How do style factors behave in times of crisis in Europe?

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Introduction

With the current economic situation and the different events happening in the last few years, the subject of economic turmoil and financial crises is a topic that is interesting to approach. Indeed, with Covid 19 hitting Europe at the beginning of 2020 and now the war in Ukraine, which has been going on for just over a year, these are typical issues that impact countries' economic and financial situations.

These unexpected events also bring uncertainty and completely change the picture for investment decisions and strategies. Investors know that economic events can significantly impact the return on their investment; this is why they try to react according to financial market conditions. Indeed, for many years, investors have tried to outperform the market with different strategies that can be short or long-term, active or passive. Furthermore, to protect against uncertainty, confident investors base their investment on style factors that explain the risk premium of the asset's returns.

Fama and French (1993) were among the first digging this subject, and they came up with their Fama French three-factor model composed of the market risk, size, and value. They conducted extensive empirical research to identify factors that consistently explain the variations in stock returns beyond the classical Capital Asset Pricing Model. Following their findings, more and more studies have been carried out on factors, leading to the discovery of many new factors. To take advantage of these different factors, investors started investing across styles to outperform the market by allocating their investment strategy to specific style factors. Style investing is an investment approach that selects stocks or other assets based on particular characteristics.

Several articles have already worked on the behavior of style factors in times of uncertainty and their interaction with certain macroeconomic factors. On the other hand, a few kinds of research have been carried on, on the European market. Indeed, most articles have focused on the US or global market. Nevertheless, the European region has faced various crises, from economic downturns and sovereign debt crises to geopolitical tensions or global pandemics. Each crisis has presented unique challenges and opportunities for investors, with style factors reacting differently to market conditions.
In addition, it can be interesting to know how to allocate the weight among factors in a portfolio to generate a higher return in the European market. These different interrogations led me to the question: "How do style factors behave in times of crisis in Europe?"

The main objective of this thesis is to analyze six fundamental style factors, which are size (SMB), value (HML), market (MKT), investment (CMA), profitability (RMW), and momentum (UMD) in crisis and general periods. Furthermore, macroeconomic variables will be used to check their possible impact on the different portfolios based on the style factors. Finally, based on the results, a portfolio strategy linked to exposure to macroeconomics will be developed to verify whether the different empirical analyses carried out make economic sense.

The first step will be the theory and literature review to lay the groundwork. Indeed, the first section of the literature review will be devoted to the theoretical framework relating to the evolution and emergence of asset pricing theory, the different multifactor models, and the emergence of many factors. In the second section, the theoretical framework will be related to the types of financial crises, and how to identify them.

Following the theoretical framework, the data section will describe the period under analysis, the economic variables, the style-based portfolios, and select periods of financial crises. Then, the methodology section will first expose the macroeconomic factor model with all the variables retained for the empirical analysis. In addition, a second part will describe how the model will be applied to have varying exposure on the entire period under analysis. Finally, to finalize the methodology and before the results, hypotheses will be formulated based on the literature on the behavior of style-based portfolios with economic variables.

After the methodology description, results will be laid out for all style-based portfolios. Then, the discussion section will discuss the deeper interpretation and the opposition to the initial hypotheses. Furthermore, in this section, an application of the results to the creation of a portfolio strategy to check whether there is any economic interpretation. The final remarks, study limitations noticed, and conclusion will be given to finalize this work.

Literature review

1. Toward style investing and multifactor models

1.1. Modern portfolio theory and the CAPM

The modern portfolio theory developed by Harry Markowitz (1952) in his work on portfolio selection is a methodology to construct of asset that maximizes the expected return given a level of risk. Markowitz suggested that a portfolio's return variance can measure the risk.

So according to Markowitz (1952), all securities portfolios now have a given risk level given the return level. Therefore, if an investor wants to bear riskier assets in his portfolio, he should be rewarded with more return, which is the same in the other way. Indeed, an investor who does not want to hold risky assets in his portfolio will be rewarded with less return. This means that the decision on the portfolio an investor wants to own depends only on his aversion to the risk (Markovitz, 1952).

In terms of risk there are two types of risk. First, systematic risk is a macro-level risk that affects many assets to one degree or another. This is also known as market risk or volatility. Then the unsystematic risk or idiosyncratic risk is attributed to specific characteristics of assets. Indeed, Markowitz (1952) showed that a portfolio's risk level is lower than the weighted sum of the variance of its individual securities. This highlights that weighting a portfolio with individual securities properly could improve a portfolio's risk-adjusted return.

Another essential step in the modern portfolio theory is the Tobin separation theorem, which shows that an investor can control the risk of his portfolio by either leverage (i.e., borrowing) or lending money at a risk-free rate. Indeed, if an investor wants to invest more in risky assets and thinks the return will be higher than risk-free, he can borrow the money to invest. However, on the other hand, if the investor prefers to temper risk, he can lend money and be sure to be rewarded with a risk-free rate (Tobin, 1958).

This combination of risk/return can be plotted on a graph called the efficient frontier. The efficient frontier represents that set of portfolios with the maximum rate of return for every given level of risk or the minimum risk for every level of return. The efficient frontier comprises a portfolio of several securities instead of individual assets except for the highest return and lowest risk assets.

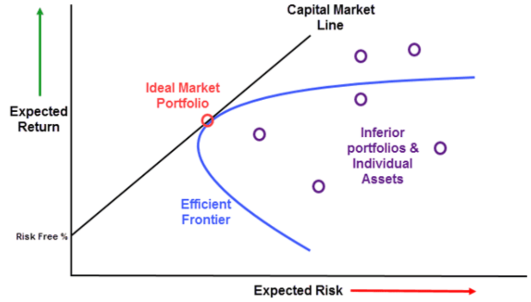

Figure 1: Modern Portfolio Theory

Later, Sharpe (1964) developed an essential step of the modern portfolio theory that will outgrowth the model of Markowitz. This capital asset pricing model considers the risk-free asset because
it is uncorrelated with all other risky investments. Then the objective was to combine this risk-free asset with a risky portfolio, which is known under the capital allocation line. The capital market line represents all the possible combinations of risk-free assets (e.g., Treasury bills) and risky assets (e.g., equities) that might be possible. Then the capital market line is a particular case of the capital allocation line because the CML will intercept the efficient frontier and result in the most efficient portfolio, the tangency portfolio (i.e., the ideal market portfolio in Figure 1). For this portfolio, the return can be maximized for a given level of risk (Sharpe, 1964).

In the CAPM, a beta coefficient measures the sensitivity to the market. Since the risk-free rate is uncorrelated with the market, they claim that the risk-free asset has a 0 beta and the market portfolio has a beta of 1. The market portfolio is a theoretical bundle of investments that regroup every asset type in the investment universe. Therefore, the expected return of this market is expected to replicate the market's expected return as a whole. The beta represents the proportion in which a given asset will fluctuate for a movement of 1 of the market. This is no more than the correlation between an investment and the market and is computed as follows:

$$\beta_i = \frac{Cov\,(R_i, R_m)}{\sigma_M^2}$$

Where:
R_i: is the return of the asset i
R_m: is the return of the market portfolio
σ_M^2 : Variance of the return of the market portfolio

The CAPM shows that a risk premium will reward investing in a risky individual asset. Indeed, it considers only one risk factor: market risk. This risk premium is, therefore, a function of the beta and the market risk premium. The market risk premium is expressed as the excess return of the market portfolio compared to the risk-free asset. The market risk premium comes from the fact that the risk cannot be diversified (in contrast to unsystematic risk), so this needs to be rewarded (Sharpe, 1964).

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

Where:
$E(R_i)$: is the expected return of the asset i
R_f: risk free rate
β_i: Beta of the asset i
$E(R_m)$: Expected return of the market portfolio
$(E(R_m) - R_f)$: is the market risk premium

1.2. Arbitrage pricing theory

Later on, the Arbitrage Pricing Theory (APT) was developed by Ross (1976). APT and CAPM assumed a linear relationship between the asset's expected return and its sensitivity to another variable.
These other variables could be economic variables such as GDP or inflation, which can be interesting for the analysis of this thesis.

CAPM assumed only one factor, which is the market risk. In contrast, the APT brings a multifactor asset pricing model based on the idea that the return can be predicted using the relationship between the asset's expected return and several systemic risk variables.

While CAPM relies on the efficient market hypothesis assumption, the APT assumes that sometimes it might be mispriced. So then, APT is an alternative to the CAPM that uses fewer assumptions. Find the below the form of the APT, which can be represented as a n factor model (Ross, 1976).

$$R_i = E(R_i) + \beta_1 * F_1 + \beta_2 * F_2 + \ \dots + \beta_n * F_n + \varepsilon_i$$

Where:
R_i: is the return of the asset I
$E(R_i)$: is the expected return of the asset i
F_1,F_2, … , F_n: are the factors explaining the asset return
β_1, β_2, … , β_n: are the beta of the asset i regarding the factor 1,2, …, n

Furthermore, one of the main limitations of the arbitrage pricing theory is that the model does not define any factor and leaves the choice of the different factors to the investor. In the following years, this led to several creations of multifactor models and the discovery of systemic factors.

1.3. Market anomalies

Fama (1970) defined the efficient market as a market with large numbers of rational profit-maximizing individuals actively competing with each other and attempting to predict future market values of individual securities. According to the efficient market hypothesis, prices of stocks reflect all available information, and the price of the securities quickly adjusts given the new information.

Then, Fama (1970) categorized market efficiency into three forms: strong, semi-strong, and weak. In the weak form, stock prices reflect all past information, including historical prices and returns. This suggests that no one can predict future price movements based on past information, and technical analysis is considered ineffective. However, fundamental analysis or private information like insider trading can still achieve abnormal returns.
In the semi-strong form, stock prices incorporate past information and all publicly available information. This means that analyzing publicly accessible information alone cannot give investors an advantage in beating the market or earning abnormal returns. Only private information, such as insider trading, could lead to outperforming the market. Finally, in the strong form of market efficiency, stock prices incorporate

all relevant information, including past, public, and private information. If the strong form holds, it implies that no one can beat the market in any way, not even through insider trading or fundamental analysis. This form suggests that stock prices quickly and accurately reflect all available information, leaving no room for investors to outperform the market (Fama, 1970) consistently.

Even if the findings of Fama (1970) were significant finding in the literature, there are still movements in the market that are inconsistent with the efficient market hypothesis. These market movements are called market anomalies and are mostly discovered from patterns in historical data. Market anomalies can be divided into three categories: fundamental, technical, and calendar.

Calendar anomalies are related to a particular period, such as on a day-to-day or month-to-month basis. One of the most common is the weekend effect which states that the closing price is likely to be lower on Monday than the closing price on Friday (Smirlock & Starks, 1986). Another well-known anomaly is the January effect, which shows that some firms generate higher returns in the year's first two months (Keim, 1983).

Technical anomalies refer to using past information to derive future stock prices. Indeed, they try to find patterns past patterns to make forecasts. Let us explain it with two examples: the use of the moving average and the trading range break. The moving average is used when the short moving average goes below the long period moving average; this is perceived as a signal for selling stock and buying if it is oppositely. On the other hand, the trading range break is based on resistance and support levels. A buy signal is when the prices reach the resistance level, and a selling signal is when the prices reach the support level (Brock et al., 1992).

The fundamental anomalies are the most important ones, including the value and size effects. The value effect states that the stock with a low price-to-book ratio has higher returns than the high price-to-book ratio. The size effect is also well known and assumed that stocks with small market capitalization performed better than stocks with a high market capitalization (Fama & French, 1993,1996). Since this is one of the essential parts of this work, this topic will be covered in detail later in the thesis.

1.4. Fundamental Multifactor Models

In the previous section, fundamental anomalies were discussed, which Fama and French (1993) used to lay the foundation of the Fama-French three-factors model. Indeed, the Fama-French model, which appeared in 1993, has three factors: size, value, and market. This is no more than an extension from the CAPM in which two risk premiums were added (i.e., value and size). The objective of adding up these two factors was to build a model from these two anomalies that would suit better to measure the market return.

$$R_i - R_f = \beta_{MKT} * \left(R_M - R_f\right) + \beta_{SMB} * SMB + \beta_{HML} * HML + \varepsilon_i$$

Where:
$(R_i - R_f)$: is the excess return of the asset i
R_M: is the return of the market portfolio
β_{MKT}: is the beta of the asset i to the market factor
β_{SMB}: is the beta of the asset i to the size factor
β_{HML}: is the beta of the asset i to the value factor
SMB: is the size factor
HML: is the value factor

The first part is the traditional CAPM and considers only the excess return versus the risk-free rate. The factor which is linked to the size of the firm is the SMB factor. This factor explains that small market capitalization generates higher returns than larger market capitalization stocks. SMB factor means Small Minus Big and is the difference between a diversified portfolio of small firms' returns and a diversified portfolio of larger-size companies. Fama and French (1993) have demonstrated that the covariance between smaller companies' stock returns is higher than larger ones. Then the second factor linked to the value of the firm is the HML factor. Fama and French (1993) have shown that value stocks outperformed growth stocks through this factor. The outperformance of the value stock is called the value premium. This means that stocks with a high book-to-market ratio had, on average higher returns than stocks with a low book-to-market ratio (Fama & French, 1993,1996).

Afterward, much research was carried out on Fama French's three-factors model, and Carhart (1997) brought a new factor to extend the initial three-factors model. Carhart added the momentum factor, the tendency for assets to continue on a given path, rising or falling. His paper, presented in 1997, was based on research on mutual funds and claimed that adding the fourth factor led to a more accurate measurement of portfolio returns (Carhart, 1997).

$$R_i - R_f = \beta_{MKT} * (R_M - R_f) + \beta_{SMB} * SMB + \beta_{HML} * HML + \beta_{UMD} * UMD + \varepsilon_i$$

Where:
$(R_i - R_f)$: is the excess return of the asset i
R_M: is the return of the market portfolio
β_{MKT}: is the beta of the asset i to the market factor
β_{SMB}: is the beta of the asset i to the size factor
β_{HML}: is the beta of the asset i to the value factor
β_{UMD}: is the beta of the asset i to the momentum factor
SMB: is the size factor
HML: is the value factor
UMD: is the value factor

Carhart (1997) added the momentum effect, which UMD represents in the multifactor model. This factor asserts that if a stock performed well in the past, there is a high probability that this asset will still perform well. UMD, which means Up Minus Down, is going long on stocks that perform well and going short on stocks that do not perform as well.

Later, Fama and French (2015) tried to improve their model and proposed a five-factor model in 2015. This model improved the three-factor model by adding two factors. These two factors added are based on the dividend discount model with this publication; a company's investing behavior and profitability are linked with the company's stock return. That's why a factor that compares companies with low profitability ratios and companies with high profitability ratios appears. This factor is RWM, meaning Robust Minus Weak. The fifth and last factor is related to the willingness of the company to have a level of investment or not. This factor is CMA, meaning Conservative Minus Aggressive ad invest is the spread between companies that invest conservatively and firms that tend to invest heavily. Find below the five factors equation:

$$R_i - R_f = \beta_{MKT} * (R_M - R_f) + \beta_{SMB} * SMB + \beta_{HML} * HML + \beta_{UMD} * UMD + \beta_{UMD} * RMW + \beta_{UMD} * CMA + \varepsilon_i$$

Where:
$(R_i - R_f)$: is the excess return of the asset i
R_M: is the return of the market portfolio
β_{MKT}: is the beta of the asset i to the market factor
β_{SMB}: is the beta of the asset i to the size factor
β_{HML}: is the beta of the asset i to the value factor
β_{UMD}: is the beta of the asset i to the momentum factor
β_{RMW}: is the beta of the asset i to the profitability factor
β_{CMA}: is the beta of the asset i to the investment factor
SMB: is the size factor
HML: is the value factor
UMD: is the value factor
RMW: is the profitability factor
CMA: is the investment factor

1.5. Style investing and the factor zoo

Humans have a natural tendency to categorize things into groups. This behavior makes processing large amounts of information more accessible, simplifying our thinking. We see this in various aspects of our lives, including our food preferences, visiting countries, people we interact with, and jobs.

