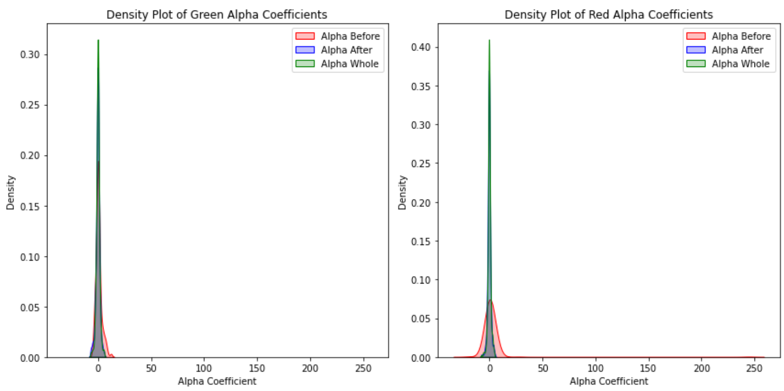
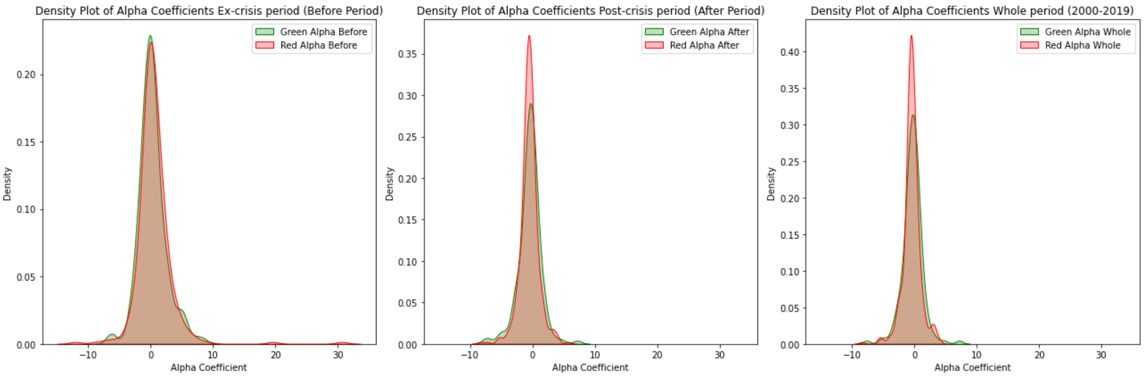


Figure A3.6: Density plot for the adjusted alphas of monthly excess returns from 5FF +QMJ+BAB for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

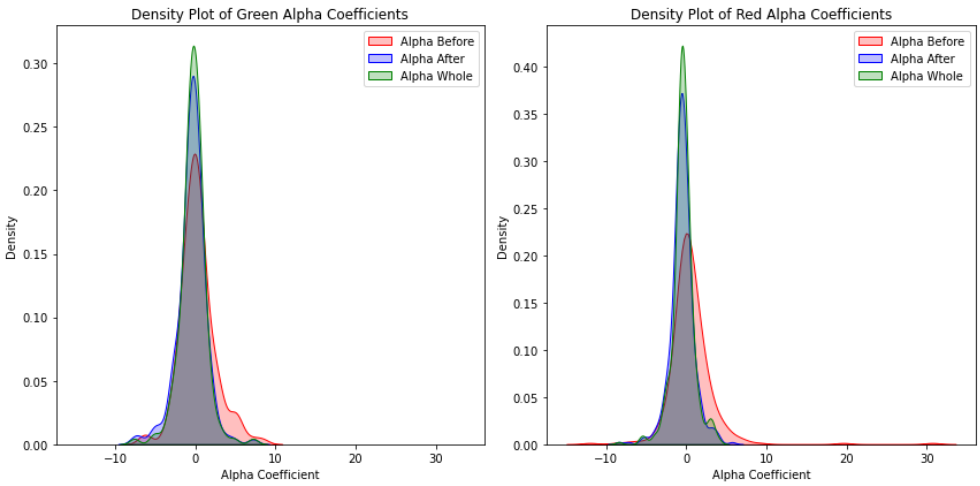
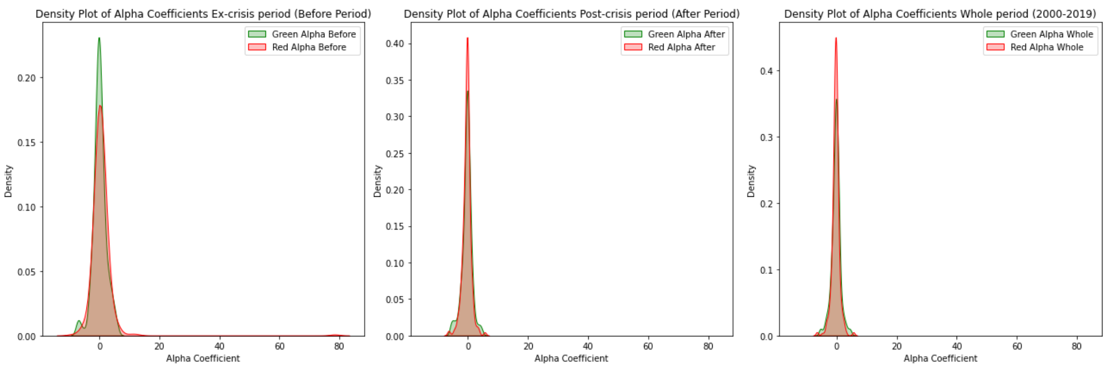


