Master thesis

Investor Sentiment and European Stock Returns, Extending the Fama-French Five-Factor Model

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STUDENT REPORT

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Abstract

This paper focuses on the European market, investigating the explanatory power of investor sentiment in an asset pricing context. While traditional asset pricing models like CAPM and the Fama-French models have largely relied on factors such as market risk, size, value, profitability, and investment patterns to explain stock returns, this research introduces a behavioral factor, investor sentiment, as an additional factor. The investor sentiment factor, constructed following Baker & Wurgler's methodology but adapted to the European market, is assessed for its explanatory power on both portfolios and individual stocks using OLS for time-series regression. The study evaluates the results using the Fama-French five-factor model as a benchmark. Due to weak results in test on portfolio is this aspect not further investigated. However, the results for individual stocks warrant further research, applying and testing time-varying betas. The introduction of dynamic conditional betas significantly impacted the model's explanatory power. Consequently, the thesis highlights the investor sentiments factor ability to enhance the explanatory power of the Fama-French five-factor model when incorporating time-varying betas for individual stocks measured by R^2 and $adj\ R^2$, while the absolute average alpha indicates that the model including the investor sentiment factors captures less of the excess returns.

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1. Introduction

Explaining and understanding the behavior of financial assets is a difficult challenge and is a topic that is very interesting for the market participant. Varius asset pricing models have been developed like the CAPM, and the Fama French three factor model, Carhart four factor model and Fama French five factor model. These models aim to explain the average returns of the financial markets, with factors such as size, value, profitability, and investment patterns (Fama & French, 1993; Fama & French, 2015). This helps the investor to better understand the financial markets and its movements. These asset pricing models builds on the theory of investors behave rational, and the markets are efficient due to the arbitrage mechanism once disequilibrium in prices are detected (Dhaoui & Bensalah, 2017).

This assumption on rationality and fully efficient market is questioned in behavioral finance, where it is argued that investors are not fully rational. Instead, behavioral finance suggest that investors' psychological states also have an impact on their decision process (Dhaoui & Bensalah, 2017). Behavioral finance literature has shown that investors in periods of high sentiment might tend to overvalue speculative stocks and opposite in low sentiment periods where bond like stocks tend to outperform more speculative stocks (Shen, Yu, & Zhao, 2017). This relation between sentiment and stocks, is explained by the theory that investors are two types: rational arbitrageurs who are sentiment-free and irrational traders prone to exogenous sentiment (Baker & Wurgler, 2007). They compete in the market and set prices and expected returns, the reason why these prices sometimes vary from the fundamental values, is that the arbitrageurs are limited in various ways. Furthermore, this deviation from the fundamental value can also stem from firm characteristics that make some stocks more difficult to value and create a broader valuation range. This uncertain future allows investors to defend valuations that fits their prevailing sentiment (Baker & Wurgler, 2007). Research have shown sentiment prone stocks tend to have some of the following characteristics, being small, volatile, significant amount of intangible assets (Berger & Turtle, 2012). Which is also some of characteristics that are challenging for the Fama French five factor model (Fama & French, 2015). This paper will therefore seek to test if an investor sentiment factor can be included as an additional factor to improve the Fama French five factor model ability to explain excess returns.

The majority of the empirical asset pricing literature focuses on the US market, and this trend extends to the study of investor sentiment, with numerous papers also investigating its role in factor modeling contexts (Berger & Turtle, 2012; Dhaoui & Bensalah, 2017; Shen, Yu, & Zhao, 2017). In contrast, the field of investor sector sentiment in Europe is notably smaller, as it has not received comparable academic attention. However, there is interest in whether methods applied to US markets can be adapted to fit the European context. Reis and Pinho (2020) demonstrated that their European sentiment index can be used as a predictor of market returns in Europe, noting that periods of low or negative sentiment are often followed by higher, positive returns (Reis & Pinho, 2020). However, it remains to be researched whether including an investor sentiment factor in an asset pricing model enhances its ability to explain excess returns in Europe. This leads to the following research question:

Does incorporating an investor sentiment factor enhance the explanatory power of the Fama-French five-factor model for excess returns of European Stocks?

To answer the research question, the method developed by Baker and Wurgler, along with insights from the European market from the papers of Reis and Pinho, will be used to construct the investor sentiment index (Baker & Wurgler, 2007; Reis & Pinho, 2020). A revised Fama-French model that includes this investor sentiment factor will be proposed and tested using commonly employed methods in the asset pricing literature. The Fama-French five-factor model will serve as the benchmark. The analysis will include both time-series tests of portfolios and individual stocks using OLS regression, focusing on both R^2 and the intercepts. Additionally, statistics such as GRS-statistics, T-statistics, and p-values will be used to evaluate the models. The concepts of time-varying betas will also be included and tested. Each test and concept will be explained and discussed throughout the report as they are used, including their relevance to the overall research objective.

2. Theory and literature review

This paper seeks to investigate how the behavioral literature on investor sentiment can be applied in a European asset pricing context. Therefore, will this chapter focus on presenting the relevant theories and models from these two fields of finance literature.

2.1 Asset pricing theory

The section on asset pricing theory will start with some of the early work in the literature to understand the development of the field. At the end, the Fama-French five-factor model will be presented, and the individual factors will be discussed along with the rationale behind their inclusion in the model.

2.1.1 CAPM

The capital asset pricing model (CAPM) marks the start of the asset pricing theory and is still widely used in finance today for things such as estimating the cost of capital. The greatest strength with the CAPM model is it simple an intuitive measuring of risk and its relationship with expected return (Fama & French, 2004).

CAPM builds on the Harry Markowitz work in portfolio theory, where he created the theory of a mean variance model. The logic behind this model is that investors choose a mean variance effective model, meaning that they minimize the variance of the portfolio return given the expected return and maximize the expected return given the variance (Lintner, 1965; Sharpe, 1964). Meaning that in an efficient marked, with rational investors then is there a tradeoff between risk and expected return. Therefore, is it the investors risk aversion very defining for the expected return of the investors mean variance portfolio (Fama & French, 2004). The CAPM builds on this by assuming that the market portfolio must be the minimum variance frontier and uses this assumption to create the CAPM. The market beta is always 1 and the beta of the individual assets are a measure of its return in variation to the market return. This means a beta of 1.2 would indicate that this asset moves more than the market and imply higher risk and therefore a higher expected return (Fama & French, 2004).

CAPM withstand of only three elements the risk-free rate, the market risk premium, and the beta of the asset. That it only contains of three components shows the simplicity of the model, which might also be one of the main reasons why its empirical record is rather poor. One of the main problems is that the relation between the beta and average return is too flat (Fama & French, 2004). This is shown by empirical test where the excess market returns are positive for assets with low beta and opposite with assets with high betas. This meaning that the model is predicting to low returns on asset with low betas, as they in reality performs better than their beta indicates (Fama & French, 2004).