Interestingly, this same categorization behavior extends to the stock market, as investors classify stocks into different styles or asset classes. Mullainathan et al. (2000) support this notion by suggesting that grouping assets into styles offers investors a convenient framework to evaluate the performance of their investments.

In the 1990s, interest in value and growth investing skyrocketed following the publication of Fama and French's paper in 1993. This surge in interest prompted investment managers to offer specialized indexes categorizing these investment styles.

Moreover, as stated by Barberis and Shleifer (2003), investment styles have their life cycles. This means that investment styles may outperform or underperform in certain market conditions. For instance, value investing may outperform growth investing in a recession, while growth investing may outperform value investing in a bull market (Barberis & Shleifer, 2003).

Style investing has become a popular investment strategy due to its benefits, such as simplifying information and offering a framework for evaluating investments. However, investors must be aware of the drawbacks of categorizing assets into styles, such as correlated movements between unrelated assets and the potential impact on market behavior. Ultimately, investors need to assess the benefits and drawbacks of style investing and make informed decisions based on their investment goals and market conditions. (Wahal & Yavuz, 2013).

Many new factors have emerged with the rise in popularity of style factor investing and the emergence of different multifactor models. Indeed, hundreds of papers have worked on factors that led to an exhaustive number of new factors. Given the significant number of new factors, Harvey Liu and Zhu (2016) published a work to gather most of them, published or not published, and assess their significance.
They tested 316 factors in their paper to explain the cross section of expected return. Most of them were proposed over the last ten years.

Cochrane, in 2011, has called this emergence of new factors "the zoo of new factors". Harvey, Liu, and Zhu (2016) concluded in their paper that the usual statistical significance cutoffs are inconsistent. Indeed, due to the plethora of new factors and data mining, many of the historically discovered factors would be deemed significant by chance. Therefore, their paper proposed a new cutoff through multiple testing frameworks.
This paper concludes by giving an exhaustive list of factors with statistical results and from which papers factors came. This is a good starting point for navigating the "factor zoo" and establishing a new benchmark to guide empirical asset pricing tests (Harvey, Liu & Zhu, 2016).

1.6. Economic variables and asset returns

Several papers have already analyzed the effect of recession or economic turmoil on different style factors and the sensitivity of investment style against critical economic variables. This section will show some research and results already obtained in the literature, which will help to set hypotheses.

Many people know that investing in the stock market can provide higher returns than other assets, despite the market being highly volatile and sensitive to fluctuations in the economic landscape. As a result, fundamental analysis is frequently performed to provide insights into the listed stocks' future trends. However, while these technics consider information such as market sentiment, earning and profit, and industry performance, they do not consider economic factors such as economic growth, inflation, or monetary policy.

Chen, Roll, and Ross (1986) were among the first to attempt to explain asset returns with the macroeconomic variables. They stated that economic forces that influence the asset return are the same theta change discount factor and expected cash flow. He found several economic variables that had an impact either on the expected cash or the discount rate. These macroeconomic variables are changes in actual consumption, unanticipated change in inflation, change in the desired production level, oil prices, unexpected changes in default premiums, and the term structure. Their findings showed that industrial production, change in the default premium, change in term structure, and, somewhat more weakly, the unanticipated inflations significantly explained the expected return. They concluded that the stock return is exposed to the economic news, which can be measured as innovation in state variables (Chen, Roll & Ross, 1986).

In 1990, Ferson and Harvey studied the variation of the economic risk premium because it was said that most predictability is associated with sensitivity to economic variables. In this work, they determined a proxy for the economic risk from previous studies. This list considers variables for which the average price of beta is nonzero. The variables used in this work were the interest rate (Merton,1973; Cox et al., 1985), the real per capita growth rate of personal consumption (Merton,1973; Breeden, 1979), the unanticipated inflation (Fama & Gibbons, 1984), the change in the treasury yield curve and the change in corporate default (Chan et al., 1985). These variables are not sure the only variables that capture all the economic risk, but they have an economic interest. Following Chen, Roll, and Ross (1986), they concluded that measures of economic risks that have been identified capture predictable variations in asset returns. Most of the predicted variations of the monthly excess returns of the portfolios are associated with their sensitivity to these economic variables (Ferson & Harvey, 1991).

Further research related to the Fama French model (Fama & French, 1996) reported evidence that the book-to-market and size factors are associated with economic fundamentals. Several economic factors have been studied, such as innovation in economic growth expectation (Liew & Vassalou, 2003; Kelly, 2003), default risk (Hahn & Lee, 2005; Petkova,2006; Vassalou & Xing, 2004), the term structure (Hahn & lee, 2005; Petkova,2006) and inflation (Kelly, 2003).

Liew and Vassalou (2000) attempt to determine whether there is any association between economic growth and size, value factors. To conduct their research, they retrieved data from 10 developed countries (i.e., Japan, Australia, Canada, France, Germany, United Kingdom, Canada, Australia, Switzerland, and the United States), representing an international panel. Their conclusion land that HML and SMB portfolios have significant information about future economic growth. It appears that high book-to-market and small capitalization stocks have a significant positive relationship between the returns of these strategies and economic growth. This means that high book-to-market ratio stocks are riskier in case of financial distress since, from this theory, it fluctuates in the same direction as the growth. In the same way, small capitalizations are riskier in periods of economic turmoil and will prosper in good economic times.

Kelly (2003) reexamined and extended work done by Liew and Vassalou (2000) on the relation between nominal economic growth and Fama French factors (Fama & French, 1996). He showed that the economic growth has different sources of risk, and the change in economic growth can be either the change in inflation or real GDP growth. His findings showed that SMB is negatively correlated with unexpected inflation and positively correlated with real economic growth. However, HML positively correlates with real GDP growth, but no consistent relation emerged with inflation (Kelly, 2003).

Vassalou and Xing (2004) used Merton's pricing model (1974) and asses the default on the equity returns. They showed that both (i.e., SMB and HML) factors are related to default risk. Small firms and high book-to-market value earns higher when the default risk is high. Except for these 2 cases, they found no significant relationship with low or high default risk (Vassalou & Xing, 2004).

Petkova (2006) contributes to further research between the size and value factors by showing a relation with the term structure and the default spread. He found that HML is a good proxy for term spread surprise factor in returns, whereas the SMB proxies for default spread surprise factor. He concluded that we cannot deny a significant relationship between them. Furthermore, he confirmed the results of Vassalou and Xing (2004) about the default risk premium (Petkova, 2006). Hahn and Lee (2005) also provided empirical support to the undeniable relation with the default risk spread and the term structure spread (Hahn & Lee, 2005).

Aretz et al. (2010) extended their research to the Carhart model. They analyze the relationship between the momentum factor and the different state variables compared to the prior literature.
They found that momentum factors strongly reflect the change in the tern structure am dot the aggregate survival probability, corresponding to the default risk (Aretz et al., 2010).

The previous working papers haven't analyzed two factors related to the Fama French five factors model (Fama & French, 2015). These two factors are the CMA and the RMW, respectively, related to the firms' investment and profitability. Leite et al. (2020) showed that previous results associated with SMB and HML factors hold with the complete set of state variables (i.e., the aggregate dividend yield and term spread, default spread, and one-month T-bill rate). However, they found that the same state variables do not proxy for the RMW factor. To overcome this situation, they added the unanticipated shock in CPI in the state's variables, and this new set of state variables seemed to be a good proxy for SMB, HML, RMW, and CMA. Furthermore, they stated that the unexpected shocks in CPI and the term structure are the most correlated with the portfolio returns (Leite et al., 2020).

Looking at the other research, similar economic variables are retrieved and analyzed. Indeed, the real GDP growth, the default risk, the term structure, or the inflation are often described as good state variables proxies for equity return. For example, Bali et. al (2014), and Lambert and Platania (2016) added the unemployment rate to their macroeconomic variables. The unemployment rate seems to be a good proxy for growth stocks and a good countercyclical measure against the default spread.

Lambert and Platania (2016) went one step further by studying the behavior of a long/short portfolio in different states through a Markov Switching Model. They analyzed it under two states; one can be assimilated to the normal state (i.e., State 1) and the other to the distressed state (i.e., State 2).
In their conclusion, they highlighted that HML stocks are highly conditional on the GDP. In state 1, GDP seems to be a good proxy for value stocks, whereas, during higher volatility (i.e., State 2), the GDP is closer to the growth stocks. Regarding the size factor, Lambert and Platania (2016) observed a trend for small caps under state one. In state 2, small capitalizations decrease with GDP growth but increase with unemployment, inflation, and volatility. Growth stocks and small caps seem to better hedge economic slowdown with their flexibility to reduce activity. On the other hand, the momentum factor has a positive relationship with GDP growth and hence is preferred in economic expansion (Lambert & Platania, 2016).

2. Financial Crises

2.1. Types of financial crises

Financial crises can be divided into two groups, first those classified using quantitative methods and the second using qualitative and judgmental analysis. The first classification using the quantitative method regroups currency and sudden stop crises, and the second group is composed of debt and banking crises.

2.1.1. Currency crises

Currency crises result in a sharp devaluation of a country's currency which can be due to several causes. In times of hyperinflation or speculative attack on the currency, the public authorities will have to defend their currency to not lose too much value. To counteract the devaluation, the central bank can use the international reserve, raise interest rates, or even impose capital control.
In case of failure to stop the depreciation of the currency, this can lead to a weak economy and lead to financial crises.

The literature has evolved along crises with different models to explain as much as possible crises. It has evolved from finding explanations in the fundamentals of the currency crises, emphasizing the scope of multiple equilibria, and then paying more attention to financial variables as triggers of financial crises.

The first model is the "KFG" model and developed by Krugman (1979), Flood, and Garber (1984). They argued that crises come from a sudden speculative attack on fixed or pegged currency on which investor reacts with rational behavior and hold currency as long as they think the exchange regime will remain the same. (Krugman, 1979; Flood & Garber, 1984).
The second model relates to doubts that investor could have about the government maintaining the currency peg and stress the importance of multiple equilibria. This is the opposite compared to the previous model, where investors no longer believe in the currency and the government. The loss of confidence in the currency and the public authorities can lead to a currency crisis (Obstfeld and Rogoff 1986).
The third model shows the importance of a balance sheet (e.g., Fiscal position and current account). Indeed, quick deterioration of balance sheets associated with fluctuation in asset prices and exchange

rates can lead to a currency crisis (Chang & Velasco, 1999). Unfortunately, none of the later empirical research has determined which model gives the best fit, but this depends on the different causes of the crisis.

2.1.2. Sudden stop

A sudden stop crisis, or a balance of payment crisis, can be defined as a crisis when capital inflow in a country decreases sharply. This can be due to foreign investors who reduce their investments in the economy, but this can also be due to domestic investors who pull out their money from the domestic economy. Usually, when capital inflows exceed the required amount to finance the current account deficit, the surplus goes to a reserve which can be used in case of a sudden stop. This likely takes place in a period of robust expansion, which drives prices higher, and this can be a significant adverse impact and lead the economy to a recession.

To explain sudden stops, models represent it with a closer association with disruption in the supply of external financing. As the third model in the currency crises, these models consider the balance mismatches in currency and maturity in the financial and corporate sectors (Calvo et al., 2006). In this model, they give more weight to international interest rates or spreads compared to sharp drops in output and total factor productivity in causing sudden stops crises. Empirical studies find that many sudden stops have been associated with global shock. Indeed, when a large capital inflow and an unexpected global shock arise, a direct reversal of capital flows leads to a sudden stop crisis.

2.1.3. Debt crises

The third type of crisis is the debt crisis, which can be found in either foreign or domestic debt crises. Foreign debt crises occur when a county cannot repay the debt to other foreign countries, either private or sovereign. Foreign debt is usually used by countries that do not have a deep market enough to borrow as much as they want or simply because the rate is very interesting in foreign countries. This is often the case for developing countries or low-income countries that can borrow from international organizations such as the world bank with flexible schedules (Claessens & Kose, 2013).

Models have been developed in two simple ways, either on the intertemporal basis or on intratemporal basis. The intertemporal hold is that the country will not default because they do not want to be banned from future learning opportunities. However, if they default to assuming their obligation, they would be excluded from using the international financial market to face any shock or economic turmoil. This means that a country would default on its obligation as long as the opportunity cost of not being able to borrow is low and the term of trade is good (Eaton & Gersovitz, 1989). On the other hand, the intratemporal model assumes that they would be incentivized to take their debt obligation to access a foreign exchange today (and not for future opportunities as is the case in the intertemporal model) with other trading partners. In contrast with the intertemporal model, the default cost would be the lowest when the term of goods is weak (Bullow & Rogoff, 1989).

Domestic debt crisis is less prevalent since the literature often assumed that the governments will always honor debt obligations (known as the typical "risk free" asset). In models tempting to explain domestic debt crisis, they often consider the Ricardian equivalence and this make government debt less relevant. The Ricardian equivalence hold that increase debt financed spending by the government to stimulate the economy will not have a positive impact on the aggregate demand. Indeed, people will understand that they will pay for this debt in the form of future taxes. This will have no impact on the aggregate demand as because consumers would save the tax cut to pay the future tax increases (Claessens & Kose, 2013).

Modeling debt crises around domestic and foreign debt crises in various countries remain something challenging. This is mainly due to the usual problem which is the endogeneity among countries (e.g. developed and emerging countries). Furthermore, debt crises are also likely to involve other type of crisis and this is not to help in identifying the root causes of the crisis. But in order to keep things simple, the risk to raise debt crisis mainly result from factor related to political economy, financial integration and institutional environment (Claessens & Kose, 2013).

2.1.4. Banking crisis

In the same category as the debt crisis, the banking crises is the last major type of financial crisis. As defined by Laeven and Valencia (2013), an event which meet these two conditions can be considered as a banking crisis:

- Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations),
- Significant banking policy intervention measures in response to significant losses in the banking system.

To consider that the crises became systemic, both have to be met and that's the method they used by Laeven and Valencia (2013) to date the crises. While the second criterion is easier to detect, the first one is more complex as there is no specific measure or threshold to identify bank runs or severe losses. For the second criterion to be met, at least three out of six following policies must be fulfilled.
The six policies considered are the following:

- Deposit freezes and/or bank holidays indicates if the government imposes restriction on withdrawal or a bank holiday,
- Significant bank nationalizations meaning that the government take a majority stake in the bank,
- Bank restructuring fiscal costs, if they represent more than 3% of the GDP, then it is considered as significant,
- Extensive liquidity support from the central bank to other depositary institutions and liquidity support provided by the treasury,
- Significant guarantees are put in place on bank liabilities, meaning that the government protects all liabilities,

- Significant asset purchases (at least 5 percent of GDP) from the central bank to affect real activity (i.e., decreased the long-end of the yield curve, a positive sign for investors, etc.).

The list above covers the main policy intervention set by the authorities in case of banking crises. Some of them are more easily quantifiable with a threshold set up (e.g., 3% of GDP for the bank restructuring fiscal cost) and others need more judgmental analysis (Laeven & Valencia, 2008).

Several studies reached the same conclusion and found that deeper causes of banking crises are often related to funding and liquidity problems but not only. Much literature describes common elements of previous crises. The list of factors remains similar, and four factors are often mentioned together. These factors are asset price increase that turned out unsustainable, credit booms that led to excessive debt burdens, the buildup of marginal loans are a systemic risk, and the failure of regulation and supervision to keep up with financial innovation and get ahead of the crisis before it erupts (Claessens et al.,2010).