Figure A3.7: Density plot for the adjusted alphas of monthly excess returns from 5FF +MOM for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

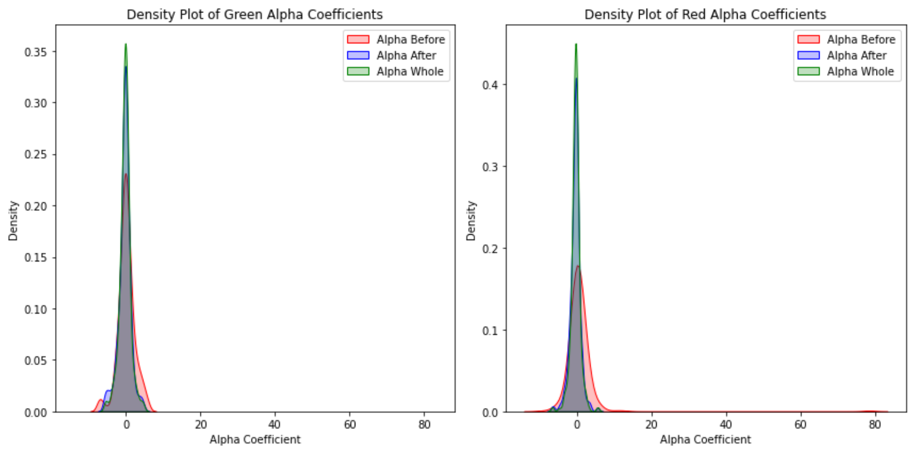
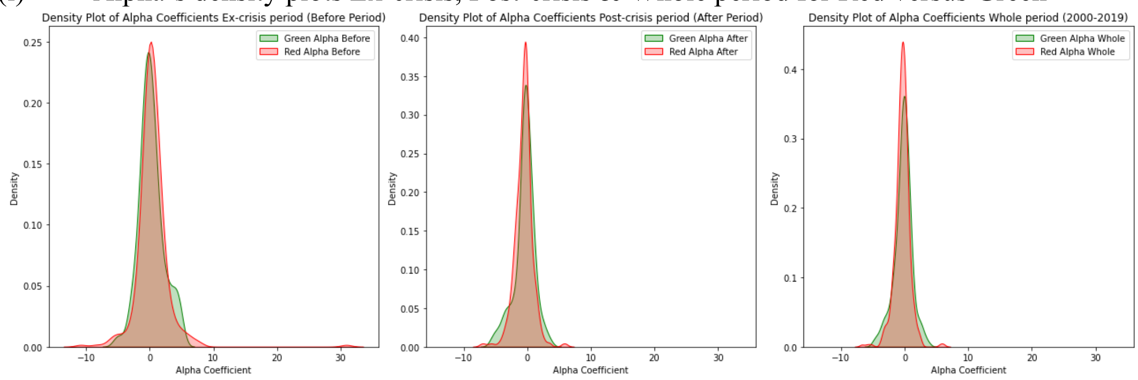


Figure A3.8: Density plot for the adjusted alphas of monthly excess returns from 5FF +FEAR for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

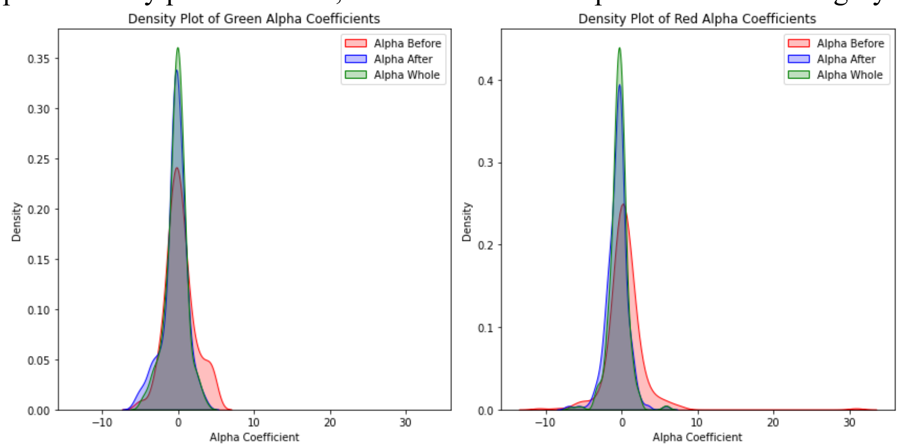
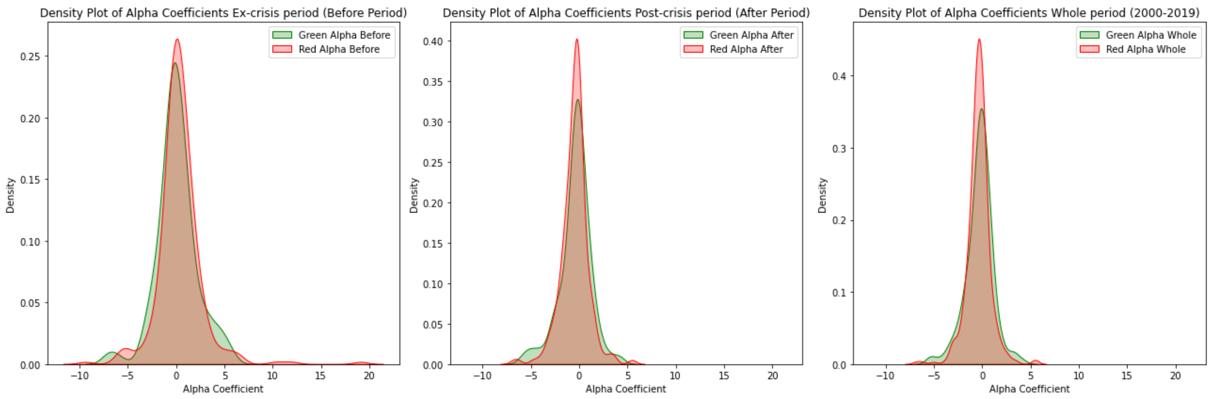