The empirical failures of the CAPM have created different stories between two groups in the finance literature. The one is the behavioralists that focuses on that it is caused by irrational pricing, and the other story is that there is a need for a more complicated asset pricing model, as the assumptions are too unrealistic in the CAPM (Fama & French, 2004).

2.1.2 Arbitrage pricing theory

The Arbitrage Pricing theory (APT) was proposed as an alternative to the CAPM and its mean variance perspective. It combines the theory of exploiting arbitrage opportunities with the ideas of a multifactor model (Ross, 2013).

The APT assumes that there are a large number of assets that all obey the linear factor model, that says that the return realization R_i for each asset is generated as the following model shows (Linton, 2019).

$$R_i = \alpha_i + \sum_{k=1}^{K} b_{ik} f_k + \varepsilon_i \quad (1)$$

f_k are random K common factors, and b_{ik} is the factor loadings. Factor loadings is sensitivity of the return on each asset to the factor k. ε_i is the idiosyncratic risk, that is asset specific as opposed to the systematic risk that is the risk of economy wide factors. There are a few assumptions about the idiosyncratic risk, it expected value is 0 and it must not be correlated with any of the common factors (Linton, 2019).

The model structure implies that the mean and therefore the expected return is:

$$\mu_i = E(R_i) = \alpha_i + \sum_{k=1}^{K} b_{ik} E(f_k) \quad (2)$$

The idiosyncratic risk is assumed to have a mean of 0, and therefore is the expected value of the idiosyncratic risk also 0 and is removed from the model 2. This can be used to rewrite the formula for rate of return of asset i.

$$R_i = E(R_i) + \sum_{k=1}^{K} b_{ik}(f_k - E(f_k)) + \varepsilon_i \quad (3)$$

As shown in equation 3 can the return of asset i be written as the expected return + sum of the change in the factors relative to the expected + an idiosyncratic part. Therefore, will a well-diversified portfolio p, which is fully hedged against factor risk have the following return (Linton, 2019).

$$R_p = \sum_{i=1}^{n} w_i R_i \quad (4)$$

Fill in the formula for R_i:

$$R_p = \sum_{i=1}^{n} w_i \alpha_i + \sum_{k=1}^{K} \sum_{i=1}^{n} w_i b_{ik} f_k + \sum_{i=1}^{n} w_i \, \varepsilon_i \quad (5)$$

As it fully hedged for factor risk, rewrite:

$$R_p = \sum_{i=1}^{n} w_i \alpha_i + \sum_{i=1}^{n} w_i \, \varepsilon_i \quad (6)$$

The portfolio is well diversified so therefore no idiosyncratic risk:

$$R_p = \sum_{i=1}^{n} w_i \alpha_i \quad (7)$$

If this portfolio is an arbitrage portfolio the return would approximately be 0, otherwise there would be an arbitrage opportunity to make money for noting. In case there is a risk-free asset then the return will approximately be the risk-free asset (Linton, 2019). Following these arguments then is the arbitrage pricing theory implying that to continuously earn returns above the risk-free rate demands that you take higher risk by exposure to different economic wide factors (Linton, 2019).

2.1.3 Multi factor asset pricing models

Eugen F. Fama and Kenneth R. French focuses on the multi factor approach, as they in 1993 propose a three-factor model, adding the factors Small minus Big (SMB) and High book value minus Low book value (HML) to the CAPM. These are included to further explain the systematic risk, which cannot be diversified, as it is not asset specific. The rationale behind these two additional factors is that it is observed that small stocks have a higher average return than large stocks and the same with high book to market value stocks also described as values firms (Fama & French, 1993). This three-factor model performed significantly better at capturing the variation in the average returns.

Carhart's four factor model extended the three-factor model by including momentum as a factor, taking the momentum pricing anomaly into consideration, that shows that last year's winners tend to outperform last year's losers. The four-factor model reduces the average pricing error relative to both the CAP and Fama French three-factor model, indicating that it improves the asset pricing models in describing the variation in average stock returns (Carhart, 1997).

Fama French three factor model has been further evolved by the authors with the two additional factors profitability (RMW) and investment pattern (CMA). The rational for the addition of these is explained by the dividend discount model, that with some manipulation shows the relation between expected return and expected profitability, expected investment and book to market value. The two additional factors were incorporated into the three-factor model to address the numerous anomalies associated with it. The results of the five-factor model tests proved stronger than those of the three-factor model, but they also challenged the importance of the HML factor. Additionally, the main issue with the model remains the asset pricing of small stocks (Fama & French, 2015).

2.1.4 Fama French five factor model

The Fama French five factor model in equation 8 is withstanding of the factors Mkt-RF, SMB, HML, RMW and CMA. The Mkt-RF is the markets excess returns relative to a risk-free rate and is taken from the CAPM. The Fama French five factor model is including four additional factors to the CAPM and what they measure and how they are created will be discussed in the coming sections.

$$R_{it} - R_{Ft} = a_i + b_i(Mkt_t - RF) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t \quad (8)$$

Size (SMB)

The size factor was discovered as anomaly of CAPM, and several studies showed that small companies on average delivered higher returns relative to the returns of large companies. These results suggested that an additional factor including a size premium would improve the CAPM, as they argue CAPM is misspecified. Whether this anomaly was directly caused because of a size factor, or just a proxy for one or more unknown but true factors, that was closely correlated with size, is uncertain and discussed in multiple studies (Banz, 1981; Reinganum, 1981).

Eugen F. Fama and Kenneth R. French builds their research on these studies and in 1992 they reject the CAPM based on their evidence that the size and book-to-market-equity, captures cross-sectional variance in the average returns, which is missed by the market return factor (Fama & French, 1992). Based on the principles of APT pricing and the multifactor approach to asset pricing Eugen F. Fama and Kenneth R. French construct their Fama French three factor model. (Fama & French, 1993) The SMB factor is calculated by taking the average returns of small stocks portfolios and minus with the average return of big stock portfolios. The small and large stock portfolios is created by defining big stocks as those in the top 90% market cap for the region, and small stocks as those in the bottom 10% of the region (French, 2024).

Value (HML)

The value factor builds on comparing the market value of a company against its fundamental values namely book values. Two variables that measures this is earning-to-price ratio (E/P) and book-to-market equity ratio (B/M), that both scales the firms stock price. If the book values are high relative to the market price of the company, then is the investor investing in the company receiving a higher proportion of the book values relative to investing in a company with a high market to book value. E/P is following the similar rational just focusing on the proportions of earnings the investor is receiving (Fama & French, 1992).