The four factors mentioned above are pretty common and were already the root causes of the great depression in 1930. However, the global financial crisis of 2008 also showed new elements that were not present in earlier financial distress. These four unique aspects are the increasing use of complex and opaque financial instruments, the increased interconnectedness among financial markets, the high degree of financial institutions' leverage, and the household sector's central role. Therefore, these additional aspects were considered a catalyst in the global financial crisis and worsened things (Claessens & Kose, 2013).

The global financial crisis brought new insight into the potential countries that could be hurt by it. Indeed, the subject countries were low to middle-income countries. However, change has been noticed and, as cited by Reinhart and Rogoff (2008), "The global made it clear that financial crises are an equal opportunity menace for high low- or middle-income countries" (Reinhart & Rogoff, 2008).

2.2. Identifying financial crises

Several models attempted to capture early signals or indicators to identify the crisis. Indeed, identifying the crises could help predict the magnitude of the crises and the geographical area that would be most affected. The different modeling approaches can be classified into four categories. The following four categories have been proposed by Frankel and Saravelos (2012) by analyzing the literature on the leading indicators.

First, Frankel and Rose (1996) use linear regression techniques to test indicators' significance in a financial crisis. They tried it on more than 100 developed countries using annual data. Compared to Frankel and Rose (1996), Sachs et al. (1996) reduced their sample of countries to 20 emerging countries and applied the same techniques. With their restricted attention on fewer countries, they claim to explain better the cross-country pattern of currency crises with the same techniques. With their restricted attention on fewer countries, they claim to explain better the cross-country pattern of currency crises.

The second category was discovered by Kaminsky et al. (1998) and is known as the" KLR approach." The paper proposed a warning system approach (i.e., the signal approach) which involves monitoring several economic variables that make economic sense. Indeed, variables selected tend to behave differently before crises and could show early signs of future trouble in the following 24 months. For each variable monitored, a threshold is assigned, and if the threshold is breached, it is considered an early signal of the financial crisis. The indicators selected were the capital account, debt profile, current account, international variables (i.e., foreign real GDP growth, interest rates, etc.), financial liberalization (i.e., credit growth, change in money multiplier, etc.), other economic variables (i.e., central bank credit to the bank system, money growth, money demand, and supply, etc.), the real sector, fiscal variables Institutional/ structural factors (i.e., exchange controls, duration of fixed exchange rate periods, etc.) and political variables (i.e., change of government, left-wing government, new finance minister, etc.).
On the other hand, Berg and Patillo (1999) and Bussiere and Mulder (1999) tested the model's performance, and it was moderately successful. Indeed, thresholds have been set within the sample, and when they tried it out of the piece, the prediction was not as good as they expected. Furthermore, they compared the models developed by Frankel and Rose (1996) and Sachs et al. (1996), and the “KLR” model seemed to be more successful than the other one.

The third category used a mixed quantitative and qualitative method using two groups. They used a crisis group and a non-crisis group, and by comparing the behavior of variables among both groups, they tried to determine the date on which occurs the crisis (Frankel & Saravelos, 2012).

The fourth and most recent crisis is related to innovations in identifying and explaining crises. This category includes using a binary recursive tree to determine thresholds of leading indicators, an artificial neural network and algorithm to select the best indicators, and a regime-switching model.
Binary recursive trees allow for interactions between the various explanatory variables and ordering among the explanatory variables (i.e., most essential variables are at the top of the tree) (Ghosh & Ghosh, 2003). Nag and Mitra (1999) tested the artificial neural network approach and compared it with the classical signal approach described above. The ANN seemed to perform better and seemed promising at this early stage. The category's last method is the regime-switching model, which shows parameters switching from different states. For example, Peria and Soldedad (2002) studied the effect of speculative attacks under two states through the regime-switching model. The "tranquil" and "speculative" states were two different states. Speculative attacks were identified by modeling reserves, exchange rates, and interest rate differences depending on the state in which the economy resides (i.e., "tranquil" or "speculative") (Peria & Soldedad, 2002).

Frankel and Saravelos (2012) extensively reviewed 83 papers from which they derived the most significant variables. To do so, they used the evidence from the 2008-09 global financial crisis. In this paper, they concluded by asserting that the growth rate of credit, foreign exchange reserve, real exchange rate, GDP growth, and the current account to GDP are the most frequent significant indicators. The two most important are measures of reserves and the real exchange rate, as per all the studies. Indeed, these two factors are represented in more than half of the paper reviewed.

Another reliable paper published by the ECB in July 2017 (Lo Duca et al., 2017) tried to derive a new database for financial crises in European countries. This paper discussed the abovementioned methods and brought several innovations and amendments relative to the existing dataset. Furthermore, the proposed approach bridges the gap between more qualitative methods (Laeven & Valencia, 2008 and 2013; Babecký et al., 2012; Reinhart & Rogoff, 2008) and quantitative methods (Frankel & Rose, 1996; Lo Duca & Peltonen, 2013).

By using both approaches, it enables to have the objectivity of the quantitative side (by using a financial stress index). Then the qualitative approach helps to separate noise or less relevant events from systemic crises. Moreover, this paper provides insight into the multivariate and univariate signaling models. It confirms previous literature (e.g., Lo Duca & Peltonen, 2013) by arguing that multivariate perform better than univariate models.

Data

1. Time and geographical scope

The period has been determined along two criteria. First, the sample period must be long enough to have sufficient data to derive an analysis of the results. Indeed, the objective is to analyze the behavior of style factors during several financial crises. Therefore, the sample needs to include as many financial crises as possible during the period.

Then another essential aspect that cannot be ignored is data availability. Of course, the most extended period would be the best, but data availability does not allow us to gather data for as long as we want. Especially in this thesis, as the scope of the research is in Europe and data are less available compared to the US or the global market.

The period considered will be from March 1998 to May 2022 and will concern only the Europe area. Given the relatively long period, the monthly periodicity has been retained for this work instead of the daily. Furthermore, monthly periodicity has been chosen instead of yearly to capture more easily the beginning and the end of the crisis period selection. In favor of the monthly return, papers with similar objectives and periods have chosen the monthly periodicity (Lambert & Platania, 2016; Bali & al, 2014).

2. Portfolio based on style factors

As shown in the previous section, numerous factors have been discovered through the literature, which has led to the factor zoo. As the objective of this research is not to identify new risk factors but to consider the exposure to these risk factors in economic turmoil, a limited number of factors have been chosen. Factors selected in the framework of this research are well-known factors that have already proved a significant effect on capturing risk exposure. Here are the definitions of the different style factors chosen for the empirical research:

1. MKT: represents the monthly excess return over the risk-free rate. In this work, the market return used is the MSCI World, characterizing the equity market risk factor.[1]

2. SMB: represents the size factor and is the difference between the return of diversified small and large capitalization stocks. SMB returns were retrieved from Fama French European 5 factors portfolio.[2]

3. HML: represents the value factor and is the difference between the returns of diversified stock with high and low book-to-market ratios. HML returns were retrieved from Fama French European 5 factors portfolio. [2]

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[1] Monthly returns retrieved from S&P Capital IQ

[2] Monthly returns retrieved from Fama/French European 5 Factors - Kenneth R. French - Data Library

4. RMW: represent the profitability factor and is the difference between the returns of diversified portfolios with low and high operating profitability stocks. RMW returns were retrieved from Fama French European 5 factors portfolio. [2]

5. CMA: represents the investment structure and is the difference between the returns of a diversified portfolio with conservative and aggressive investment companies. CMA returns were retrieved from Fama French European 5 factors portfolio. [2]

6. UMD: represents the momentum factors and is the difference between a diversified portfolio of well-performing and bad-performing stocks during the last 12 months. UMD returns were retrieved from the European Momentum factor portfolio.[3]

3. Economic variables

We must quantify the economic environment with critical variables to assess how style factors behave during financial crises. Indeed, these variables should affect the different style factors and also be affected by macroeconomic shocks (e.g., financial crisis and economic turmoil).

Since the economic variables will be used in a macroeconomic factor model, monthly actual and forecasted data will be retrieved. The actual and forecasted data need will be explained in the methodology section for the macroeconomic factor model. In this work, the following economic variables will be considered:

1. GDP: The gross domestic product (GDP) is the standard measure of the value added created by producing goods and services in a country during a specific period. As such, it also measures the income earned from that production or the total amount spent on final goods and services (less imports).
   The data retrieved are the annual growth rates of the GDP every month in Europe[4] and the forecasted growth rate of GDP in Europe. Due to data unavailability the forecasted annual growth rate of GDP[5] was retrieved quarterly and not monthly.

2. UNEMP: The unemployment rate is the percentage of unemployed people in the labor force. Consequently, measuring the unemployment rate requires identifying who is in the labor force. The labor force includes people who are at the age of working and are either employed or unemployed. Data retrieved are the actual monthly unemployment rate[6] and the quarterly forecasted unemployment rate.[7]

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[3]Monthly returns retrieved from European Momentum Factor - Kenneth R. French - Data Library
[4] Data retrieved from FRED – Federal Reserve Bank of St. Louis' website: https://fred.stlouisfed.org/series/EA19LORSGPORGYSAM
[5] Data retrieved from OECD's website: https://data.oecd.org/gdp/real-gdp-forecast.htm#indicator-chart
[6] Data retrieved from FRED – Federal Reserve Bank of St. Louis' website: https://fred.stlouisfed.org/series/LRHUTTTTEZM156S
[7] Data retrieved from OECD's website: https://data.oecd.org/unemp/unemployment-rate-forecast.htm

3. INF: The consumer price index (CPI) was chosen as an indicator to measure inflation. The CPI is the change in the prices of a basket of goods and services that specific households typically purchase. Inflation is measured in terms of the annual growth rate. Therefore, the data retrieved are the actual annual growth rate of the CPI every month[8] in Europe. And the forecasted data are the annual growth rate of CPI every quarter[9] in Europe.

4. TSTR: The term structure is the difference between the long-term and short-term interest rates. In this case, if the long-term yields are higher than short-term yields, this is considered a standard yield curve and signals that the economy is in an expansionary mode. On the other hand, if short-term yields are higher than long-term yields, this is considered an "inverted" yield curve and signifies that the economy is about to be or enter a recessive period. The data retrieved is the difference between actual monthly long-term and short-term interest rates[10]. For the forecasted data, the data retrieved is the difference between the predicted long-term and short-term interest rates[11] in Europe.

4. Financial crises and distressed periods

The financial crises were retrieved from a work of the European Central Bank (ECB) (Lo Duca et al., 2017). Indeed, the database provides a good benchmark for financial crisis detection, especially regarding the chronological definition of the crisis period. Moreover, the dataset has been validated by various financial stability experts from various policy institutions.

Furthermore, compared to other literature focusing either on the qualitative or quantitative method to delimit crises, they used a mix of both. First, they used qualitative analysis to detect events that could be relevant, and then quantitative criteria were set to check whether this could be considered a systemic crisis.

Compared to the database done by Detken et al. (2014), this dataset is better to be considered given that qualitative analysis was done with the information collected directly from national authorities. Datasets constructed by Laeven and Valencia (2013) and Babecky et al. (2012) were also reviewed to compare with the ECB crises dataset. All events in their datasets and not in the ECB database were analyzed cautiously by the respective national authority of the event.
These were several points that showed the reliability of the dataset used. It covers all European member states and Norway from 1970 -2016.

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[8] Data retrieved from FRED – Federal Reserve Bank of St. Louis' website: https://fred.stlouisfed.org/series/OECDCPALTT01GYM
[9] Data retrieved from OECD's website: https://data.oecd.org/price/inflation-forecast.htm
[10] Data retrieved from OECD's website: https://data.oecd.org/interest/short-term-interest-rates.htm#indicator-chart
[11] Data retrieved from OECD's website: https://data.oecd.org/interest/short-term-interest-rates-forecast.htm#indicator-chart

Among the complete set, the period of crises arbitrarily selected to analyze the behavior of style factors are the followings:

1. 06/2000-06/2002: From 1998 to 2000, an annual growth rate that exceeded 3% in Europe, the successful introduction of the euro in 1999, a global stock market boom, and employment growth showed an excellent European economy. After that, but unexpectedly, 2000 gave way to sluggish growth and increasing pessimism. This downturn has resulted from the quasi simultaneously slowdown of all components of domestic demands and world trade. (European Central Bank, 2002). The ECB database lists 13 European countries out of 29 in economic turmoil (Lo Duca et al., 2017).

2. 01/2008-12/2009: One of the most well-known crises is the global financial crisis, the biggest one since the great depression (1929). The Great Recession was caused by a combination of weaknesses in the financial system and a series of events triggered by the US housing market crash. When homeowners abandoned their mortgages, the value of mortgage-backed securities held by investment banks declined, leading to collapses or bailouts in 2007-2008, known as the subprime mortgage crisis. The inability of banks to lend and homeowners to pay back resulted in the Great Recession that began in the US. The interconnectedness of the economy and the financial sector facilitated the spread of the crisis from the United States to Europe. In the ECB Database, 28 countries out of a total of 29 countries faced economic distress during this period (Lo Duca et al., 2017).

3. 06/2010-06/2012: After a short recovery from the great recession, the EU succumbed to the sovereign debt crisis. This combined crisis with the great recession had catastrophic consequences for European countries' economic growth, investment, employment, and fiscal position. The shock waves from the great recession crisis, high sovereign debts, deficit spending, and high cost of borrowing resulted in widespread failure in the EU's financial system. It started with Greece, and then Cyprus, Spain, Portugal, and Ireland followed and requested a bailout to recover their economy. The peak of the crisis was from 2010 to 2012; this is why this period (i.e. 2010-2012) has been selected, but the European situation remained unstable until 2014. In the ECB database, 26 countries out of a total of 29 countries were facing economic turmoil during this period (Lo Duca et al., 2017).

4. 02/2020-07/2021: The Covid 19 pandemic was an exogenous global shock and economically impacted the world. In February 2020, the coronavirus started to spread around the globe, including large parts of Europe. The coronavirus (COVID-19) has created unprecedented shock and caused a sharp economic downturn. The pandemic put the real economy and financial markets under extraordinary stress, leading to an intense fragmentation of euro-area financial markets. This led to severe shocks in the stock market during March (i.e., Black Monday and Black Thursday). From 19 February to 23 March, the MSCI World declined by 34% (ECB Economic Bulletin, 2020).

5. 03/2022-05/2022: The unjustified Russian invasion of Ukraine started in March 2022 and is still ongoing (For the sake of this research, the period stopped in May 2022 as the data were retrieved until May 2022). The war caused a significant impact on the European economy, particularly in energy and food markets, resulting in limited supply and skyrocketing prices never seen before. Compared with other economic regions, the euro area has been particularly impacted because the Euro area depends heavily on energy imports, which account for more than half of Europe's energy use. In addition, the war exacerbated the inflationary pressures in the euro area during the post-pandemic recovery, resulting in increased consumer prices, particularly for energy and food.

Methodology

The thesis aims to identify particular behavior of style factors in times of financial crises. The analysis will be done on the overall period (i.e., March 1998 to May 2022) and the sub-periods selected in the previous section. Indeed, two sets of periods will be analyzed, the first on the overall period will be considered the base case, and the subs periods of crises selected will be considered as the period of uncertainty and economic turbulences.

A macroeconomic multifactor model will be built for each portfolio described in the style-based portfolio section (i.e., MKT, SMB, UMD, CMA, HML, and RMW). The objective will be to study the evolution of the exposure of the different portfolios to the economic variables over time. To explore the evolution of the exposure, a time-varying beta methodology will be applied and further detailed in the below section.