Figure A3.9: Density plot for the adjusted alphas of monthly excess returns from 5FF+FEAR+MOM for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

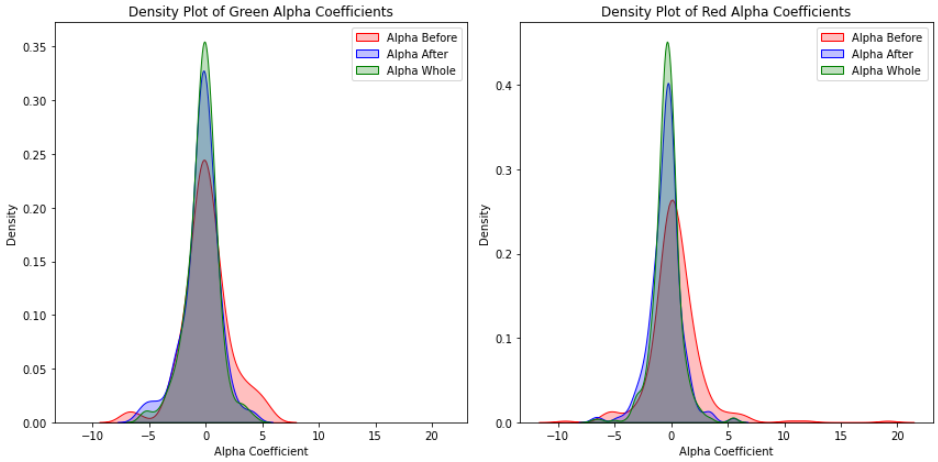
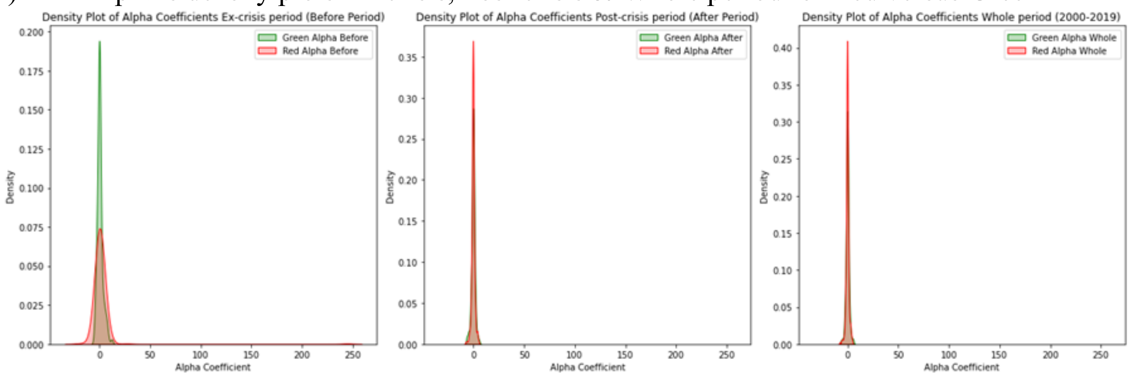


Figure A3.10: Density plot for the adjusted alphas of monthly excess returns from 5FF +UK/EUR for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