Fama and French (1992) test the E/P as well as the B/M in their study exploring factors that can help explaining average returns on the US market. Their study shows that when combined with the size factor is E/P becoming insignificant as it is information seems to be absorbed by the size and B/M factors (Fama & French, 1992).

Fama and French builds their value factor incorporating this relation between B/M and the average returns, by constructing the factor high minus low B/M. The break points of the B/M is the 30th and 70th percentiles of the big stocks of the region. The factor is then the average returns of high B/M minus the average returns of the low B/M (French, 2024).

Profitability (RMW) and investment (CMA)

The profitability factor and investment factor build on the value factor and its use of the B/M ratio. Both profitability and investments are related to the average returns and their relation can be explained using dividend discount model (DDM). The DDM model in equation 9 is stating that the market value of a stock is the discounted value of its expected dividend per share (Fama & French, 2015).

$$m_t = \sum_{r=1}^{\infty} E(d_{t+\tau}) \; / \; (1+r)^t \quad (9)$$

The equation 9 is the DDM model, where m_t is the share price at time t.
$E(d_{t+\tau})$ is the expected dividend per share for the period defined as $t+\tau$, r is the long-term average expected stock return (Fama & French, 2015).

This model can with a bit of manipulation help explain the relationship. Assuming there are two similar stocks with the same future expected dividends with different prices, then the low-price stock will have a higher long-term average expected return. Assuming the stocks are priced rational, must the future dividends of the lowest priced stock be more uncertain, and therefore this lower price (Fama & French, 2015). The expected dividend part $E(d_{t+\tau})$ can be rewritten using its relation with expected profitability, expected investment and B/M. Profitability determines the pool of money available for dividends, while expected investment indicates the proportion of this pool that will be allocated to investments and therefore not available for distribution as dividends (Fama & French, 2015).

$$M_t = \sum_{r=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau}) \ / \ (1+r)^t \quad (10)$$

$Y_{t+\tau}$ are the total equity earnings(profitability) for the period $t + \tau$ and $dB_{t+\tau}$ is the change in total book equity(investment). Then dividing with the book value at time t.

$$\frac{M_t}{B_t} = \frac{\sum_{r=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau}) \ / \ (1+r)^t}{B_t} \quad (11)$$

Playing with this equation 11 and the relations it implies there can be made three statements about the expected stock returns. Firstly, by fixing the everything except the current value of the stock (M_t) and the expected long term stock return (r). Then a low current value (or equivalent high B/M), implies there is higher long term expected returns, as the rate is used to discount the dividends, everything else is kept fixed (Fama & French, 2015).
Secondly by fixing everything expect expected future earnings ($Y_{t+\tau}$) and expected stock return(r), then is higher expected future earnings implying higher future returns, as the current value of the stock (m_t) is kept fixed.
Thirdly by fixing everything else than expected return and change in book equity ($dB_{t+\tau}$). Then will a higher expected growth in investments imply a lower expected return, as everything else is kept fixed (Fama & French, 2015).

This leads to saying that the value factor that uses B/M, is noisy proxy for the expected returns, as the second and third statements above shows that even with a fixed B/M, then can the expected returns change as a reaction to changes in book equity (investments) and change in expected earnings (profitability). Therefore, to improve the Fama French three factor, these additional two factors profitability (RMW) and investments (CMA) is included in the model (Fama & French, 2015).

Similar to the construction for the factor HML is the RMW and CMA constructed by creating portfolios with the breakpoints of 30th and 70th percentiles sorted by respectively operating profit (OP) and investments (INV) (French, 2024). The RMW is then calculated by taking the average return of the robust operating profitability portfolio minus the average return of the weak operating profitability portfolios. The CMA is the average returns of the conservative investment portfolios minus the average returns of the aggressive investment portfolios (French, 2024).

2.2 Investor sentiment literature

Researchers in behavioral finance suggest an alternative model that differs from the standard finance theory about rational investors forcing the prices to the fundamental value. This alternative model focuses on the effect of investor sentiment. Delong, Schleifer, Summers and Waldman (1990) argue that investors are affected by sentiment, by analyzing the effect of noise traders in the market (De Long, Shleifer, Summers, & Waldmann, 1990). Schleifer and Vishny (1997) laid out the assumption that betting against investor sentiment can be costly and risky, for rational and arbitrage investors. This weakens the assumption of rational investor forcing the prices to the fundamentals, as it limits arbitrage (Shleifer & Vishny, 1997).

Investor sentiment is defined as a general optimism or pessimism towards future asset returns. This is a variable that is very hard to directly measure and the closest to a direct measure is through survey, which is a costly and time-consuming method. Therefore, has there been multiple different approaches to measure it indirectly using different economic variables as proxies. Lee et al. (1991) used the closed fund discount as a variable for measuring investor sentiment (Lee, Shleifer, & Thaler, 1991). Neal and Wheatly (1998) test three of the most used economic variables for investor sentiment respectively discounts of closed-end funds, the ratio of odd-lot sales to purchase and net mutual fund redemptions. They find that the discounts of closed-end funds and net mutual fund redemptions shows the best evidence (Neal & Wheatley, 1998).

Baker and Wurgler (2006, 2007), builds on the past research of different sentiment proxies and create a monthly sentiment index based on six sentiment proxies. The investor sentiment index they propose is using Principal Component Analysis to gather sentiment elements from the six following components: the closed-end fund discount, share turnover, the number of IPOs, the first day IPO return, the share of equity issues relative to debt issues, and the dividend premium (Baker & Wurgler, 2006; Baker &

Wurgler, 2007). The Baker and Wurgler investor sentiment index and methodology is widely used in research as the measurement of investor sentiment.

Berger and Turtle (2012) study the impact of investor sentiment on cross-section of equity returns, focusing on the characteristics of sentiment prone stocks, when controlled for the Fama French five factors and the momentum factor. Their results show sentiment-prone stocks tend to exhibit opaque characteristics, and the effect of sentiment is significant (Berger & Turtle, 2012). Dhaoui and Bensalah (2017) shows that a model incorporating investor sentiment as additional factors to the Fama French five factor model in some cases performs better on US market (Dhaoui & Bensalah, 2017). Yang and Zhou (2015) uses Baker and Wurgler's methodology to create a Chines sentiment index, and shows it has a significant effect on excess returns, after they are controlled for the Fama French three factor model (Yang & Zhou, 2015).

The investor sentiment index has mainly been tested on the US market and to some degree on the Chinese market but is only to a very small degree tested on the European market. Reis and Pinho (2020), creates a European investor sentiment index using Baker and Wurgler methodology, but with European investor sentiment proxies. Their European investor sentiment index shows clear relation with Baker and Wurgler's investor sentiment index. Furthermore, is the European investor sentiment index showing promising results in being a predictor of markets return both in-sample and out-of-sample (Reis & Pinho, 2020). The European investor sentiment has yet to be tested in a factor model context using a Fama French three- or five factor model.