1. Macroeconomic factor model

The macroeconomic factors model assumes that the returns to each asset are correlated with only the surprise in some factors related to the aggregate economy, such as inflation or interest rate. For this work, the economic factors retained for the multifactor model are discussed in the previous section.

The term "surprise" can be defined by the actual value minus the expected/forecasted value. This is why the actual and forecasted times series had to be retrieved in the data section for each economic variable. This is the component of the factor that was unexpected by the market. This contrasts the idea in the fundamental model, which represents the independent variable differently. As explained above, the model will be applied on two distinct set of periods (Pinto & Podkaminer, 2018). The model is written as follows:

$$\mathrm{R_i} = \mathrm{a_i} + \beta_{\mathrm{i1}} * \mathrm{F_{i1}} + \beta_{\mathrm{i2}} * \mathrm{F_2} + \ \dots + \beta_{\mathrm{in}} * \mathrm{F_n} + \varepsilon_{\mathrm{i}}$$

Where:
R_i: is the return of the asset i
a_i: is the expected return of the asset i
F_1,F_2, … , F_n: are the surprise in the factor 1,2,…,n
$\beta_1, \beta_2, \dots, \beta_n$: are the sensitivity of the asset i regarding the surprise in the factor 1,2, …, n

This formula will be applied to all the portfolios. Find below the application of the formula to the SMB portfolio with our selected economic variables. The same procedures will be used for the five other portfolios (i.e., MKT, HML, UMD, RMW, CMA).

$$\mathrm{SMB}_t - \mathrm{E}(\mathrm{SMB}_t) = \beta_{\mathrm{SMB,GDP,t}} * \mathrm{GDP}_t + \beta_{\mathrm{SMB,UNEMP,t}} * \mathrm{UNEMP}_t + \ \beta_{\mathrm{SMB,TSTR,t}} * \mathrm{TSTR}_t \ + \beta_{\mathrm{SMB,INF,t}} * \mathrm{INF}_t + \varepsilon_{\mathrm{SMB}}$$

Where:
SMB_t: is the return of the SMB portfolio at time t
$E(SMB_t)$: is the expected return of the SMB portfolio built by taking the last 12 months average returns
$\beta_{SMB,GDP,t}$: is the sensitivity of the SMB portfolio to the surprise in the GDP growth factor at time t
$\beta_{SMB,UNEMP,t}$: is the sensitivity of the SMB portfolio to the surprise in the unemployment factor at time t
$\beta_{SMB,TSTR,t}$: is the sensitivity of the SMB portfolio to the surprise in the term structure factor at time t
$\beta_{SMB,INF,t}$: is the sensitivity of the SMB portfolio to the surprise in the inflation factor at time t
GDP_t: is the unexpected part of the GDP growth at time t
$UNEMP_t$: is the unexpected part of the unemployment rate at time t
$TSTR_t$: is the unexpected part of the term structure at time t
INF_t: is the unexpected part of the inflation at time t
ε_{SMB}: is the portion of the model not explained by the other factors

2. Time-varying beta

The traditional return-based style analysis (RBSA) has been used in several applications to get an overview of the historical exposures of the fund. Although this model has been reliable, a better methodology has been developed to improve the accuracy of the risk exposure over time. Indeed, the major drawback of the RBSA is the assumption that the investment style remains the same over the entire analysis period (Swinkels & van der Sluis, 2002). Bollen and Whaley (2007) recognize the importance of time-varying exposures to correctly and accurately assess performance. Rolling window beta analysis and the Kalman approach can be used to set up this time-varying beta (Bollen & Whale, 2007).

The rolling windows regression analysis consists of a linear regression on a "window" that is shifted over the period (i.e., month over month, day over day, etc.). As shown in Figure 2, the process is pretty simple. Data used for the linear regression is moving along the complete sample of data while inserting one new data point and removing the oldest data point at each incrementation.

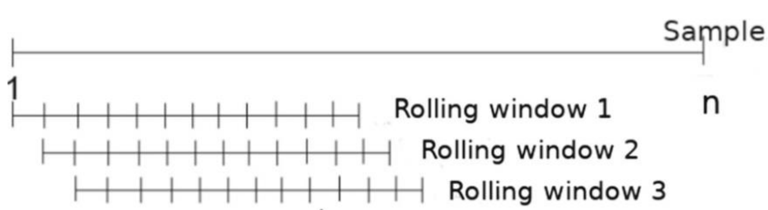


Figure 2: Rolling Window Regression schema

The window size is defined as preliminary and can affect the exposure. For example, funds that change their orientation frequently should use a shorter view, and those with a more stable exposure should use a longer window for an estimate. Using smaller windows helps to capture recent exposures quicker but at the cost of statistical accuracy (Swinkels & van der Sluis, 2002).

The Kalman approach can be either the Kalman filter or the Kalman smoother. The difference between the Kalman filter and the Kalman smoother is the conditioning of the information set. The Kalman filter uses information up to time t, whereas the Kalman smoother uses the complete information (meaning information up to time t and information from t to the end of the data set). This is why the Kalman filter is used more for prediction and the Kalam smoother for descriptive purposes. To briefly explain the approach of the Kalman filter, it is based on two central equations: the measurement equation and the transition equation. In the case of the multifactor model, the measurement equation would be the multifactor equation, and the transition equation will follow a random walk. The process is based on a recursive model, meaning the estimate is adjusted at each iteration given the new information. For instance, the coefficient estimated at the time (t-1) is used as a guess for the estimation at time t. The estimated coefficient at time t is then computed optimally using the new information, which is shifted from one period to another (Zainudin et. al, 2021).

Swinkles and Van der Sluis (2002) compared the Kalman filter and the rolling window regression. In this comparison, they used a window size of 36 months and showed that the Rolling Windows analysis took more time to adapt to the situation. The advantage of the Kalam filter technique is that this does not require any window size selection, as the algorithm determines the optimal window length to trade off the time variation of style exposure and the accuracy with which they are estimated. This is why the Kalman approach outperforms the rolling window analysis in the case of the high volatility of the investment style.

In the context of this work, the method that will be applied is the rolling window regression. This choice was made because of the complexity of implementing the Kalman filter. Indeed, good technical skills are needed to implement this model in statistical tools. Since the econometric model is not the main focus of this thesis, the simplest model has been preferred.

Thus, a rolling window regression will be applied to the six equations previously stated. The results obtained and explained in the following section will detrain the window size. The fixed window size selected will move month over month. Indeed, a multiple-rolling regression will be performed every month from March 1998 to May 2022. It will enable us to analyze the exposure of the six portfolios to the four economic variables monthly throughout the entire period under analysis[12].

3. Hypothesis build-up

Based on the literature review, some hypotheses can be drawn to test the results that will be obtained. Two sets of hypotheses will be determined. The first will be made under the normal economic state, and the second set of hypotheses will be based on economic uncertainty.

The following hypotheses are made for the overall period (i.e., 1998 to 2022), assuming it is under normal economic conditions.

[12] RStudio was used for the rolling regression and statistics associated. Excel was used for the basic calculation and graphs

1. Liew and Vassalou (2000) and Kelly (2003) reported that economic growth represented by GDP growth has a positive association with the value, size, and market portfolio returns.

2. Hah and Lee (2006) and Petkova (2006) found that SMB has a non-significant relationship with the term structure factors. On the other hand, they identified a significant positive relationship between the term structure and the value portfolio (i.e., HML). Aretz et al. (2007) found a significant negative relationship between the term structure factor and the market and the momentum portfolio.

3. Aretz et al. (2007) found a strong pricing factor in unexpected inflation. In his work paper, Kelly (2003) showed that market portfolio and size portfolio return are significantly negatively affected by inflation. On the other hand, Kelly (2003) found a non-significant relationship for the value of HML portfolio returns. However, Aretz et al. (2007) stated in more recent works that the HML portfolio has a positive exposure to unexpected inflation.

4. For the case of the unemployment rate, Lambert and Platania (2016) concluded that there is a significant positive relationship with the market, size, and momentum factors. On the other hand, they found no significant relationship with profitability and value portfolios returns.

As mentioned in the literature section, Lambert and Platania (2016) studied the exposure of the different factors to the macroeconomic variables. Thanks to a Markov switching model, they found exposure for various states, and one of the economic states was in an economic slowdown. Therefore, the following hypotheses are made for the sub-periods selected under distressed economic conditions.

1. The GDP factor has a significant positive relationship with the market but a significant negative relationship with the size and value portfolios returns. For the momentum portfolio, no significant relationship has been pointed out by Lambert and Platania.

2. The Unemployment factor has a significant positive relationship with the market portfolio and the size portfolio during periods of economic turmoil. However, no significant relationship was found for the value and the momentum portfolios.

3. The inflation factor found no significant relationship except for the momentum portfolio, which has a significant positive relationship according to the research of Lambert and Platania (2016).

Results

In this section, the results from the window rolling regression to identify how the different factor portfolios retrieved in Europe behaved during the period 1998 to 2022 and especially during financial crises. First, the different results obtained on the window size selection and the multicollinearity among economic variables will be presented, and then the influence of the macroeconomic variable on the various fundamental factor portfolios.

1. Window size selection

The beta coefficients are estimated over a sliding window of observations in time-varying beta models, such as rolling window regression. The window size is a crucial parameter in determining the number of observations used to estimate the beta coefficients at a given time.

The choice of window size is important because it determines the trade-off between bias and variance in estimating the beta coefficients. In this case, three different periods were chosen for the rolling window regression and represented the reality at the time of the regression as much as possible.
The three windows selected are 12 months, 24 months, and 36 months. As I have retrieved monthly data, this means that for each regression, there will be a regression with 12, 24, and 36 data points. Therefore, the R-squared and the adjusted R-squared will be used to determine the best window size.

R-squared is commonly used to assess the goodness of fit of regression models, including rolling window regression. The R-squared measures the proportion of the variance in the dependent variable explained by the model's independent variables. The R-squared value can show how well the model fits the data over time when using rolling window regression. As the window progresses, the R-squared value can be calculated for each window. This allows us to observe the model's performance over time and see if there are changes in the relationship between the dependent and independent variables. The R-squared is between 0 and 1. The closer it is to 1, the better the fit between the model and the data. The formula to determine the R-squared is the following:

$$\mathrm{R}^2 = 1 - \frac{\text{Unexplained Variance}}{\text{Total Variance}} = 1 - \frac{\text{SSE}}{\text{SST}}$$

Where:

SSE: Sum of Squared Errors. It is also called the Residual Sum of Squares
SST: Sum of the difference between the observed dependent variables and its mean

In our case, it is preferable to use the adjusted R-squared, which is why I intend to examine the average adjusted R-squared for each regression. Indeed, the adjusted R-squared is calculated from the R-squared, and it is preferable to use it in this case because we are comparing models with different numbers of observations. Indeed, the adjusted R-squared considers the number of independent variables and the number of independent variables in the analyzed model. Below is the formula to obtain the adjusted R-squared from the R-squared:

$$\text{Adjusted } R^2 = 1 - \frac{(1 - R^2)(n - 1)}{(n - p - 1)}$$

Where:
n: Number of observations
p: Number of independent variables
R^2: R-squared of the sample

Looking at the adjusted R-squared obtained in Table 1, we can see that the adjusted R-squared are not high, but the Adjusted R-squared using a 12 months window size is slightly better compared to the 24 and 36 months. So then, the rest of the analysis will be carried on with the 12 months window size results.

Adjusted R-Squared	MKT	SMB	HML	UMD	CMA	RMW
12 Months	0.0379	0.0548	0.0147	0.0606	0.0725	0.1090
24 Months	0.0240	0.0491	-0.0187	0.0221	0.0313	0.0431
36 Months	0.0243	0.0196	-0.0192	0.0066	0.0273	0.0313

Table 1: Mean Adjusted R-Squared Summary- Source: Own calculations

2. Multicollinearity of the independent variables

As Aretz et al. (2007) mentioned in their study on the impact of macroeconomic factors on factors portfolios, they insisted on controlling the correlation between the macroeconomic variables. Indeed, correlation among the different macroeconomic factors can lead to misinterpretation of the impact. Therefore, a variance inflation factor has been computed for each regression to avoid multicollinearity among the independent variable.

The variance inflation factor is widely used to detect multicollinearity between independent variables in multiple regression models. Indeed, the variance inflator factor measures how much the behavior of an independent variable is influenced by its interaction with the other independent variables. Usually, the more significant the variance inflation factors, the larger the probability of having substantial multicollinearity among variables. To compute it, find the below formula used:

$$\text{VIF} = \frac{1}{1 - R_i^2}$$

The R_i^2 is the unadjusted coefficient of determination for regressing the i^{th} independent variables on the remaining ones. Below, find the usual interpretation of the value of the VIF:

- VIF <4: Variables are not correlated

- 4 < VIF < 10: variables are correlated
- 10 < VIF: Variables are highly correlated and the multicollinearity needs to be corrected.

Looking at our values, find below in Table 2 the VIF value obtained in the two periods under analysis (i.e., Overall periods and distressed periods).

VIF	GDP	UNEMP	TSTR	INF
Distressed periods	1.2714	1.3556	1.2515	1.2597
Overall period	1.0023	1.0025	1.0049	1.0048

Table 2: Mean of Variance Inflation Factor Summary- Source: Own calculations

Here for both periods, there is no evidence of multicollinearity noticed. Indeed, the values obtained are between 1.0023 and 1.3556, which is much below the threshold of 4. Furthermore, we can add that the values are even lower in the overall period, possibly due to the number of observations.

3. Rolling regression results

This section will describe the exposure obtained for the six style-based portfolios to their economic variables. The result will show the difference between the two periods under analysis (i.e., the distressed period and the overall period). Each section will be dedicated to the result of one style portfolio regarding GDP growth, the unemployment rate, the term structure, and inflation.

3.1. MKT portfolio

From 1998 to 2022, the market portfolio has an average monthly return of 0.068% and monthly volatility of 5.0408. The skewness is negative (i.e., 1.1885), meaning that the expected return is more frequently small gains and few significant losses. For the kurtosis, which equals 3.3010 (cf. Table 13), the larger the kurtosis, the higher the risk. Indeed, it measures the "fatness" of the curve, and when it is high, the tails extend farther and have a higher probability for extreme returns. The kurtosis can be either mesokurtic (i.e., kurtosis =3), leptokurtic (Kurtosis > 3), or platykurtic (i.e., kurtosis < 3).

From the descriptive statistics of the rolling regression, we can look at the sensitivity of the market portfolio to the four macroeconomic variables: GDP growth, inflation, unemployment rate, and term structure. As explained before, the sensitivity will be against the unexpected part of the macroeconomic factors. Indeed, the difference between the forecast and the actual value of these factors has been computed to get the times series for each.

During the period under analysis (i.e., from 1998 to 2022), the market portfolio has the highest exposure to the term structure factor with a mean of -0.1135. This means that on the whole period, when the “surprise” in the term structure factor increase, the market portfolio experiences a negative return. The unemployment variable is the most volatile, with a standard deviation equal to 1.8869.

This is also the term structure with the highest coefficient during the distressed period. Nevertheless, compared to the entire period, the p-value is higher than the 5% threshold; the null hypothesis cannot be rejected. Unemployment is still the most volatile, but we can see that it is more volatile in economic turmoil, with a standard deviation equal to 2.8495 compared to 1.8869 for the complete period analysis. We can also note that the intercept is much higher in distressed periods (i.e., 0.3162) than in the overall period (i.e., 0.1390), meaning that the part not explained by the four economic factors is higher.

Looking at the evolution of the sensitivity of the different variables (cf. Figure 4), we can see that during the economic turmoil in 2001-2002, the portfolio had a robust negative exposure to GDP growth and a solid positive exposure to unemployment. The market portfolio also had a higher positive exposure to the term structure during the period 2009-2010, but on the other hand, during the Covid crisis, the sensitivity was negative.