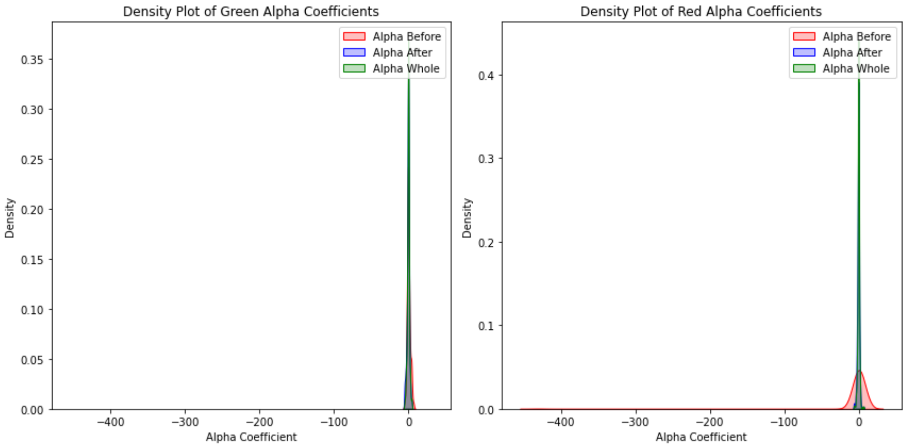
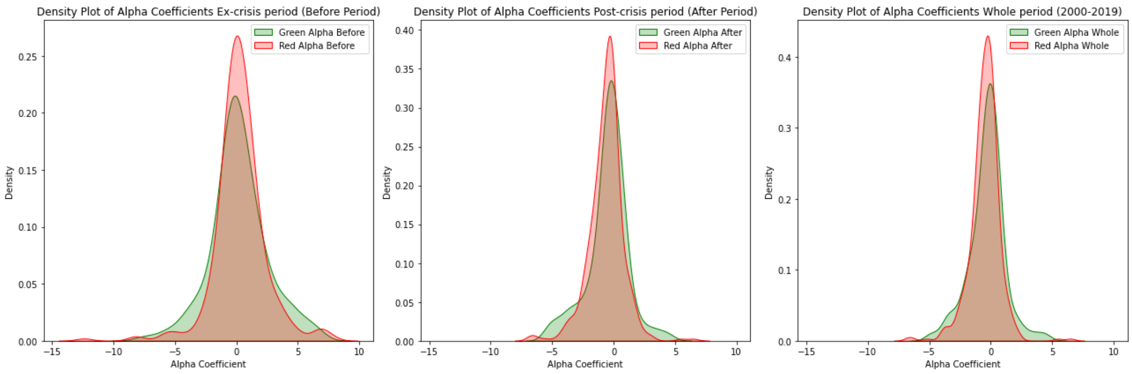


Figure A3.11: Density plot for the adjusted alphas of monthly excess returns from 5FF + GOLD for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha's density plots Ex-crisis, Post-crisis & Whole period for each Category

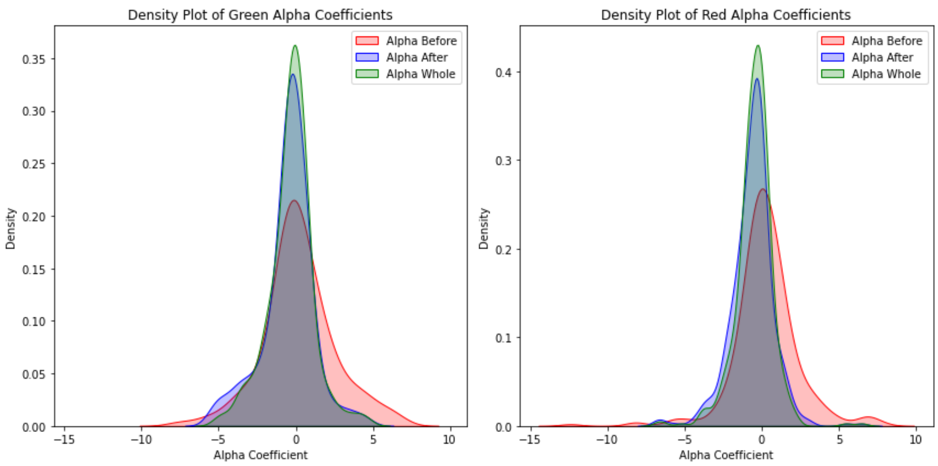
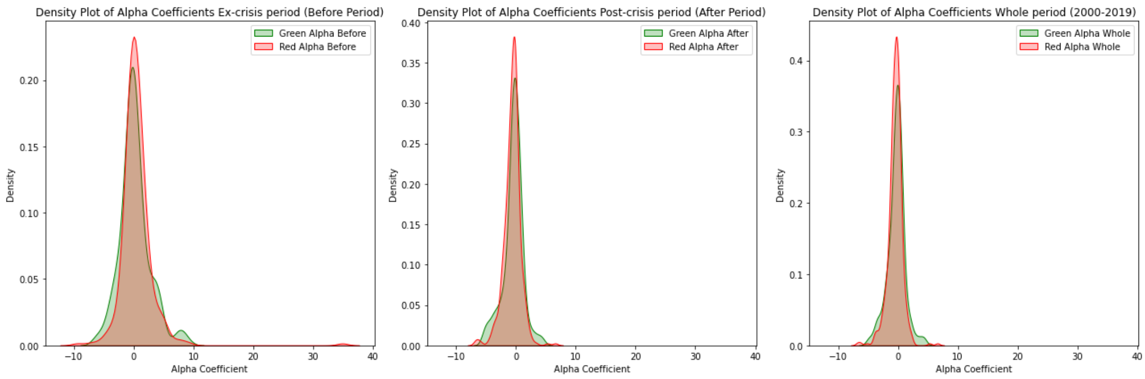


Figure A3.12: Density plot for the adjusted alphas of monthly excess returns from 5FF+UK/EUR +GOLD for the Green & Red assets

(i) Alpha's density plots Ex-crisis, Post-crisis & Whole period for Red versus Green



(ii) Alpha’s density plots Ex-crisis, Post-crisis & Whole period for each Category