3. European investor sentiment index

The European sentiment index in this paper is created following the same methodology as Baker and Wurgler, however with different proxies. The sentiment index developed by Baker and Wurgler was tailored for the US market, thus utilizing US-based proxies (Baker & Wurgler, 2007). Several studies have adopted the Baker and Wurgler methodology in various markets, adapting the proxies according to each market's characteristics. In the European market, proxies include the Consumer Confidence Index (CCI), the Economic Sentiment Indicator (ESI), the Volatility Index (VSTOXX), the price of gold, and the spread between 10- and 3-year German Treasury bond yields (Reis & Pinho, 2020). Each investor sentiment proxy is suspected to withstand of an idiosyncratic part, a sentiment component, and a non-sentiment-related component. This is the reason for five proxies and not just one or two proxies is used. The index method using five proxies helps ensuring that the idiosyncratic part is removed in the construction of the investor sentiment index(Baker & Wurgler, 2007).

3.1 Investor sentiment proxies

The sections below will focus on each of the sentiment proxies individually, explaining the reasoning behind their use and why they are considered as investor sentiment proxies. Furthermore, these insights will also provide an expectation of how the individual proxies are likely to affect the investor sentiment index, specifically whether they are expected to have a positive or negative impact on the index.

Consumer confidence index

The Consumer Confidence Index (CCI) serves as an indicator for predicting the future trends of household consumption and savings. It relies on responses from a selected population regarding their sentiment of the general economic situations, unemployment, and their ability to make savings. The index is measured on a scale with values above 100 indicating a positive outlook for the future and likelihood to spend money on major purchases the next 12 months, while values below indicating a less optimistic sentiment (OECD data, 2024; Reis & Pinho, 2021).

Several studies have highlighted the CCI's effectiveness as a proxy for investor sentiment. Qiu and Welch (2004) used UBS/Gallup investor sentiment survey data to validate its ability to assess investor sentiment. Their research found that the CCI performs better than the closed-end fund discount when validated against the UBS/Gallup investor sentiment survey data. Additionally, the CCI has shown more promising results in explaining the excess returns of small stocks (Qiu & Welch, 2004).

Economic sentiment indicator

The ESI is an indicator produced by the European Commission, similar to the CCI, based on survey responses. The aim of the ESI is to gain insights into economic beliefs from both the demand and supply sides of the economy. ESI is therefore built on five sectoral confidence indicators: Industrial confidence indicator, Services confidence indicator, Consumer confidence indicator, Construction confidence indicator and the Retail trade confidence indicator. It is measured and reported monthly, making it a faster way to observe changes in the economy than economic indicators such as GDP (Gelper &

Croux, 2010). Similarly to the CCI, its values above 100 indicate a positive attitude towards the future, and vice versa (European Commison, 2024).

Multiple studies have been using the ESI as a measure of investor sentiment. Fernandes, Goncalves, and Vieira (2013) used it combined with the CCI to analyze the effect of investor sentiment on future market returns in Portugal (Fernandes, Gonçalves, & Vieira, 2013). They found that investor sentiment had a negative impact on future market returns over a 1–12-month horizon. This supports the theory that when investor sentiment is high, investors justify higher prices, which is due to mispricing rather than an increase in value. Consequently, future returns are expected to be low following periods of high sentiment, as prices have been driven too high and need to be corrected. Additionally, investor risk aversion might change due to shifts in sentiment. (Fernandes, Gonçalves, & Vieira, 2013).

VSTOXX

The VSTOXX is the European version of the US VIX, as they both measure expected volatility but on two different markets. The VSTOXX measures the volatility of the EURO STOXX 50 index options, whereas the VIX is based on the S&P 500 index options (EUREX, 2024). The VSTOXX measures fear rather than confidence and is therefore expected to impact investor sentiment in the opposite way of the CCI and ESI. Some research suggests that from a behavioral point of view, fear is a more powerful motivator than confidence, and therefore the VSTOXX can be important in terms of adding explanatory power to the investor sentiment index (Smales, 2017). Furthermore, test results have suggested that the VIX, the equivalent of VSTOXX, drives returns across firm size, value, and industries, which could indicate that it might have a positive impact on the investor sentiment index's ability to improve current asset pricing models (Smales, 2017).

The price of gold

The price of gold is included as an investor sentiment proxy based on its dual role as both a hedge and a safe haven in major European stock markets. Gold is considered a safe haven, meaning it is viewed as an asset where investors can seek refuge in response to severe market shocks and uncertainties (Baur & McDermott, 2010). This relation between severe market shocks and the safe haven effect is generally most prominent in developed markets such as Europe. The motivation for investors to use gold as a safe haven is that gold tends to hold or increase its value if stock markets experience large negative returns (Baur & McDermott, 2010). As this proxy is the price of gold, the data is expected to be non-stationary, and therefore might need to be transformed to ensure stationarity. An increase in the gold price would likely impacting investor sentiment negatively, as the theory suggests investors are turning to gold as a safe haven during times of uncertainty.

Spread between the German 10- and 3-year treasury.
Additionally, the spread between German 10-year and 3-year treasury bonds(spread) is also considered. German treasuries are similar to gold, an asset that investors seek during uncertain times, when they become more risk averse, as bonds from stable economies like Germany carry very low default risk (Gómez-Puig, Sosvilla-Rivero, & del Carmen Ramos-Herrera, 2014). Furthermore, can an inverted yield curve serve as an indicator of low sentiment, as it means that short-term rates are higher than long-term yields. This implies that investors receive lower rewards for binding their money in long-term bonds compared to short-term ones. Such a scenario indicates uncertainty and pessimism about the economy in the years ahead and can be viewed as an indicator of potential economic recession (Reis & Pinho, 2020).

4. Investor sentiment

The next sections will focus on the construction the investor sentiment index explaining the methodology, the data used for the index and also how this data is processed. Furthermore, the correlations of the investor sentiment index with its lagged version, the market (EURO STOXX 600), and the Fama-French five factors will be investigated. The EURO STOXX 600 will be used as the market index throughout the report because it covers a broad range of sectors and includes large, mid, and small-cap stocks with its 600 constituents, replicating almost 90% of the underlying European market.

4.1 Investor sentiment construction

Baker and Wurgler constructed the investor sentiment index by applying the concepts of PCA (Baker & Wurgler, 2007). PCA is a dimensionality reduction technique, that is used to reduce the dimensions of data. In this example is the technique used to reduce the five investor sentiment proxies (five dimension) onto one dimension, the investor sentiment index. The PCA uses the covariance matrix of the observations and seeks to explain this variance-covariance structures with a linear combination of the initial values, in this case the five investor sentiment proxies. The best fit model is measured by calculating the eigenvectors and eigenvalues of the covariance matrix. The first principal component is the eigenvector with the highest eigenvalue, which is capturing most of the common variance of the data (VanderPlas, 2016). The loadings of this first principal components are the linear combination of the investor sentiment proxies that is utilized to construct the investor sentiment index (Baker & Wurgler, 2007).