To conclude if there is a significant difference between the mean exposure in the overall period and the distressed period, we tested at a 5% significant level. Therefore, for the market portfolio, we cannot conclude that there are substantial differences between the exposure to the macroeconomic variables during the entire period and the distressed period (cf. Table 16).

MKT	Intercept	GDP	UNEMP	TSTR	INF
Distressed periods	0.3162	-0.1575	-0.0917	-0.1699	0.0936
Overall period	0.1390	0.0711	0.0748	-0.1135	0.0886

Table 3: Mean Exposures of the MKT Portfolio- Source: Own calculations

3.2. HML portfolio

The HML portfolio has an average monthly return of 0.269% and a monthly standard deviation equal to 2.8972. The skewness and kurtosis are respectively equal to 0.3895 and 2.8648 (cf. Table 13).
The value portfolio has the highest sensitivity to the unemployment factor with a coefficient equal to 0.1049. As for the unemployment factor, the HML portfolio is positively exposed to the term structure factor. On the other hand, the GDP growth has a negative coefficient. Based on the 5% significance level, inflation and unemployment are below the threshold, and the remaining factors are above.

In the distressed periods, the highest exposure is still to the unemployment factor. Nevertheless, the coefficient's mean is no longer statistically significant at the 5% level. The intercept and the inflation remain negative as it is for the entire period, but the coefficients are higher for both. Indeed, the intercept and the inflation were respectively equal to -0.0598 and -0.0737, whereas, during the distressed periods, it is equal to -0.2459 and -0.1478. In comparison, the term structure has switched from positive to negative, and the GDP growth has changed from negative to positive exposure. Looking at the result's significance during the distressed period, only the inflation is below the threshold of 5%.

Regarding the evolution over time (cf. Figure 6), GDP and Unemployment showed strong negative sensitivity in 2001-2002. Then, at the end of the global financial crisis (i.e., from 2009 to the beginning of

2010), we note that GDP and term structure have negative coefficients before becoming positive at the beginning of the European sovereign debt crisis. Finally, from the beginning of 2022 (i.e., the beginning of the Russian invasion), there is a significant drop to negative exposure of the inflation factor and the term structure.

To conclude, no significant difference at the 5% level has been found except for the inflation factor, with a statistically significant difference between the coefficients in the distressed period and the entire period (cf. Table 16).

HML	Intercept	GDP	UNEMP	TSTR	INF
Distressed periods	-0.2459	0.0742	0.1428	-0.0776	-0.1478
Overall period	-0.0598	-0.0992	0.1049	0.0446	-0.0737

Table 4:Mean Exposures of the HML Portfolio- Source: Own calculations

3.3. SMB portfolio

The SMB portfolio has an average monthly return of 0.210% and monthly volatility equal to 2.0902 from 1998 to 2022. The Skewness and the Kurtosis are respectively equal to -0.2069 and 1.3677 (cf. Table 13).

The results obtained for the size portfolio during the entire period are a positive sensitivity to the GDP growth (i.e., 0.1081), and the remaining factors show a negative exposure. Among all the elements, unemployment has the highest coefficient in absolute value. Therefore, the unemployment and inflation factors are considered statistically significant at a 5% level.

The analysis of the distressed period gives us the same direction (i.e., negative or positive) for the exposure to the different factors. Nevertheless, all the factors except inflation are much higher and show a higher exposure to the size portfolio. This would mean that during economic turmoil, the return of the size portfolio would be more sensitive to the evolution of macroeconomic variables.

To confirm what has been said above, we can notice in Figure 5 that the size portfolio is more exposed to unemployment, GDP, and rate structure during the economic crisis than in general. In the periods 2001-2022, 2009-2011, and 2020-2021, there are several peaks and troughs.

The test of the significant difference between the coefficient between the entire period and the distressed period gave us two statistically significant coefficients at a 5% level. The two macroeconomic factors are unemployment and the term structure, which confirms again the findings above (cf. Table 16).

SMB	Intercept	GDP	UNEMP	TSTR	INF
Distressed periods	0.0125	0.1495	-0.6008	-0.1541	-0.0363
Overall period	0.0040	0.1081	-0.2045	-0.0140	-0.0369

Table 5: Mean Exposures of the SMB Portfolio- Source: Own calculations

3.4. RMW portfolio

The average monthly return of the profitability portfolio is equal to 0.816%, and the monthly volatility is equal to 1.0200. The skewness and the kurtosis are respectively equal to -1.2835 and 6.6147 (cf. Table 13). The kurtosis seems high in this case, meaning the distribution is leptokurtic. As explained before, this generally depicts higher risk but higher possible returns. The profitability portfolio has the highest kurtosis and is the most skewed to the left.

On the complete period, the analysis shows that the RMW portfolio has the highest exposure to the GDP growth factor. Still, it is also the factor that has the most volatile coefficient. The inflation and unemployment factors also have a positive direction but are slightly above 0, whereas the coefficient of the term structure is negative and slightly below 0. To summarize the overall period, except for the GDP, the portfolio based on the firm's profitability does not show high exposure to other macro variables.

During economic crises, the RMW portfolio has not significantly changed in direct exposure (i.e., negative or positive). The coefficient of the GDP is still positive but lower compared to the entire period. The same conclusion can be drawn for the inflation and the term structure but with a negative exposure. However, the exposure to unemployment is still positive but strengthened (i.e., from 0.0179 to 0.0386). The most significant change compared to the analysis under the entire period is the portfolio's expected return which lands at 0.2206.

Regarding the evolution of the coefficient of the term structure, we can notice substantial positive exposure in 2008, 2010, end of 2012, 2015, and 2021. Except for 2015, which was not included in our distress periods subset of data, we can see a more robust exposure during financial distress. As was the case for several other portfolios, the exposure to the unemployment rate was volatile and high from 2000 to 2002. Then, it remained pretty stable over time. The GDP also has a high negative sensitivity in mid-2002, and then it has some positive peak but is not notably correlated with the sub-periods of financial distress selected (cf. Figure 7).

To conclude, we cannot reject the null hypothesis at the threshold of 5% to assert that the coefficients of the unemployment rate, the GDP growth, and the term structure are significantly different in the distressed period compared to the overall period. The inflation factor is the only one where the null hypothesis can be rejected (cf. Table 16).

RMW	Intercept	GDP	UNEMP	TSTR	INF
Distressed periods	0.2206	0.1011	0.0386	-0.0086	0.0725
Overall period	-0.0086	0.1434	0.0179	-0.0462	0.0062

Table 6: Mean Exposures to the RMW Portfolio- Source: Own calculations

3.5. UMD portfolio

The portfolio built based on the momentum of the stocks has a monthly average monthly return of 0.326% and a monthly volatility equal to 1.7104. The kurtosis and the skewness are respectively equal to 0.9261 and -0.3482.

On the overall period, the momentum portfolio is exposed negatively to unemployment and the term structure respectively equal to -0.3426 and -0.0287. To compare the two factors, the momentum is more sensitive to unemployment, which is also considered significant at the 5% level. Regarding the other factors, the GDP is close to 0, and the exposure to inflation is positive and equal to 0.1003.

During the distress periods, the exposure of the unemployment factor is still negative but much more substantial than for the overall period. Indeed, it reaches a coefficient of -1.1345 compared to -0.3426 in the entire period. Additionally, the inflation is still positive but higher, with a coefficient of 0.1727. On the other hand, the term structure factor had a negative exposure, but in the crisis period, the coefficient became positive (i.e., 0.1423). Inflation, unemployment, and term structure coefficients are all statistically significant at the 5% level.

According to the graphs in Figure 8, some peaks of positive inflation exposure can be highlighted. Indeed, the beginning of 2000, 2008, 2012, and 2020 are the highest peaks of inflation exposure. Looking at the term structure, there are two periods of higher positive exposure (2010 and 2020) and one period of higher negative exposure (i.e., late 2012). In addition, the portfolio had an important negative exposure to unemployment from 2000 to mid-2002, which has undoubtedly driven negatively the mean of the coefficient for the distressed period. Indeed, except from 2000 to 2002, the coefficient is around 0 for the rest of the periods. Finally, strong sensitivity in 2002 (i.e., negative), 2009, and 2020 (i.e., positive) can be observed for the GDP growth.

Regarding coefficients statistically different between the entire period and the sub-periods selected for crises, two macroeconomics seem to differ significantly. Similarly, to the SMB portfolio, the macro factors are the term structure and the unemployment rate (cf. Table 16).

UMD	Intercept	GDP	UNEMP	TSTR	INF
Distressed periods	0.3133	0.1013	-1.1345	0.1423	0.1727
Overall period	0.2810	0.0065	-0.3426	-0.0287	0.1003

Table 7: Mean Exposures of the UMD Portfolio- Source: Own calculations

3.6. CMA portfolio

The average monthly return of the portfolio build based on the firm's investment strategy equals 0.120%, and the monthly average volatility is similar to 2.0215. The skewness and the kurtosis are respectively equal to 0.3488 and 2.4320. Compared to the other portfolios, the HML and CMA portfolios are skewed to the right (cf. Table 13).

The portfolio has the highest exposure to the unemployment factor overall, and note that the exposure is negative (i.e., 0.0961). This means that the portfolio returns decrease when the unexpected part of the unemployment rate increases. The coefficient of the inflation factor is also negative but close to 0 and non-significant at the 5% level. On the other hand, the CMA portfolio has a positive exposure to GDP growth and term structure. Among all the macroeconomic factors in the overall period, only the unemployment factor is significant at the 5% level.

During the period selected in economic turmoil, similarly to the UMD portfolio, the unemployment and inflation factors have the same direction (i.e., negative). Still, the power of the exposure is much higher. The sensitivity to unexpected GDP growth and term structure also remains in the same direction (i.e., positive) as in the overall period but with a decreasing exposure for the GDP and an increase for the term structure.

Over the period, the inflation coefficients appear relatively stable, and no peaks or troughs seem to emerge. Conversely, the exposure to GDP showed substantial negative exposure starting in 2001 to mid-2002, followed by a solid positive exposure in 2003 and a solid negative exposure in 2004. As mentioned, no clear tendency can be drawn on the GDP, mainly due to the high volatility (cf. Figure 9).

We cannot reject the null hypothesis for all macroeconomic factors for the CMA portfolio. Therefore, we cannot conclude formally that there is a significant difference in the exposure between the overall period and the sub-period under crisis selection (cf. Table 16).

CMA	Intercept	GDP	UNEMP	TSTR	INF
Distressed periods	0.0387	0.0073	-0.2472	0.0664	-0.0350
Overall period	0.0117	0.0272	-0.0961	0.0365	-0.0038

Table 8: Mean Exposures of the CMA Portfolio- Source: Own calculations

Discussion

In this section, the different results obtained before will be discussed more in-depth. Furthermore, results that seem significant and bring real insight into the portfolio's behavior during a crisis will be highlighted. Then, the different hypotheses elaborated at the end of the literature review section will be answered whether we obtained elements to discuss.

To reply to the initial question of the thesis, the results obtained will be applied to the construction of several portfolios. Indeed, allocation among fundamentals factors portfolios will be done regarding the different results obtained during the crisis and overall periods.

The last section of the discussion will be related to the study's limitations and the empirical research. Indeed, as it happened in empirical research, data obtained, methodology used, or parameter choice can bias the results and could be further improved for future research.

1. Hypotheses

The thesis's main objective was to analyze if some fundamental factors behave better than others in times of crisis. And then looking further at how these fundamental factors react in times of trouble to the unexpected part of macroeconomic variables: GDP growth, inflation, term structure, and unemployment rate.

Looking at the hypothesis stated before, Liew and Vassalou (2004) and Kelly (2003) noted that the economic growth represented by the GDP growth has a positive association with the value, size, and market portfolio. Our findings confirm that the size portfolio confirmed the hypothesis on the overall period with an exposure trend that is positive on the overall period. However, the HML portfolio shows negative exposure in the overall period. This is our observation compared to previous research, but we cannot take it formally as none of them have been statistically significant in the analysis.

Compared to the overall period, Lambert and Platania (2016) reported a positive relationship with the market but a negative relationship with the size and value portfolio during economic turmoil. Our results showed the opposite: a negative association with the market portfolio return and a positive sensitivity with the value and the size portfolio. Except for the size portfolio, the mean exposure to the GDP is not statistically significant.

The second hypothesis was about the exposure of the different portfolios to the term structure for the whole period considered as the normal case. Hah, and Lee (2006) and Petkova (2006) found a negative relationship between the momentum and the market portfolio, and the term structure. Our results show that the momentum and the market portfolio have a negative relationship with the unexpected part of the term structure in the overall period. On the other hand, concerning the value portfolio, we found a positive exposure to the term structure, which aligns with the hypothesis.

Aretz et al. (2007) stated that the inflation factors should be a strong pricing factor and have a strong relationship with the different portfolios. More specifically, a strong negative relationship between the size and market portfolios and a positive exposure to the value portfolio. In the distressed period, Lambert and Platina found no significant association with the different portfolios except for the momentum portfolio, which noticed a positive sensitivity. The results confirmed the findings for the size portfolio in the overall period but not for the value and the market portfolio. On the other hand, the results showed a significant positive relation between the return of the momentum portfolio and the inflation in the distressed period.

Compared to the results of Platania and Lambert (2016), our findings showed a negative sensitivity between the unemployment rate and the size portfolio. Still, they confirmed the positive sensitivity with the market and value portfolio during the period. Conversely, the results showed negative sensitivity to the market and size portfolio during the distressed periods.

2. Application and interpretation

In this section, results obtained before will be applied to the allocation of portfolios. Four different portfolios are going to be built with four different strategies. The idea is to observe whether the portfolio constructed based on the results obtained while considering their exposure would outperform the other strategies. Let us first explain the four different portfolios allocation:

- Portfolio 1: This portfolio is used as the benchmark. The data retrieved for this one is the EURO STOXX 600, an excellent proxy for representing the European equity market.

- Portfolio 2: In this portfolio, we used the portfolios constructed based on the style factors (Size, value, momentum, etc.) and allocated equally among the six portfolios. It means that we gave 16.67% to each style portfolio.

- Portfolio 3: This portfolio will apply a long-short strategy, and no constraints are set up for the short or long position. Indeed, the allocation will be based on the exposure to the different macroeconomic parameters for each portfolio. Only the mean exposure computed for the various factors portfolio deemed statistically significant were retrieved to build the different weights. In Table 9, we can find only the coefficients where the mean was statistically significant; for the others, it has been replaced by zero. Then, total exposure for all the macroeconomic factors was computed to give weight to the different macroeconomic factors. Furthermore, to not give more weight to the macroeconomics factors that have more significant exposure with the various portfolios, each exposure has been divided by the number of the exposure non-equal to zero.

  To clarify, let us consider how the UMD weight was computed. The UMD portfolio is the only one with significant exposure to the abnormal return. It means that the total exposure to the abnormal return equals the exposure of the UMD portfolio (i.e., 0.28). For the unemployment rate, the UMD has an exposure of -0.3426. Since there are four portfolios non-equal to zero for the unemployment rate, the exposure retrieved for the exposure of the UMD portfolio to the unemployment rate is -0.085 (i.e., -0.3426 divided by 4). And then the process is the same for the GDP, term structure, and inflation.

In the end, the weight allocated is obtained by summing all the exposure of the UMD portfolio to the different macroeconomic factors (i.e., 0.2810 -0.0857 +0.0251 = 0.2204), and this is divided by the total exposure between all the macroeconomic factors and all the portfolio (i.e., 0.2296). This is how the weight of 96% of the UMD portfolio during the overall period has been allocated. Moreover, the process is the same for all the portfolios.