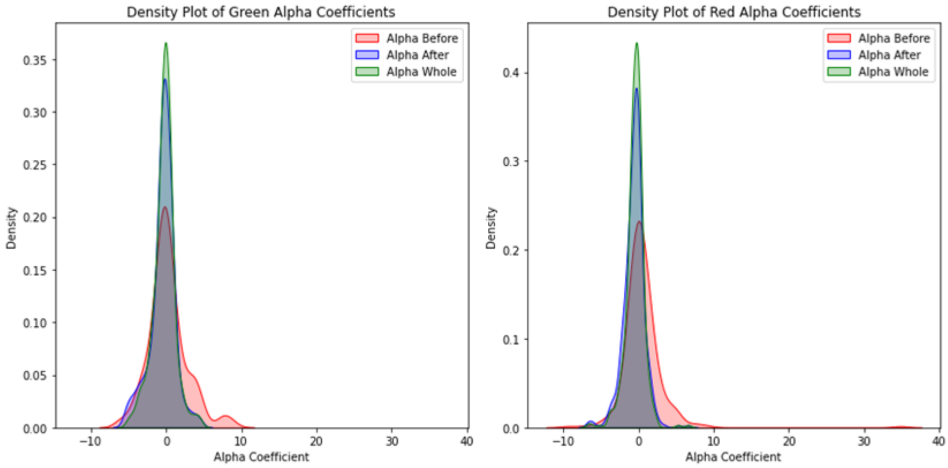


Table A4.1: EU crisis events

Country	Main Issue	Period	Sources
Iceland	Banking and Financial Crisis	October 2008 - December 2009	Ólafsson (2011); Benediktsdóttir et al. (2017); wikipedia: 2008–2011 Icelandic financial crisis
Greece	Debt Crisis and Austerity Measures	April 2009 - Bail out	Lapavitsas & Sergis (2014); Kouretas et al (2010); wikipedia: Greek government-debt crisis
Ireland	Banking Crisis and Property Market Collapse	January 2010 - December 2010	McCann, et al (2014); McArdle (2012); wiki: Irish property bubble
Portugal	Debt Crisis and Economic Challenges	March 2010 - 2014	Perelman et al. (2014); wikipedia: 2010–2014 Portuguese financial crisis
Spain	Banking Crisis and Property Market Collapse	April 2012 - Bail out	Gentier, (2012); wikipedia: 2008–2014 Spanish financial crisis
Cyprus	Banking Crisis and Debt Contagion	June 2012 - March 2013	Zenios (2013); wikipedia: 2012–2013 Cypriot financial crisis
Italy	High Debt, Slow Growth, and Market Pressure	January 2008 - Ongoing	Romano (2021); wikipedia: 2008 Italian government crisis
Ukraine	Political Crisis and Conflict (Russian Annexation of Crimea, War in Eastern Ukraine)	February 2014 - Ongoing	Bock et al. (2015); wikipedia: Russo-Ukrainian War
United Kingdom	Brexit Referendum and Decision to Leave the EU	June 2016 - December 2019	Jones (2021); Kanwal (2022); wikipedia: Brexit
Global	Lehman Brothers Collapse and Global Financial Crisis	September 2008 - Ongoing	Mawutor (2014); wikipedia: Bankruptcy of Lehman Brothers
Europe	European Immigration Crisis Began	2011 - Ongoing	Minteh, Binneh (2016); Heidenreich et al (2019)
Europe	Europe Migration Crisis and Refugee Inflow	2015 - 2016	Heidenreich et al (2019); wikipedia: 2015 European migrant crisis

Source: Research articles and Wikipedia sources

Table A4.2: Impact of sentiment: Author Name, Market Analyzed, Time period and Conclusion.

Author(s)	Market(s) Analyzed	Time Period	Conclusion
Da et al (2011)	US stock market	2004-2010	Using Google search volume data to create investor crisis attention.
Vozlyublennaia et al (2014)	Various security indexes in broad investment categories	2012-2013	Investigated the relationship between investor attention index and security index performance. Found that higher investor attention correlated with increased short-term volatility.
Da et al (2015)	US stock market	2010-2014	Demonstrated that Google search activity can predict US stock market activity. Increased search volume was associated with subsequent market movements.
Bijl et al(2016)	US stock market	2013-2015	Confirmed the predictive nature of Google search activity for the US stock market. Identified that spikes in search volume preceded price fluctuations.
Kostopoulos et al(2020)	German market	2016-2019	Extended predictive analysis to the German market. Found a positive relationship between search volume and stock price movements in Germany.
Bank et al (2011)	US stock market	2008-2010	Established internet search volume as a proxy for overall firm recognition, capturing investor attention. Firms with higher search volumes experienced increased trading activity.
Takeda et al (2014)	Japanese equities market	2010-2013	Explored the association between Japanese equities returns and Google search volume. Found a significant link between search activity and subsequent stock returns in Japan.

Table A4.3: Cross-sectional averages of time-series moments for monthly excess simple returns from the two categories before and after winsorization

Asset Class		Green Securities Returns	Grey Securities Returns	Red Securities Returns
Period	Summary stats			
2004-2019 Entire	Mean	0.48	0.59	0.34
	Variance	195.53	138.85	175.19
	Skewness	1.28	1.44	1.55
	Kurtosis	8.66	14.94	16.60
	Min	-57.59	-74.13	-73.97
	Max	140.12	275.62	233.94
	T; n	162; 150	162; 2007	162; 367
9/2008-2019 crisis	Mean	0.11	0.55	0.05
	Variance	197.43	144.56	192.38
	Skewness	1.19	1.51	1.61
	Kurtosis	8.12	16.17	16.69
	Min	-57.59	-74.13	-73.97
	Max	140.12	275.62	233.94
	T; n	106; 150	106; 2007	106; 367
2004-8/2008 pre-crisis	Mean	1.94	0.74	1.43
	Variance	185.54	119.73	109.15
	Skewness	1.71	1.11	1.05
	Kurtosis	11.10	8.40	8.45
	Min	-51.06	-59.44	-53.39
	Max	131.09	172.48	107.79
	T; n	56; 121	56; 1615	56; 279

The table shows the first four moments of Green, Grey and Red returns (in percentage, %) and the minimum and maximum after the winsorization returns within the three subperiods. The table includes the results from before and after winsorization at 95% and the number of cross-sectional (n) securities, and the total months include every security (T). The time window is spitted in 3 periods: ex-Global Crisis period (1/2004 till 08/2008), Global Crisis and after (9/2008 till 12/2019), and the entire period (1/2004 till 12/2019).