The data applied to the PCA has to be stationary and standardized. Therefore, is the ADF test used to test for stationarity and the standard scaler is used to scale the data. Baker and Wurgler prepares the data for the sentiment index using two different methods, the first is using the "raw" data that is adjusted for stationarity and then scaled (Baker & Wurgler, 2007). The standard scaler method is used for scaling, it scales the data around its mean with a standard deviation of 1. It ensures the data is on the same scales and can be compared and plotted together, but still preserving the essential information and shape of the data. The second method is by regressing each of the sentiment proxies to some major macroeconomic factors, to remove the influence of the economic fundamentals from the sentiment proxies, and as before ensuring stationarity and scaling (Baker & Wurgler, 2007). Baker and Wurgler shows that the macro fundamentals only explain a little of the common variation in their six proxies and therefore is the "raw" index looking and performing almost the same as the one controlled for fundamentals (Baker & Wurgler, 2007). In this section is the sentiment index SENT created using the "raw" method.

Baker and Wurgler also investigated if some of the proxies might have a lagged effect on the investor sentiment index. Therefore, are all the proxies tested with a lag to ensure the index is correct specified (Baker & Wurgler, 2006). The first step in this methodology is creating a composite index by estimating the first principal component of the five proxies and their first lag. This result in an index with 10 components one for each of the proxies and their lagged versions. This index is the used to pick the "best" version of each proxy, by comparing and choosing the version that have the highest correlation with this first stage index (Baker & Wurgler, 2006). SENT_L is then constructed by applying the five proxy versions with the highest correlations with the first stage index to the PCA, for calculating the first principal component (Baker & Wurgler, 2006).

Data for SENT and SENT_L

The data is monthly data starting Jan. 1999 to Nov. 2023 meaning that the data span over 299 months, with 299 observations for each variable. January 1999 was selected as the starting point because it marks the first observation of VSTOXX, which has the shortest historical data among the variables. Reis and Pinho extended the research period by first incorporating VSTOXX data from 1999 and utilizing the four other proxies for the period prior to that (Reis & Pinho, 2020). Additionally, the data concludes in November 2023, as this is the latest available data point for the CCI.

Variable	Stationarity (ADF)	Source
CCI	P-value: 0.0405	https://data.oecd.org/leadind/consumer-confidence-index-cci.htm
ESI	P-value: 0.0004	https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en
VSTOXX	P-value: 0.0027	FactSet
GOLD	P-value: 0.9166	FactSet
Spread	P-value: 0.4477	FactSet

Stationarity

Stationarity is tested using the Augmented Dickey-Fuller test, where the null hypothesis states that the data is non-stationary (Wooldridge, 2013). When using the data for a PCA stationarity is needed, and therefore the p-value is used to test if the null-hypothesis can be rejected in favor for the alternative hypothesis stating that non-stationarity is rejected. Three of the proxies rejects the null- hypothesis and is therefore stationary. The graph below supports this test result as there are no visible trend in VSTOXX, ESI and CCI.

Figure 1 - Plot of the investor sentiment proxies VSTOXX, ESU and CCI.

Price of gold and the spread does not reject the non-stationarity, and they are therefore reconstructed to ensure stationarity. This reconstruction involves calculating the monthly change and using this as the variable instead of the original level. Following this transformation, the null hypothesis is rejected in favor of the alternative hypothesis, indicating that the data is now stationary. Figure 2 show the non-stationarity is particularly evident in the graph of gold prices, which is expected given the tendency of prices to exhibit upward trends and thus non-stationarity. The non-stationarity is not as visible in the plot of the spread, but there is a visible downwards trend from 2010 to 2023.

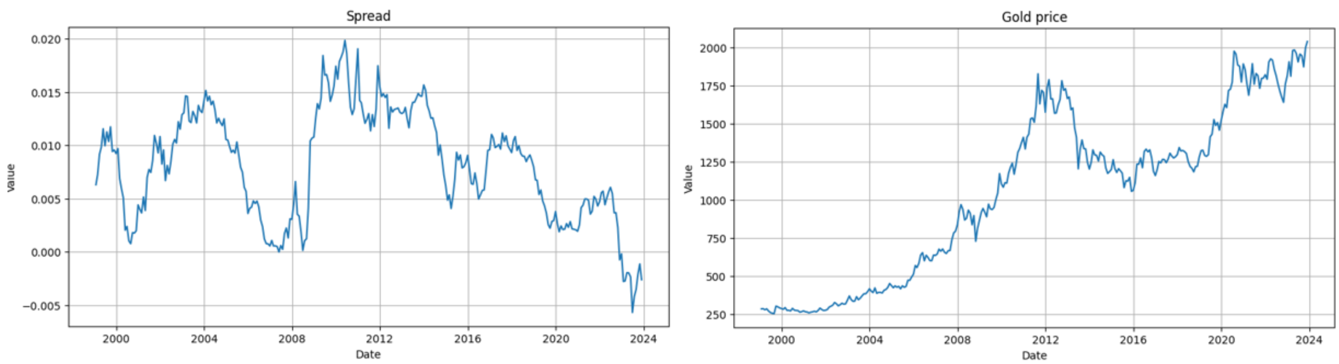

Figure 2 - Plot of the investor sentiment proxies spread and gold price.

The non-stationarity of the spread was unexpected, as unlike prices, spreads are more bound to an interval. It is difficult to envision the spread continuing to decrease or increase infinitely. Therefore, the results from the ADF test were validated using both the Phillips-Perron (PP) test and the Zivot-Andrews (ZA) test, that both are test for stationarity, but in slightly weaker forms. The PP test yielded a p-value of 0.283, indicating that the null hypothesis cannot be rejected and thus supporting the ADF results, which did not reject non-stationarity. This was also consistent with the results of the ZA test, although the p-value of 0.059 is close to rejecting the null hypothesis. Figure 3 present the reconstructed data as changes instead of levels, which clearly demonstrate stationarity.