Below is the complete formula to land to the weight of the UMD:

$$\frac{(\frac{0.2810}{1}+\frac{0}{1}+\frac{(-0.3426)}{4}+\frac{0}{2}+\frac{0.1003}{4})}{0.2810+0.1434+(-0.1346)+(-0.0798)+0.0195}=0.958\ \approx 96\%$$

The table below shows the detailed weight allocation for the overall period and how it has been constructed.

Coefficients	MKT	SMB	HML	UMD	CMA	RMW	Total
Abnormal	0.0000	0.0000	0.0000	0.2810	0.0000	0.0000	0.2810
GDP	0.0000	0.0000	0.0000	0.0000	0.0000	0.1434	0.1434
UNEMP	0.0000	-0.0511	0.0262	-0.0857	-0.0240	0.0000	-0.1346
TSTR	-0.0567	0.0000	0.0000	0.0000	0.0000	-0.0231	-0.0798
INF	0.0221	-0.0092	-0.0184	0.0251	0.0000	0.0000	0.0195
Total	-0.0346	-0.0604	0.0078	0.2204	-0.0240	0.1203	0.2296
Weight	-15%	-26%	3%	96%	-10%	52%	100%

Table 9: Weight Allocation in the entire period- Source: Own calculations

- Portfolio 4: This last portfolio also applied a long/short strategy. The same work done for the global period was done for the distressed period with regard to the exposure to different macroeconomic factors. This analysis allowed us to obtain the weight allocation that should be used during economic turbulence. When the period is considered to be in economic turmoil (i.e., five selected periods in the data section), the weight obtained by the exposure in the crisis period will be applied to the portfolio. This means that outside the crisis periods, the allocation of weights is the same as for portfolio 3, and during the crisis, the weights determined in Table 10 are used.

Coefficients	MKT	SMB	HML	UMD	CMA	RMW	Total
Abnormal	0.1581	0.0000	0.0000	0.0000	0.0000	0.1103	0.2684
GDP	0.0000	0.1495	0.0000	0.0000	0.0000	0.0000	0.1495
UNEMP	0.0000	-0.2003	0.0000	-0.3782	-0.0824	0.0000	-0.6609
TSTR	0.0000	-0.0770	0.0000	0.0712	0.0000	0.0000	-0.0059
INF	0.0234	0.0000	-0.0370	0.0432	0.0000	0.0181	0.0477
Total	0.1815	-0.1278	-0.0370	-0.2638	-0.0824	0.1284	-0.2011
Weight	-90%	64%	18%	131%	41%	-64%	100%

Table 10 : Weight Allocation in distressed periods- Source: Own calculations

Now that the portfolio strategies are described and the methodology is clearer, let us look at the performance of the different portfolios. In Figure 3, find a graph representing the performance of the four portfolios. To compare them more quickly, this graph has been constructed with a base of 100 and then evolved according to the different returns of the portfolios. Table 17 shows the other statistics regarding the performance of the four portfolios. The period under analysis is from March 1998 to May 2022.

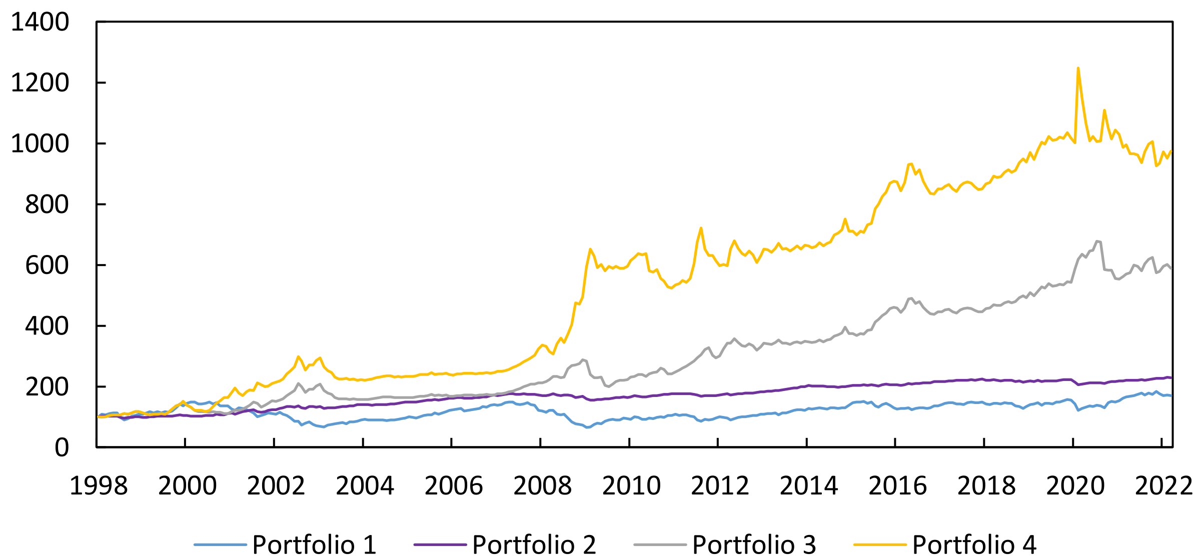


Figure 3:Portfolios Returns – Source: Own Graph

Looking at the different portfolios' performance, we can see that portfolios 3 and 4 outperformed portfolios 1 and 2. Moreover, portfolio two slightly outperformed Portfolio 1.

Portfolio 1, which is the benchmark, underperformed all other portfolios. Except for a few months at the beginning of 2000, the benchmark is below the multifactor portfolios for the entire period under analysis. From this observation, we can notice that investing in a multifactor portfolio is better in performance, whatever the economic situation.

Portfolio 2 is equally weighted between the six factors, which means 16.67% for each factor portfolio. Even if it performed better than the benchmark, we cannot say it performed very well compared to portfolios 3 and 4. Especially from 2007, Portfolios 3 and 4 vastly outperformed Portfolio 2. This observation suppose that the methodology used in portfolios 3 and 4, using the different exposures to the macroeconomic factors to construct the weight allocation, would be efficient. Indeed, both portfolios have been built depending on how they react to the different economic factors, and in terms of performance, this is positively affected.

The comparison between portfolio 3 and portfolio 4 also showed a significant difference in terms of return. The performance difference can be explained by the methodology of constructing the two portfolios. Indeed, portfolio 3 holds the same weight (i.e., weights determined in Table 9) during the entire period under analysis. In contrast, portfolio 4 has the same weight as portfolio 3 except in the period under economic turbulences (i.e., weights determined in Table 10). Looking at the evolution of the returns between the two portfolios, in Figure 3, we notice that portfolio 4 started to outperform mid-2000, and the most significant observation is in 2008 and 2009, where portfolio 4 vastly outperformed portfolio 3. The same can also be observed in early 2020 when Covid started.

This means that looking at the exposure of the different portfolios in the overall and crisis periods to establish the allocation of weights leads to higher returns. In addition, the difference between portfolios 3 and 4 allows us to say that the allocation of weights should be distinct among the factors between the period of normal economic conditions and the period of economic turbulence. Indeed, the factors seem to behave differently, and to take advantage of the situation or at least to protect against it, the weights should be reallocated in times of crisis.

Then, let us evaluate the allocation weight between normal economic conditions and economic under turbulence among the different factors.

With a weight equal to -15% in the overall period and -90% in economic distress, the position to the market portfolio is still short, but the weight allocated is much higher. This means the market portfolio return is much more negative in an economic crisis, which makes perfect sense.

The size portfolio weighted -26% in the overall period and 64% in economic distress. This means that in crisis, the trend of the weight allocated to the size portfolio is the opposite, with a higher proportion allocated to the size factor.

In general, the value portfolio showed a weight of 3%, which is very low compared to the other factors, but in times of crisis, we observed that portfolio 4 is slightly more exposed to the value factor with a weight of 18%. Nevertheless, compared to the other factors, it seems that the value factor is not the one with the highest risk premium, whatever the economic situation.

The momentum factor weighted 96% in the normal conditions period and 131% in the distressed periods, which show a similar trend with a long position for both situations but slightly more weighted during crises.

The CMA portfolio weighted -10% outside the crisis periods in the portfolio but, on the other hand, has a long position of 41% in the portfolio during economic turmoil. This means that compared to the other factors, the CMA factors showed weaker general returns but better returns during economic turbulence.

The profitability factor showed a positive weight of 52% in the entire period, but looking at the weight allocated to the profitability factor in the crisis, it changed dramatically. Indeed, a short position of -64% is taken during the weaker economic situation. This means that from a favorable economic situation to a recession, the returns associated with the profitability factors are strongly different.

An important point is the short and long exposure between the two weight allocations. Indeed, during the global period, the total short position is equal to -52%, whereas, in the weight allocation for crisis periods, the total short position is equal to -154%. And the total long positions are respectively equal to 152% and 254% for the weight allocation strategies. In terms of net exposure, both strategies have a net exposure of 100%. Still, regarding gross exposure, the weighted allocation during the crisis has a total gross exposure equal to 408%, compared to 204% for the other weighted allocation strategy.

3. Limitations and improvements

As we reach the final stage of the work, it is crucial to reflect on what we have accomplished and evaluate what worked well and what areas we can improve for future research. In addition, it is important to take a step back and identify the main challenges faced in the analysis during the post-phase.
Firstly, as the study has been carried out in Europe, data availability is weaker than if we had done it in the US or the Global market. Indeed, we had to estimate and approximate some data points to get what was expected. For the economic data, the unexpected part of the variables was computed by making the difference between the forecast and the actual values. As the monthly forecasts were not found, quarterly data have been retrieved for inflation, the unemployment rate, and the term structure. On the other hand, the actual data were all retrieved every month, which means that for these variables, the unexpected part has been computed by making the difference between monthly and quarterly data.

The number of coefficients deemed significant over the years was low in the rolling window regression. Indeed, few of the coefficients of the macroeconomics variables were statistically significant at a threshold of 5% level on the rolling regression done with the three different window sizes (i.e., 12, 24, 36 months). Another method that could have been used is the Kalman filter. Swinkels and Van der Sluis (2006) reported that the Kalman filter shows less mean squared and absolute deviation, which might increase the number of significant results for future works.

Then, the European crises were selected based on the European central bank's database and historical analysis of Europe's more considerable economic turbulences. To define a sub-period of time in the overall period as an economic turmoil, most countries in the database must have listed it as in a distressed financial period. When most countries were in crisis, the whole European region was considered in trouble. On the other hand, economic turbulence started and ended with delays in some countries. Therefore, the segmentation of the different distressed periods was not accurate and consistent in Europe. Using the database was a great start to finding the most critical crises across Europe. However, adding a corroborative method to identify European crisis periods would help to have a more accurate beginning and end of the selected sub-periods.

At the end of the thesis, a portfolio construction application has been set up regarding the results obtained. The portfolio strategy was a simple long/short strategy without constraints on the short and long positions. This led to different gross exposure in portfolio 4 depending on whether we are in distressed period allocation or the overall period weight allocation. In future research, setting some constraints and comparing the different strategies based on the trade-off risk/return might be interesting.

Conclusion

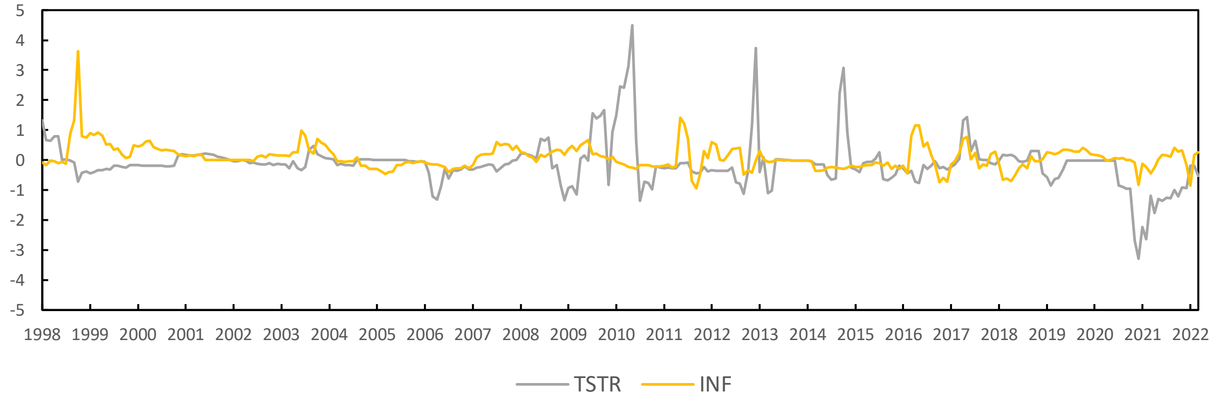
Previous kinds of literature have already worked on the topic but with some differences in fundamental factors or economic variables selection, geographical scope, or even with another methodology. Especially focusing on the European market through six styles factors: the market, the size, the value, the momentum, profitability, and the firm's investment strategy. Indeed, as highlighted during the work, most of the studies focus on the global or the US market, where the data are much better regarding availability.

To conduct the empirical research, an analysis of the exposures to the economic variables of the different style-based portfolios was carried on from 1998 to 2022. Exposures to unexpected GDP growth, unexpected inflation, unexpected unemployment rate change, and unexpected term structure change have been retrieved through a rolling window regression. The exposure found was retrieved for two periods: the entire period and the other is the five subs periods selected and considered in economic turmoil. This analysis of the two distinct economic states highlights differences in exposure. In addition, we noted weak statistical significance in the coefficients obtained through the rolling window regression, meaning that we cannot take formally that all the results were not obtained by chance.

Although the weak statistical significance, we tested if the results obtained through exposure to macroeconomics are economically interesting and can be exploited. To do so, an application to a portfolio construction strategy was made. Indeed, a comparison between four approaches has been performed, and the strategy considering the exposure to the macroeconomics and the economics states overperformed the three others. The weight allocation built for distressed periods overperformed the other strategies and is more efficient in times of crisis. To answer the initial question of the thesis, in times of crisis, a short position should be taken for the market and investment factors and a long position for the value, size, momentum, and profitability factors with a more substantial exposure to the momentum. We can also highlight that the weight allocation is significantly different for the size and the investment factors between economic turmoil and normal condition.

Even though the weight allocation seems fruitful, remarks highlighted in the limitations and improvements section should be considered. Indeed, ways of improvement have been proposed. It might be interesting to further dig into the topic by adding these different points. Furthermore, to be more rigorous in the empirical research and reach more statistical significance, a more robust method to deal with the limitations highlighted should be further explored for future research.