Table A4.4: First four moments of the time-series factors

i: First four moments of time-series classical factors

Period	4^{th} moments	MKTRF	SMB	HML	RMW	CMA	FEAR
2004-2019 (Entire)	Mean	0.58	0.18	-0.02	0.36	0.03	1.28
	Variance	25.75	3.01	4.54	2.10	1.69	390.06
	Skewness	-0.69	-0.06	0.41	-0.26	0.64	1.12
	Kurtosis	2.09	0.19	0.90	0.53	2.03	2.06
09/2008-2019 (Crisis)	Mean	0.48	0.16	-0.22	0.43	0.03	1.12
	Variance	31.25	3.11	5.94	2.65	1.94	423.34
	Skewness	-0.61	0.07	0.61	-0.36	0.66	1.01
	Kurtosis	1.64	0.07	0.36	0.11	1.87	1.77
2004-8/2008 (Pre-Crisis)	Mean	0.84	0.25	0.48	0.17	0.04	1.69
	Variance	12.32	2.75	0.79	0.72	1.07	261.25
	Skewness	-0.81	-0.41	-0.04	0.00	0.46	0.00
	Kurtosis	0.77	0.78	-0.27	-0.34	1.43	-1.20

The table shows the first four moments of the six factors within each of the four subperiods and the whole period. MKTRF, SMB, HML, CMA and RMW are the Fama-French Market, Size, value, profitability, and investment factors; and FEAR is the implied volatility factor. The results are expressed as percentages (%). The time window is spitted in 3 periods: ex-Global Crisis period (1/2004 till 08/2008), Global Crisis and after (9/2008 till 12/2019), and the entire period (1/2004 till 12/2019).

ii: First four moments of crisis sentimental factors

Period	4th moments	AVG FEARS	PCA FEARS	US CRISIS	EU CRISIS	RGEPU
2004-2019 (Entire)	Mean	0.09	0.02	0.60	0.62	2.44
	Variance	92.84	2.77	136.26	136.56	388.29
	Skewness	0.02	0.15	4.33	4.28	1.33
	Kurtosis	0.31	0.73	29.27	29.01	3.75
09/2008-2019 (Crisis)	Mean	0.80	0.10	2.83	2.91	2.64
	Variance	88.86	2.55	150.92	150.87	421.33
	Skewness	-0.10	0.08	4.80	4.76	1.42
	Kurtosis	0.86	1.70	30.54	30.34	4.19
2004-8/2008 (Pre-Crisis)	Mean	-1.66	-0.16	-4.82	-4.96	1.95
	Variance	98.21	3.26	59.18	57.97	307.72
	Skewness	0.33	0.35	1.48	1.47	0.94
	Kurtosis	-0.41	-0.64	1.11	1.10	1.39

The table shows the first four moments of the 4 crisis factors within each of the four subperiods and the whole period. FEARS and CSI factor are crisis sentimental factors and the results are expressed as percentages (%). The time window is spitted in 3 periods: ex-Global Crisis period (1/2004 till 08/2008), Global Crisis and after (9/2008 till 12/2019), and the entire period (1/2004 till 12/2019).

Table A4.5: Correlation of the six factors

i: Correlation matrix for the period 1/2004-8/2008 (Pre-Crisis)

Variables	FEAR	Mkt-RF	SMB	HML	RMW	CMA
FEAR	100%	-44.55%	20.34%	-23.72%	2.99%	17.16%
Mkt-RF	-44.55%	100%	18.47%	31.06%	-5.60%	-32.79%
SMB	20.34%	18.47%	100%	32.74%	-14.16%	-0.05%
HML	-23.72%	31.06%	32.74%	100%	-48.91%	10.71%
RMW	2.99%	-5.60%	-14.16%	-48.91%	100%	-26.39%
CMA	17.16%	-32.79%	-0.05%	10.71%	-26.39%	100%

ii: Correlation matrix for the period 9/2008-12/2019 (Crisis period)

Variables	FEAR	Mkt-RF	SMB	HML	RMW	CMA
FEAR	100%	-65.45%	15.84%	-23.39%	19.24%	16.57%
Mkt-RF	-65.45%	100%	-4.12%	51.73%	-42.86%	-21.36%
SMB	15.84%	-4.12%	100%	-3.83%	-8.61%	-21.97%
HML	-23.39%	51.73%	-3.83%	100%	-82.39%	34.50%
RMW	19.24%	-42.86%	-8.61%	-82.39%	100%	-32.32%
CMA	16.57%	-21.36%	-21.97%	34.50%	-32.32%	100%

iii: Correlation matrix for the period 1/2004-12/2019

Variables	FEAR	Mkt-RF	SMB	HML	RMW	CMA
FEAR	100%	-61.15%	16.97%	-22.11%	16.29%	16.68%
Mkt-RF	-61.15%	100%	0.38%	49.27%	-38.47%	-23.13%
SMB	16.97%	0.38%	100%	1.02%	-9.49%	-16.97%
HML	-22.11%	49.27%	1.02%	100%	-79.67%	31.09%
RMW	16.29%	-38.47%	-9.49%	-79.67%	100%	-31.21%
CMA	16.68%	-23.13%	-16.97%	31.09%	-31.21%	100%

The table shows the correlation (%) of the six factors within the periods 1/2004-8/2008, 9/2008-12/2019, and 1/2004-12/2019. MKTRF, SMB, HML, CMA and RMW are the Fama-French Market, Size, value, profitability, and investment factors; and FEAR is the implied volatility factor.