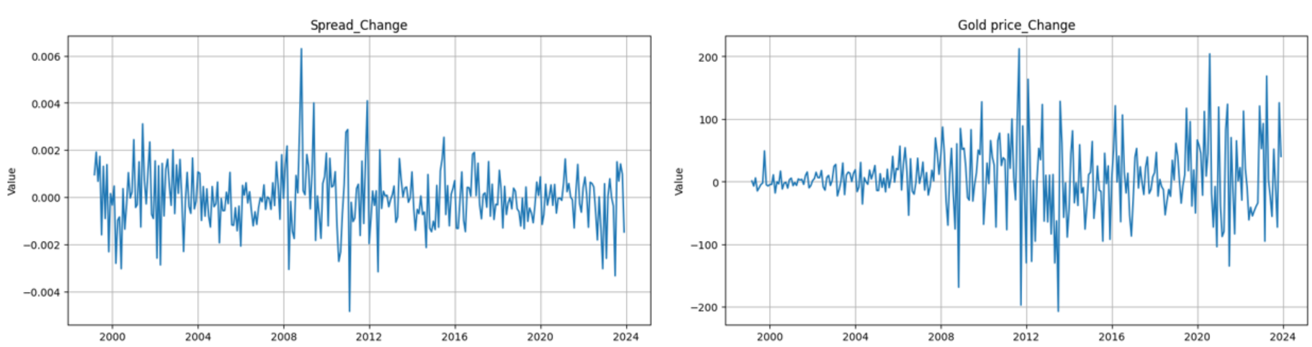

Figure 3 - Plot of the reconstructed investor sentiment proxies change in spread and change in gold price.

4.2 SENT and SENT_L

The investor sentiment index SENT constructed using the loadings from the first principal component is written in equation 12. The sentiment proxies ESI and CCI positively influence the investor sentiment index. This relation is intuitively understandable since investor sentiment is expected to be high when both consumer confidence and general economic sentiment are high. VSTOXX has a negative impact on the investor sentiment which aligns with expectations as VSTOXX is a measure of uncertainty and fear in the market. Additionally, is the change in the spread and the return on gold having a negative impact on the investor's sentiment. A positive return in gold suggests that more investors are flocking to an asset often perceived as a safe haven during uncertain times, indicating low sentiment and uncertainty. This rational regarding gold aligns with the PCA result as a positive change in gold prices has a negative impact on the investor sentiment index. The impact of the different proxies on the investor sentiment index is consistent with past research, as the same proxies have a positive impact on the investor sentiment and opposite (Reis & Pinho, 2020).

$$SENT = 0{,}629ESI + 0{,}578CCI - 0{,}481VSTOXX - 0{,}197\Delta Spread - 0{,}0136\Delta Gold \quad (12)$$

The explained variance in the PCA is 41,03%, this is close to the results of past research but slightly lower, as Reis and Pinho (2020) retained 46% of the variance on the European market and Baker and Wurgler (2006) achieved 53% retained variance on the US market. Both past papers used significantly longer data period, which might be the reason for this slightly higher explained variance (Baker & Wurgler, 2007; Reis & Pinho, 2020).

SENT_L

Following the methodology outlined in Section 4.1 is the proxy versions with the highest correlation to the first-stage index used to construct SENT_L. The results of this process are illustrated in Figure 4, and these outcomes are employed to construct SENT_L. CCI and ESI are used in their current form, while the three other proxies are employed in lagged versions, meaning they are shifted by one month.

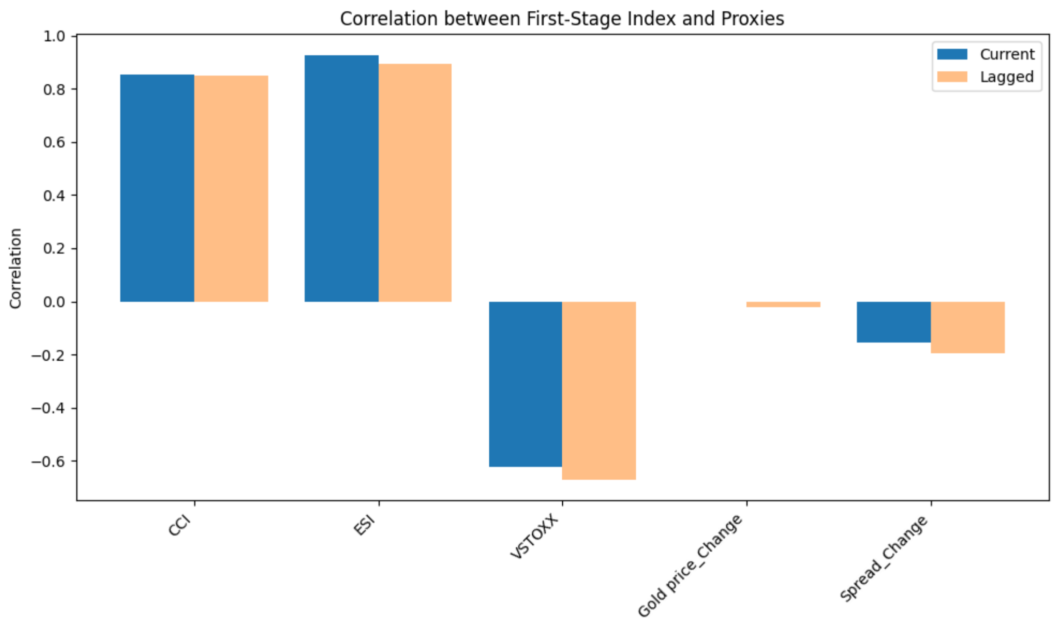

Figure 4 - Correlations with first stage index.

Applying this approach to the PCA results yields a retained variance of 42.58% and the investor sentiment index is constructed following equation 13. While the level of impact each proxy has on the investor sentiment varies slightly is the direction of their effect on investor sentiment consistent. Although the impact levels have changed, it is still the same proxies that have the highest impact and the same ones that have the lowest impact on investor sentiment.

$$SENT_L = 0{,}623ESI_t + 0{,}562CCI_t - 0{,}504VSTOXX_{t-1} - 0{,}203\Delta Spread_{t-1} - 0{,}013\Delta Gold_{t-1} \quad (13)$$

4.2.1 Correlations SENT and SENT_L

SENT and SENT_L are visualized in Figure 5, illustrating the movement of the two versions of the investor sentiment index. The lagged investor sentiment index and the non-lagged investor sentiment index are closely related, with a correlation of 0.96, as clearly illustrated in the graph. SENT_L appears to have slightly lower values when the index reaches its lows, but otherwise, it is challenging to see any patterns in the indifferences.