Appendices



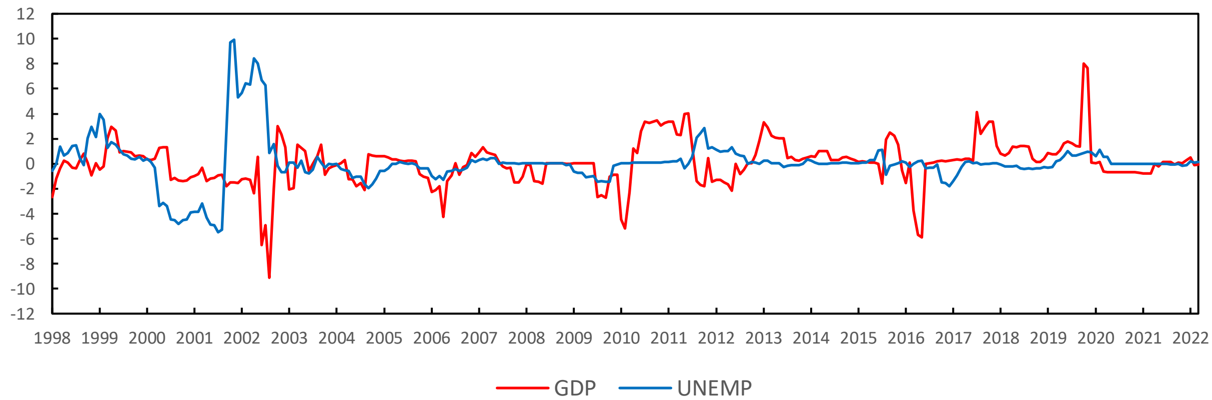
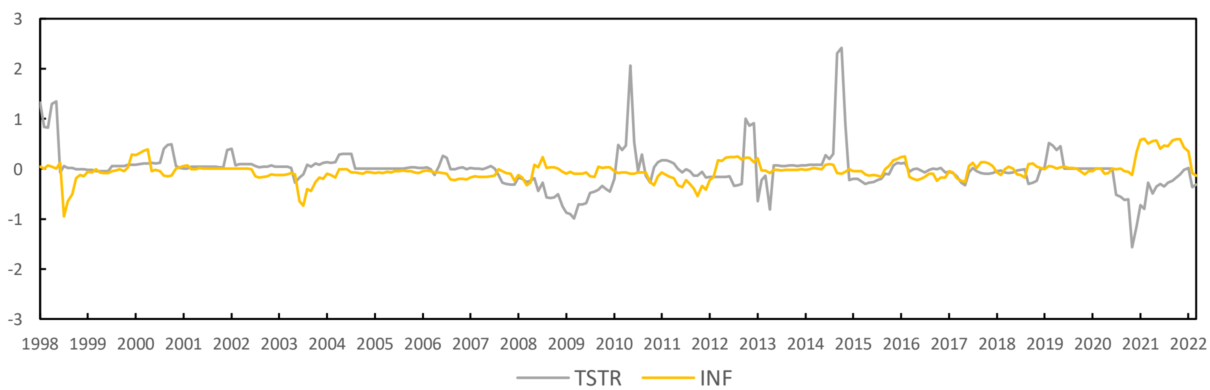


Figure 4: Exposure to the market portfolio of the unexpected GDP growth, unemployment rate, term structure and the inflation over the complete period under analysis (1998-2022) - Source: Own graphs



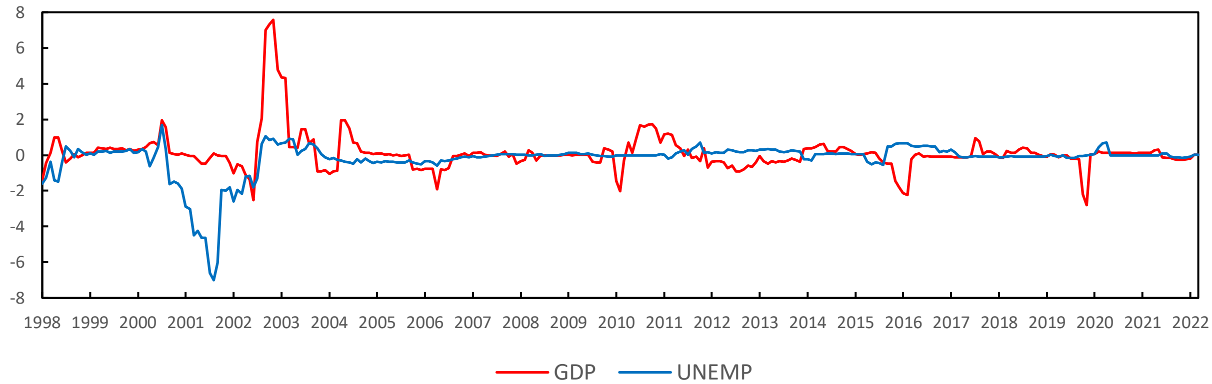
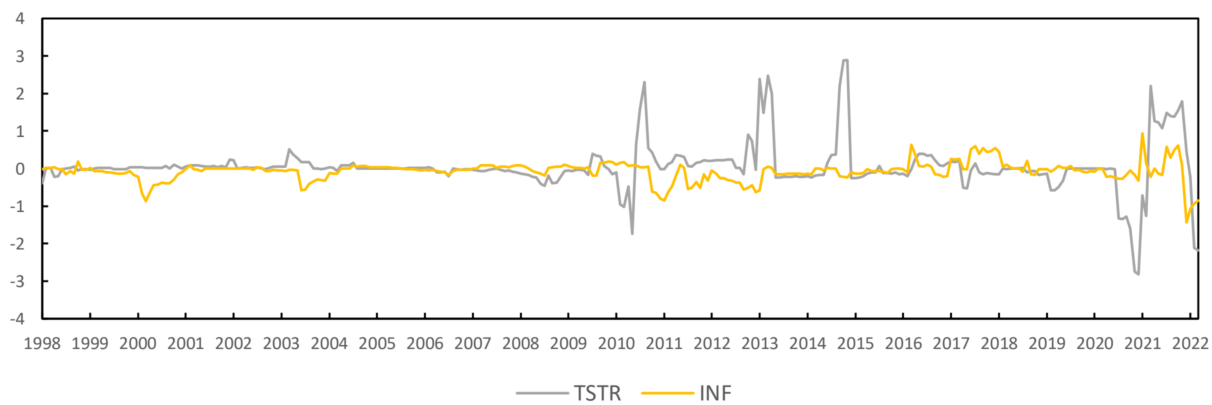


Figure 5: Exposure to the size portfolio of the unexpected GDP growth, unemployment rate, term structure and the inflation over the complete period under analysis (1998-2022) - Source: Own graphs



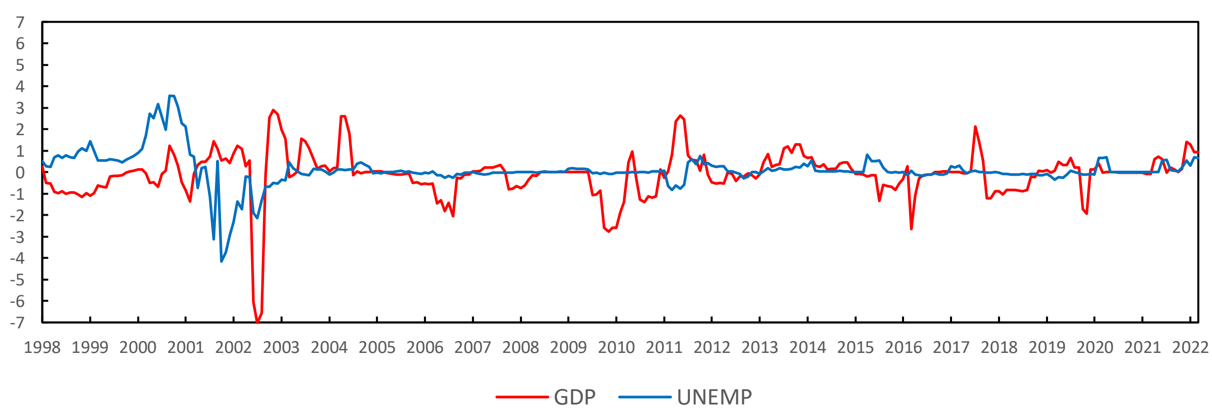
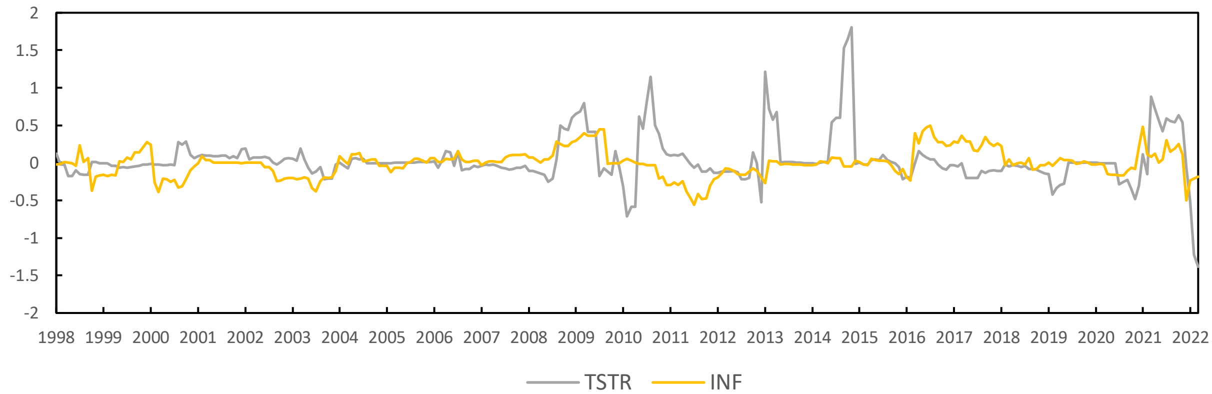


Figure 6: Exposure to the value portfolio of the unexpected GDP growth, unemployment rate, term structure and the inflation over the complete period under analysis (1998-2022) - Source: Own graphs



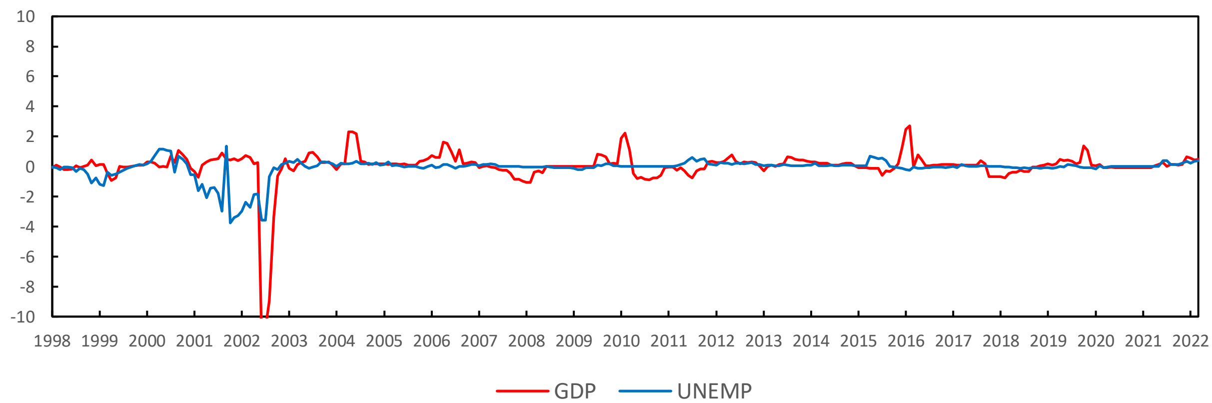
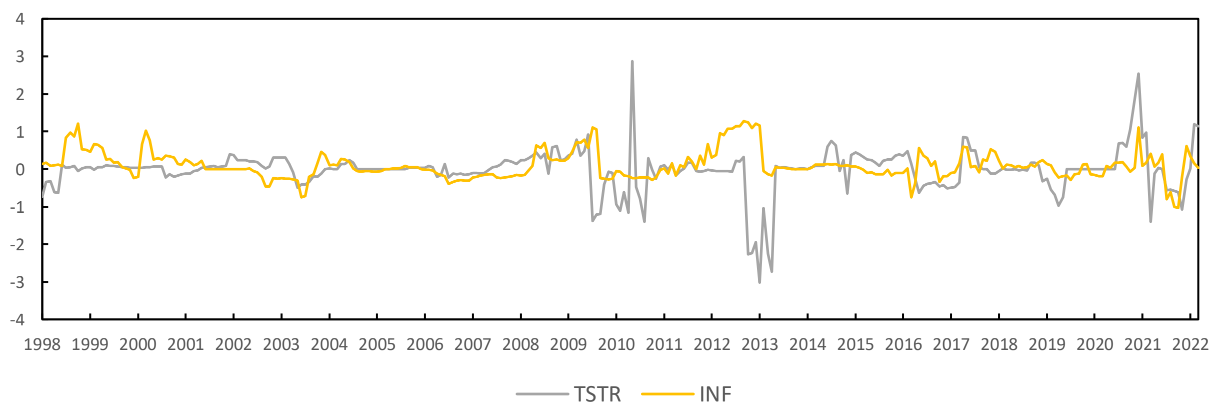


Figure 7: Exposure to the profitability portfolio of the unexpected GDP growth, unemployment rate, term structure and the inflation over the complete period under analysis (1998-2022) - Source: Own graphs



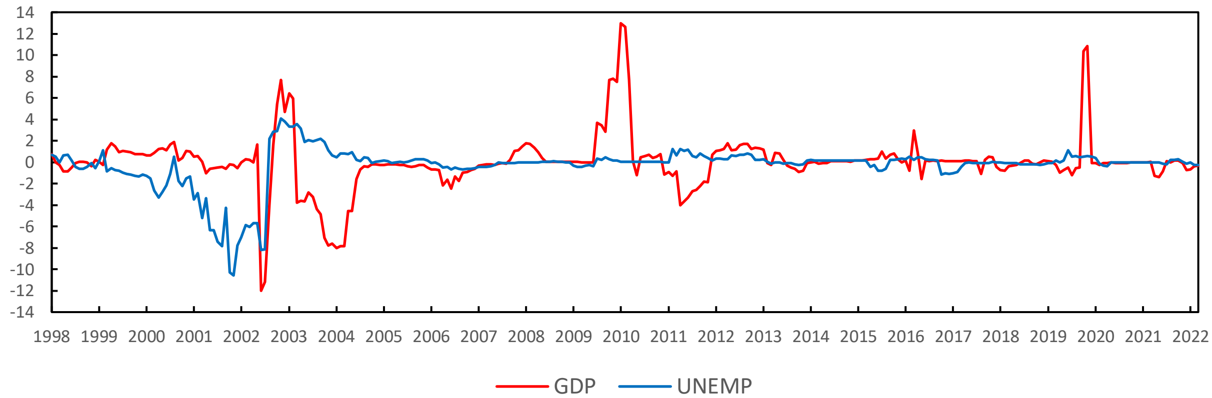
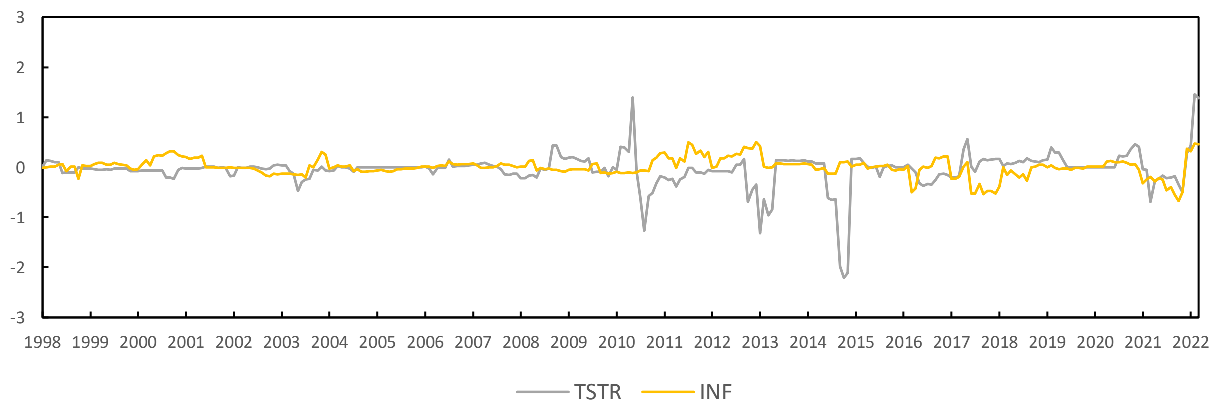


Figure 8: Exposure to the momentum portfolio of the unexpected GDP growth, unemployment rate, term structure and the inflation over the complete period under analysis (1998-2022) - Source: Own graphs