Table A4.6: Correlation of the six sentimental crisis factors

i: Correlation matrix for the period 1/2004-8/2008 (Pre-Crisis)

Variables	avg FEARS	PCA FEARS	CSI US	CSI EU	GEPU	RGEPU
avg FEARS	100%	86.49%	18.11%	16.28%	8.79%	-16.22%
PCA FEARS	86.49%	100%	15.29%	14.01%	13.47%	-7.51%
CSI US	18.11%	15.29%	100%	99.84%	67.52%	13.11%
CSI EU	16.28%	14.01%	99.84%	100%	67.75%	13.19%
GEPU	8.79%	13.47%	67.52%	67.75%	100%	43.56%
RGEPU	-16.22%	-7.51%	13.11%	13.19%	43.56%	100%

ii: Correlation matrix for the period 9/2008-12/2019 (Crisis Period)

Variables	avg FEARS	PCA FEARS	CSI US	CSI EU	GEPU	RGEPU
avg FEARS	100%	90.78%	9.18%	9.31%	12.38%	28.24%
PCA FEARS	90.78%	100%	15.62%	15.89%	15.39%	41.53%
CSI US	9.18%	15.62%	100%	99.95%	-6.79%	11.32%
CSI EU	9.31%	15.89%	99.95%	100%	-6.89%	11.41%
GEPU	12.38%	15.39%	-6.79%	-6.89%	100%	31.71%
RGEPU	28.24%	41.53%	11.32%	11.41%	31.71%	100%

iii: Correlation matrix for the entire period 1/2004-12/2019

Variables	avg FEARS	PCA FEARS	CSI US	CSI EU	GEPU	RGEPU
avg FEARS	100%	89.31%	13.74%	13.52%	15.88%	16.24%
PCA FEARS	89.31%	100%	16.46%	16.40%	15.09%	27.40%
CSI US	13.74%	16.46%	100%	99.94%	18.37%	11.51%
CSI EU	13.52%	16.40%	99.94%	100%	18.79%	11.57%
GEPU	15.88%	15.09%	18.37%	18.79%	100%	25.18%
RGEPU	16.24%	27.40%	11.51%	11.57%	25.18%	100%

The table shows the correlation (%) of the six sentimental factors within the periods 1/2004-8/2008, 9/2008-12/2019, and 1/2004-12/2019. AVG FEARS, PCA FEARS, US CSI, EU CSI, GEPU and RGEPU factors.

Table A4.7: Correlation of the six sentimental crisis factors and the six proxy portfolios factors

i: Correlation matrix for the period 1/2004-8/2008

Variables	FEAR	Mkt-RF	SMB	HML	RMW	CMA	A.FEARS	PCA FEARS	CSI US	CSI EU	GEPU	RGEPU
FEAR	100%	-44.5%	20.3%	-23.7%	3.0%	17.2%	18.3%	16.2%	-3.7%	-4.0%	3.3%	5.2%
MktRF	-44.5%	100.0%	18.5%	31.1%	-5.6%	-32.8%	-12.9%	-18.1%	-33.3%	-33.0%	-30.2%	-18.9%
SMB	20.3%	18.5%	100.0%	32.7%	-14.2%	-0.1%	-8.7%	-9.6%	-35.5%	-35.4%	-26.5%	-21.1%
HML	-23.7%	31.1%	32.7%	100.0%	-48.9%	10.7%	0.0%	0.8%	-34.9%	-34.9%	-15.9%	-10.7%
RMW	3.0%	-5.6%	-14.2%	-48.9%	100.0%	-26.4%	17.0%	10.4%	9.0%	8.7%	-13.7%	-13.6%
CMA	17.2%	-32.8%	-0.1%	10.7%	-26.4%	100.0%	-2.1%	-1.7%	11.0%	11.4%	5.0%	9.0%
A.FEARS	18.3%	-12.9%	-8.7%	0.0%	17.0%	-2.1%	100.0%	86.5%	18.1%	16.3%	8.8%	-16.2%
PCA FEARS	16.2%	-18.1%	-9.6%	0.8%	10.4%	-1.7%	86.5%	100.0%	15.3%	14.0%	13.5%	-7.5%
CSI US	-3.7%	-33.3%	-35.5%	-34.9%	9.0%	11.0%	18.1%	15.3%	100.0%	99.8%	67.5%	13.1%
CSI EU	-4.0%	-33.0%	-35.4%	-34.9%	8.7%	11.4%	16.3%	14.0%	99.8%	100.0%	67.8%	13.2%
GEPU	3.3%	-30.2%	-26.5%	-15.9%	-13.7%	5.0%	8.8%	13.5%	67.5%	67.8%	100%	43.6%
RGEPU	5.2%	-18.9%	-21.1%	-10.7%	-13.6%	9.0%	-16.2%	-7.5%	13.1%	13.2%	43.6%	100%