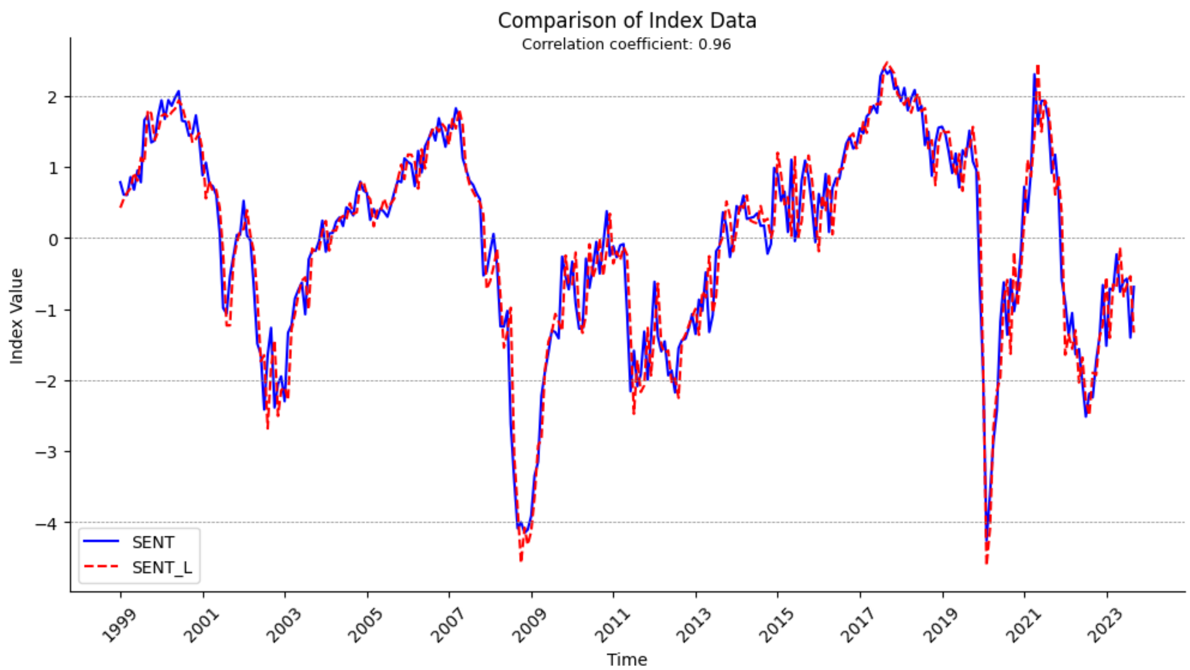

Figure 5 - Graph of the two investor sentiment indexes SENT and SENT_L and their correlation.

The graph shows a very large decreases in sentiment in the period of end 2007 and into 2008, reaching its lowest point by the beginning of 2009. This clearly indicates that investor sentiments are capturing the crisis in 2008, as expected, with sentiment being particularly low during this crisis period. A similar but faster decrease in investor sentiments can be seen in 2020 where the stock market crashed because of Covid-19 pandemic, that caused worldwide lockdowns. The investor sentiment indexes also appear to capture peaks, such as those around 2000 and 2007, corresponding to the peaks of the dot-com bubble and the housing bubble, respectively.

Correlations with the market

Figure 6 illustrates that SENT and SENT_L are relatively highly correlated with the EURO STOXX 600 index, which represents the European stock market. SENT has a correlation coefficient of 0.5, while SENT_L has a slightly lower correlation of 0.49, possibly due to the slightly lower values at local minimums. These correlations are higher than the results of Reis and Pinho that experience a correlation of 0,27 with EURO STOXX 600 over their entire period. However, when examining the period from 2009 to 2019, Reis and Pinho observed a significantly higher correlation of 0.85, which aligns with the graph showing EURO STOXX and the investor sentiments appear closely correlated in that period (Reis & Pinho, 2020).

Generally, the two investor sentiment indexes show more volatility than the EURO STOXX 600 index, particularly during periods of drastic decreases in the EURO STOXX 600. This is clearly illustrated during crisis-periods such as the one in 2008, where the investor sentiments move significantly more than the EURO STOXX 600. Similar observations can be made with Reis and Pinho's EURsent index, which also includes the 2008 crisis. In contrast, Baker and Wurgler's US investor sentiment index appears to be much more stable during this period(Baker & Wurgler, 2006; Reis & Pinho, 2020). This greater degree of movement in the sentiment indexes relative to the market was expected, as past research has shown investor sentiment tend to have its strength on the more uncertain, volatile, hard to value stocks, which also moves more than the market (Berger & Turtle, 2012).

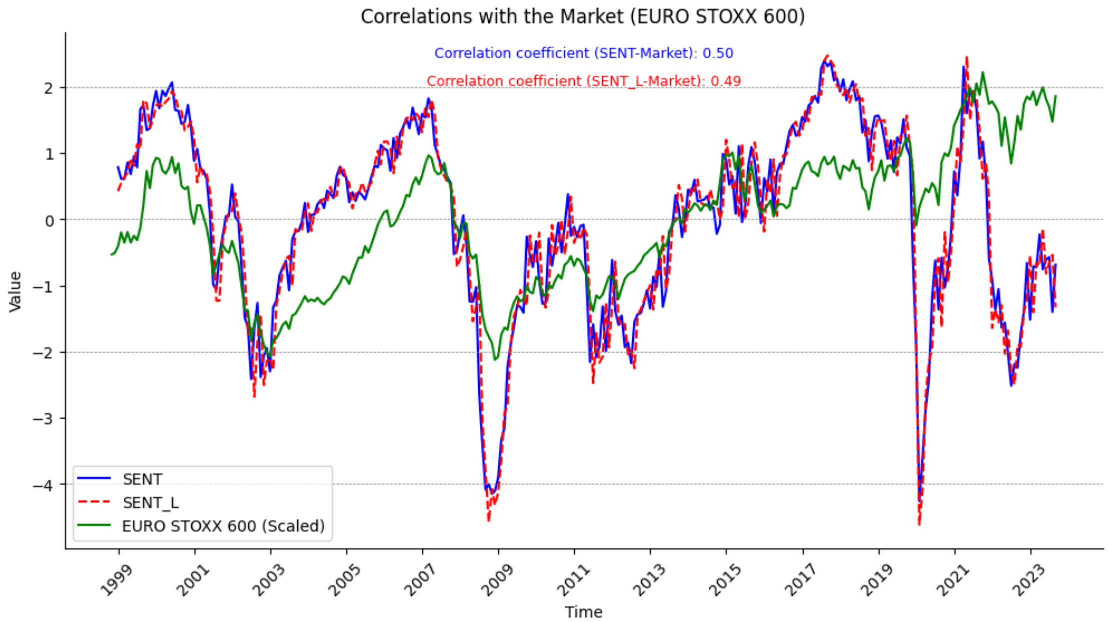

Figure 6 - Graph of the two investor sentiment indexes SENT and SENT_L with the EURO STOXX 600 index and the investor sentiments correlations with the EURO STOXX 600.

Correlation with Fama French factors

The data for the European Farma French five factor model is from the Kenneth French data library. The data is monthly starting Jan. 1999 to Nov. 2023 (French, 2024). The correlation matrix below shows that the SENT is only to a very little degree correlated with the other factors. This indicates that it is holding some information that the other factors are not. If SENT is found to significantly improve the Fama French five factor model ability to explain excess returns, it could enhance current models by incorporating new information that is almost non-correlated with existing factors. Similarly, the SENT_L demonstrates comparable results and is also minimally correlated with other factors.