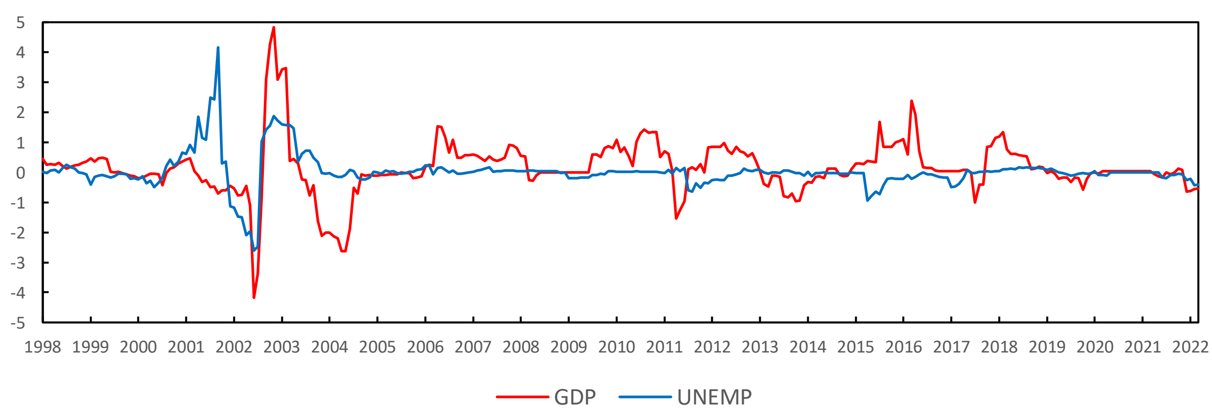


Figure 9: Exposure to the investment portfolio of the unexpected GDP growth, unemployment rate, term structure and the inflation over the complete period under analysis (1998-2022) - Source: Own graphs

Adjusted R-Squared						
	MKT	SMB	HML	UMD	CMA	RMW
	12 Months					
Mean	0.0379	0.0548	0.0147	0.0606	0.0725	0.1090
Median	-0.0333	0.0268	-0.0129	0.0274	0.0405	0.0696
Min	-0.3454	-0.3256	-0.3474	-0.3403	-0.3426	-0.3169
Max	0.8184	0.6884	0.8375	0.8302	0.7670	0.7530
	24 Months					
Mean	0.0240	0.0491	-0.0187	0.0221	0.0313	0.0431
Median	-0.0392	0.0355	-0.0472	-0.0151	0.0066	0.0153
Min	-0.1353	-0.1397	-0.1451	-0.1428	-0.1413	-0.1241
Max	0.6143	0.3946	0.4139	0.4266	0.4122	0.3889
	36 Months					
Mean	0.0243	0.0196	-0.0192	0.0066	0.0273	0.0313
Median	-0.0278	0.0097	-0.0454	-0.0123	0.0193	0.0105
Min	-0.0790	-0.0873	-0.0899	-0.0844	-0.0821	-0.0707
Max	0.4934	0.1582	0.2346	0.2967	0.2855	0.3001

Table 11: Adjusted R-squared retrieved for the different portfolios on the 3 window size tested- Source: Own calculations

Variance Inflation Factor (VIF)				
	GDP	UNEMP	TSTR	INF
	Distressed periods			
Mean	1.2714	1.3556	1.2515	1.2597
Std	0.3510	0.4644	0.3492	0.2400
Min	1.0023	1.0025	1.0049	1.0048
Max	2.7448	3.1495	2.9850	2.0004
Median	1.0709	1.1615	1.1197	1.1690
	Overall period			
Mean	1.4516	1.3991	1.4103	1.5076
Std	0.8861	0.4513	0.5890	0.9267
Min	1.0023	1.0009	1.0021	1.0048
Max	13.7802	3.1495	5.4509	13.5671
Median	1.1376	1.2026	1.2056	1.2264

Table 12: Variance inflation factor for each macroeconomics variables on the 2 periods under analysis- Source: Own calculations

	MKT	SMB	HML	UMD	CMA	RMW
Mean	0.0680	0.2101	0.2688	0.3258	0.1203	0.8164
Median	0.8879	0.2200	0.2400	0.3900	0.0000	1.0200
Std	5.0408	2.0902	2.8972	1.7104	2.0215	4.3318
Min	-24.3041	-7.3300	-11.3000	-5.4000	-7.3000	-26.0900
Max	14.2546	8.8300	12.0900	6.4000	8.7700	13.6500
Kurtosis	3.3010	1.3677	2.8648	0.9261	2.4320	6.6147
Skewness	-1.1885	-0.2069	0.3895	-0.3482	0.3488	-1.2835

Table 13:Descriptive statistics on the returns of all portfolio for the complete periods (i.e. 1998-2022) - Source: Own calculations

Overall period					
	Intercept	GDP	UNEMP	TSTR	INF
			MKT		
Mean	0.1390	0.0711	0.0748	-0.1135	0.0886
Std	1.4031	1.7995	1.8869	0.7736	0.4203
t-stat	1.6896	0.6743	0.6764	-2.5020	3.5941
p-value	0.0922	0.5006	0.4993	0.0129	0.0004
Min	-4.5306	-9.1254	-5.4852	-3.2899	-0.9427
Max	4.1066	8.0153	9.9236	4.4963	3.6299
Median	0.1865	0.1076	0.0135	-0.1400	0.0107
			HML		
Mean	-0.0598	-0.0992	0.1049	0.0446	-0.0737
Std	1.0469	1.0916	0.7878	0.6342	0.2611
t-stat	-0.9751	-1.5509	2.2706	1.1987	-4.8191
p-value	0.3303	0.1220	0.0239	0.2316	0.0000
Min	-3.8740	-7.0340	-4.1596	-2.8189	-1.4336
Max	5.3099	2.8952	3.5455	2.8908	0.9391
Median	-0.1290	-0.0093	0.0046	-0.0006	-0.0311
			SMB		
Mean	0.0040	0.1081	-0.2045	-0.0140	-0.0369
Std	0.6896	1.0918	1.0060	0.4038	0.1969
t-stat	0.0978	1.6887	-3.4672	-0.5928	-3.2006
p-value	0.9222	0.0923	0.0006	0.5538	0.0015
Min	-1.7914	-2.8003	-7.0006	-1.5669	-0.9503
Max	2.2575	7.5727	1.6869	2.4182	0.6011
Median	-0.0617	0.0116	-0.0018	0.0020	-0.0459
			UMD		
Mean	0.2810	0.0065	-0.3426	-0.0287	0.1003
Std	1.4149	2.6239	1.9060	0.5746	0.3750
t-stat	3.3883	0.0425	-3.0667	-0.8512	4.5622
p-value	0.0008	0.9661	0.0024	0.3954	0.0000
Min	-4.8567	-12.0064	-10.5759	-3.0180	-1.0297
Max	3.8106	12.9683	4.0761	2.8712	1.2757
Median	0.4336	0.0029	0.0004	0.0135	0.0377

	Intercept	GDP	UNEMP	TSTR	INF
			CMA		
Mean	0.0117	0.0272	-0.0961	0.0365	-0.0038
Std	0.7415	1.2149	0.6807	0.3198	0.1808
t-stat	0.2683	0.3824	-2.4077	1.9485	-0.3612
p-value	0.7887	0.7025	0.0167	0.0523	0.7182
Min	-2.4567	-11.5285	-3.7615	-1.3831	-0.5587
Max	4.0236	2.7107	1.3549	1.8063	0.4964
Median	-0.0268	0.1029	0.0091	-0.0046	0.0006
			RMW		
Mean	-0.0086	0.1434	0.0179	-0.0462	0.0062
Std	0.4879	0.9057	0.5807	0.3422	0.1795
t-stat	-0.2995	2.7016	0.5270	-2.3018	0.5856
p-value	0.7648	0.0073	0.5986	0.0221	0.5586
Min	-1.8652	-4.1758	-2.6054	-2.2075	-0.6725
Max	1.0668	4.8312	4.1609	1.4578	0.5051
Median	-0.0130	0.0480	-0.0098	-0.0054	0.0039

Table 14: Descriptive statistics on the exposure of the different portfolio to the macroeconomics variables on the complete period under analysis (i.e. 1998-2022) - Source: Own calculations

Distressed periods					
	Intercept	GDP	UNEMP	TSTR	INF
			MKT		
Mean	0.3162	-0.1575	-0.0917	-0.1699	0.0936
Std	1.3845	1.5878	2.8495	0.9746	0.3529
t-stat	2.2263	-0.9667	-0.3135	-1.6987	2.5837
p-value	0.0284	0.3361	0.7546	0.0927	0.0113
Min	-4.5306	-2.7270	-5.4852	-3.2899	-0.9427
Max	3.0537	4.0252	9.9236	4.4963	1.4125
Median	0.2118	-0.6669	0.0168	-0.1033	0.1077
			HML		
Mean	-0.2459	0.0742	0.1428	-0.0776	-0.1478
Std	1.3476	0.8058	1.2428	0.7686	0.2859
t-stat	-1.7783	0.8975	1.1199	-0.9835	-5.0402
p-value	0.0785	0.3717	0.2656	0.3279	0.0000
Min	-2.6736	-2.5998	-4.1596	-2.8189	-1.0657
Max	5.3099	2.6480	3.5455	2.3030	0.9391
Median	-0.5961	-0.0036	0.0041	0.0203	-0.0550
			SMB		
Mean	0.0125	0.1495	-0.6008	-0.1541	-0.0363
Std	0.7566	0.5828	1.5807	0.4380	0.2054
t-stat	0.1613	2.5008	-3.7048	-3.4285	-1.7227
p-value	0.8722	0.0141	0.0004	0.0009	0.0882
Min	-1.7914	-1.1257	-7.0006	-1.5669	-0.5422
Max	1.2489	1.9443	1.6869	2.0590	0.6011
Median	0.0150	0.0262	-0.0013	-0.0632	-0.0523
			UMD		
Mean	0.3133	0.1013	-1.1345	0.1423	0.1727
Std	1.7349	1.4758	2.5765	0.6396	0.3227
t-stat	1.7600	0.6687	-4.2918	2.1689	5.2145
p-value	0.0816	0.5053	0.0000	0.0326	0.0000
Min	-4.8567	-4.0026	-10.5759	-1.3970	-0.2828
Max	3.2326	7.6927	1.2393	2.8712	1.1071
Median	0.6110	0.0056	-0.0010	0.0644	0.1163

	Intercept	GDP	UNEMP	TSTR	INF
			CMA		
Mean	0.0387	0.0073	-0.2472	0.0664	-0.0350
Std	1.0288	0.4585	0.9776	0.3668	0.2173
t-stat	0.3670	0.1543	-2.4646	1.7633	-1.5717
p-value	0.7144	0.8777	0.0155	0.0811	0.1194
Min	-1.7500	-1.0531	-3.7615	-1.3831	-0.5587
Max	4.0236	1.0546	1.3549	1.1474	0.4842
Median	-0.2015	-0.0026	0.0019	0.0488	-0.0110
			RMW		
Mean	0.2206	0.1011	0.0386	-0.0086	0.0725
Std	0.4147	0.5510	0.7419	0.3519	0.1629
t-stat	5.1846	1.7885	0.5071	-0.2384	4.3350
p-value	0.0000	0.0769	0.6133	0.8121	0.0000
Min	-0.7189	-1.5316	-2.0839	-1.2597	-0.3144
Max	1.0668	1.4194	4.1609	1.4578	0.5050
Median	0.1593	0.0355	-0.0023	-0.0306	0.0172

Table 15:Descriptive statistics on the exposure of the different portfolio to the macroeconomics variables on the pre-selected distressed period (i.e. 2000-2022 / 2008-2009)/2010-2012/2020-2021/2022) - Source: Own calculations

	Distressed Period	Overall Period	t-stat	p-value
		MKT		
Intercept	0.3162	0.1390	1.0705	0.2851
GDP	-0.1575	0.0711	-1.1680	0.2435
UNEMP	-0.0917	0.0748	-0.5274	0.5982
TSTR	-0.1699	-0.1135	-0.5087	0.6112
INF	0.0936	0.0886	0.1133	0.9099
		HML		
Intercept	-0.2459	-0.0598	-1.2182	0.2239
GDP	0.0742	-0.0992	1.6459	0.1006
UNEMP	0.1428	0.1049	0.2770	0.7819
TSTR	-0.0776	0.0446	-1.3877	0.1660
INF	-0.1478	-0.0737	-2.2191	0.0271
		SMB		
Intercept	0.0125	0.0040	0.0971	0.9227
GDP	0.1495	0.1081	0.4701	0.6386
UNEMP	-0.6008	-0.2045	-2.2745	0.0235
TSTR	-0.1541	-0.0140	-2.7321	0.0066
INF	-0.0363	-0.0369	0.0265	0.9789
		UMD		
Intercept	0.3133	0.2810	0.1626	0.8709
GDP	0.1013	0.0065	0.4358	0.6633
UNEMP	-1.1345	-0.3426	-2.7330	0.0066
TSTR	0.1423	-0.0287	2.2971	0.0221
INF	0.1727	0.1003	1.8057	0.0717
		CMA		
Intercept	0.0387	0.0117	0.2350	0.8144
GDP	0.0073	0.0272	-0.2327	0.8161
UNEMP	-0.2472	-0.0961	-1.3864	0.1664
TSTR	0.0664	0.0365	0.7029	0.4825
INF	-0.0350	-0.0038	-1.2526	0.2111
		RMW		
Intercept	0.2206	-0.0086	4.4324	0.0000
GDP	0.1011	0.1434	-0.5419	0.5882
UNEMP	0.0386	0.0179	0.2455	0.8062
TSTR	-0.0086	-0.0462	0.9015	0.3679
INF	0.0725	0.0062	3.3278	0.0010

Table 16: Difference between the mean coefficient obtained for the 2 periods under analysis- Source: Own calculations

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
Mean	0.28%	0.30%	0.67%	0.87%
Std Dev	0.0448	0.0133	0.0347	0.0429
Min	-14.80%	-5.19%	-16.04%	-10.55%
Max	13.73%	4.58%	12.53%	24.67%

Table 17: Descriptive statistics of the 4 portfolios created - Source: Own calculations

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Executive Summary

Financial crises are not something new, and investors have had to deal with them for decades. Especially in the current situation, in the recovery of Covid-19 and currently hit by the Russian invasion of Ukraine. These various unexpected events directly impact the financial market, and to protect against investors, they must allocate their investments accordingly.

This thesis mainly focused on style factors and how these style factors behave in times of crisis. The following style-based portfolios have been used for the study: market, size, value, momentum, profitability, and investment firm's strategy. Their exposures to four macroeconomic variables under normal and distressed economic conditions were computed through a rolling window regression to analyze their behavior. The four macroeconomics selected to carry on the analysis are GDP growth, inflation, the unemployment rate, and the term structure, and the whole period under analysis is from 1998 to 2022.

The two economic states are compared regarding exposure to the economic variables. Then an application of the results is applied to a portfolio construction strategy. The portfolio built based on the results obtained outperformed the other in terms of return. The following conclusion can be taken regarding the different style factors. In times of crisis, a short position should be taken for the market and investment factors and a long position for the value, size, momentum, and profitability factors with more substantial exposure to the momentum. We can also highlight that the weight allocation seems to be significantly different for the size and the investment factors between economic turmoil and normal condition.

The conclusion suggests an outperformance based on the results obtained, but this needs to be taken carefully as the statistical significance of the coefficients obtained is weak. Furthermore, at the end of the work, suggestions related to the limitations are made to improve the analysis further.

Key words: Style investing, Financial crises, Style Factors, Multifactor model, Macroeconomic factors, Rolling window regression

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