ii: Correlation matrix for the period 9/2008-12/2019

Variables	FEAR	Mkt-RF	SMB	HML	RMW	CMA	A.FEARS	PCA FEARS	CSI US	CSI EU	GEPU	RGEPU
FEAR	100.0%	-65.4%	15.8%	-23.4%	19.2%	16.6%	3.9%	9.8%	17.2%	17.0%	1.8%	24.9%
Mkt-RF	-65.4%	100.0%	-4.1%	51.7%	-42.9%	-21.4%	-26.0%	-30.5%	-36.9%	-37.2%	-10.5%	-34.6%
SMB	15.8%	-4.1%	100.0%	-3.8%	-8.6%	-22.0%	-15.6%	-15.3%	-15.8%	-16.1%	-18.0%	-13.3%
HML	-23.4%	51.7%	-3.8%	100.0%	-82.4%	34.5%	-14.3%	-16.8%	-14.9%	-15.2%	-7.0%	-13.1%
RMW	19.2%	-42.9%	-8.6%	-82.4%	100.0%	-32.3%	15.0%	19.4%	22.6%	22.9%	3.4%	14.9%
CMA	16.6%	-21.4%	-22.0%	34.5%	-32.3%	100.0%	7.1%	7.3%	29.8%	29.7%	5.4%	28.9%
A.FEARS	3.9%	-26.0%	-15.6%	-14.3%	15.0%	7.1%	100.0%	90.8%	9.2%	9.3%	12.4%	28.2%
PCA FEARS	9.8%	-30.5%	-15.3%	-16.8%	19.4%	7.3%	90.8%	100.0%	15.6%	15.9%	15.4%	41.5%
CSI US	17.2%	-36.9%	-15.8%	-14.9%	22.6%	29.8%	9.2%	15.6%	100.0%	100.0%	-6.8%	11.3%
CSI EU	17.0%	-37.2%	-16.1%	-15.2%	22.9%	29.7%	9.3%	15.9%	100.0%	100.0%	-6.9%	11.4%
GEPU	1.8%	-10.5%	-18.0%	-7.0%	3.4%	5.4%	12.4%	15.4%	-6.8%	-6.9%	100.0%	31.7%
RGEPU	24.9%	-34.6%	-13.3%	-13.1%	14.9%	28.9%	28.2%	41.5%	11.3%	11.4%	31.7%	100.0%

iii: Correlation matrix for the entire period 1/2004-12/2019

Variables	FEAR	Mkt-RF	SMB	HML	RMW	CMA	avg FEARS	PCA FEARS	CSI US	CSI EU	GEPU	RGEPU
FEAR	100.0%	-61.2%	17.0%	-22.1%	16.3%	16.7%	7.5%	11.4%	12.3%	12.1%	0.6%	20.3%
Mkt-RF	-61.2%	100.0%	0.4%	49.3%	-38.5%	-23.1%	-22.9%	-27.0%	-35.7%	-35.8%	-11.2%	-31.6%
SMB	17.0%	0.4%	100.0%	1.0%	-9.5%	-17.0%	-13.8%	-13.7%	-19.2%	-19.4%	-15.4%	-15.2%
HML	-22.1%	49.3%	1.0%	100.0%	-79.7%	31.1%	-13.0%	-14.0%	-19.9%	-20.3%	-15.2%	-12.4%
RMW	16.3%	-38.5%	-9.5%	-79.7%	100.0%	-31.2%	15.6%	17.3%	22.4%	22.6%	7.0%	10.4%
CMA	16.7%	-23.1%	-17.0%	31.1%	-31.2%	100.0%	4.7%	4.8%	25.4%	25.3%	3.7%	24.7%
avg FEARS	7.5%	-22.9%	-13.8%	-13.0%	15.6%	4.7%	100.0%	89.3%	13.7%	13.5%	15.9%	16.2%
PCA FEARS	11.4%	-27.0%	-13.7%	-14.0%	17.3%	4.8%	89.3%	100.0%	16.5%	16.4%	15.1%	27.4%
CSI US	12.3%	-35.7%	-19.2%	-19.9%	22.4%	25.4%	13.7%	16.5%	100.0%	99.9%	18.4%	11.5%
CSI EU	12.1%	-35.8%	-19.4%	-20.3%	22.6%	25.3%	13.5%	16.4%	99.9%	100.0%	18.8%	11.6%
GEPU	0.6%	-11.2%	-15.4%	-15.2%	7.0%	3.7%	15.9%	15.1%	18.4%	18.8%	100.0%	25.2%

RGEPU	20.3%	-31.6%	-15.2%	-12.4%	10.4%	24.7%	16.2%	27.4%	11.5%	11.6%	25.2%	100.0%

The table shows the correlation (%) of the six sentimental factors and the six proxy portfolios factors within the periods 1/2004-8/2008, 9/2008-12/2019, and 1/2004-12/2019. AVG FEARS, PCA FEARS, US CSI, EU CSI, GEPU and RGEPU factors. MKTRF, SMB, HML, CMA and RMW are the Fama-French Market, Size, value, profitability, and investment factors; and FEAR is the implied volatility factor.