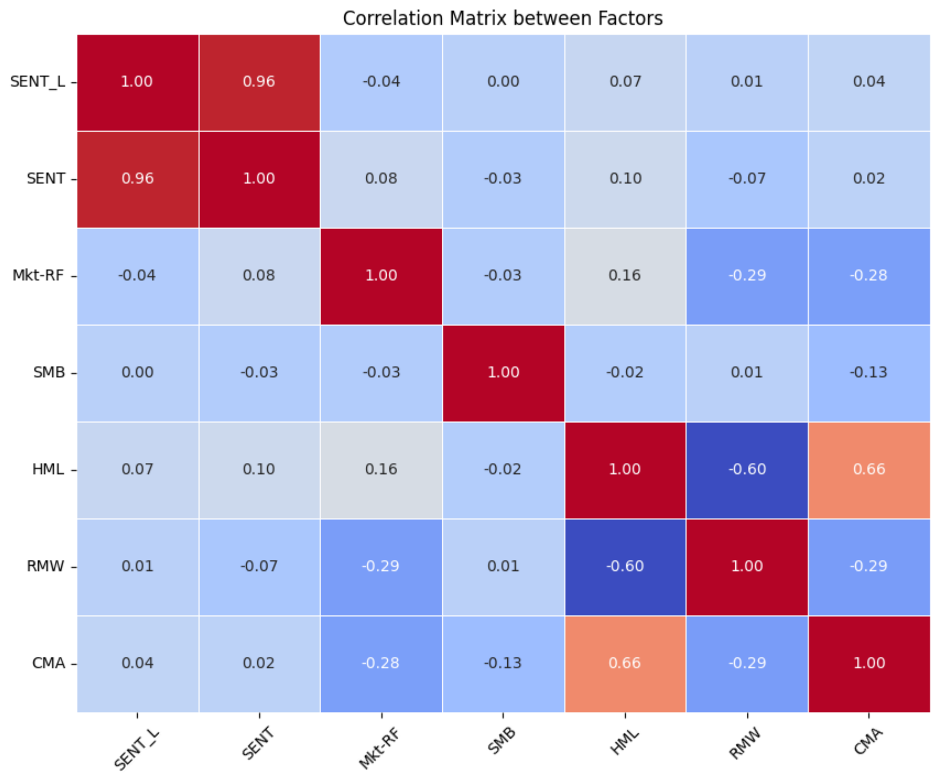

Figure 7 - Correlation matrix with SENT, SENT_L and the European Fama French five factors.

5. Purified investor sentiment index

The next sections will focus on the construction of the investor sentiment indexes PSENT and PSENT_L that is "purified" for some major macroeconomic factors by orthogonalization. The methodology and the data processing will be discussed as well as this investor sentiments versions correlation with the Fama French five factors.

5.1 Construction of purified investor sentiment index

As mentioned in earlier sections, Baker and Wurgler introduced two methods of creating their investor sentiment index. The method used in the sections above employs the sentiment proxies raw controlling only for stationarity and scaling the data. The second method involves orthogonalization to remove the influence of some of the major macroeconomic indicators (Baker & Wurgler, 2006). The orthogonalization process involves using OLS for regressing the investor sentiment proxies against three chosen macroeconomic factors whose influence is intended to be removed from the data. The residuals from these regressions are then saved as the "purified" investor sentiment proxies. This method helps isolating the unique component of investor sentiment by stripping away variations that can be attributed to macroeconomic factors. Similar to the “raw” method, are these “purified” proxies scaled and controlled for stationarity (Baker & Wurgler, 2006). The removal of the influence of major macroeconomic indicators on the sentiment proxies is done with the goal of ensuring that the PCA captures more of the common sentiment component and less of the influence from macroeconomic indicators. By using this methodology, the investor sentiment index should provide a purer measurement of investor sentiment (Baker & Wurgler, 2006).

However, Baker and Wurgler demonstrated that the two indexes performed almost similarly, suggesting that orthogonalization was a secondary concern (Baker & Wurgler, 2006). They had a slight increase in the common variance suggesting the orthogonalized proxies is slightly more correlation with each other. This increase also indicates that the raw investor sentiment index is not significantly influenced by macroeconomic indicators. If the raw sentiment index had been driven by the macroeconomic conditions, then the orthogonalized index would have been expected to exhibit a lower common variance (Baker & Wurgler, 2006).

Macroeconomic factors

The macroeconomic factors are collected as monthly data, which delimited the pool of macroeconomic indicators, as a significant part of them are reported on quarterly and annual basis (Eurostat, 2024). For this research, the Harmonized Index of Consumer Prices, Industrial Production Index, and the Unemployment rate were chosen as macroeconomic indicators. These are similar but not exactly the same indicators as the ones used by both Reis and Pinho, as well as Baker and Wurgler (Baker & Wurgler, 2007; Reis & Pinho, 2020). The Industrial Production Index is selected because it is reported monthly and can serve as an indicator of GDP growth. Consequently, it is expected to have a broad impact on the investor sentiment proxies. Moreover, is the Harmonized Index of Consumer Prices picked to measure inflation, while Unemployment rate is also acknowledged as a component that describes business cycles and therefore also cleansed for (Baker & Wurgler, 2007; Reis & Pinho, 2020). Similar to the construction of the raw sentiment index, consideration is given to whether the proxies lags can enhance the index, as some of them may have a delayed influence on investor sentiment (Baker & Wurgler, 2006).

Data PSENT and PSENT_L

The data is monthly data from January 2000 to November 2023, spanning 287 months, with 287 observations for each variable. The orthogonalized investor sentiment index uses a slightly shorter timeframe than the raw methodology. This is because the earliest available data for unemployment in the European Union starts in January 2000, which sets the new starting point.

Variable	Type	Source
CCI	Sentiment proxy	https://data.oecd.org/leadind/consumer-confidence-index-cci.htm
ESI	Sentiment proxy	https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en
VSTOXX	Sentiment proxy	FactSet
GOLD	Sentiment proxy	FactSet
Spread	Sentiment proxy	FactSet
Industrial Production index	Macroeconomic factor	Eurostat database
Harmonized index of consumer	Macroeconomic factor	Eurostat database
Unemployment rate	Macroeconomic factor	Eurostat database

Purified proxies

In the Figures 8 and 9 are the raw proxies plotted against the orthogonalized proxies. All data is scaled using the standard scaler, which scales the data around its mean with a standard deviation of 1. This ensures that the data is on the same scale, allowing for comparison and plotting together, while preserving the essential information and shape of the data. CCI and VSTOXX, along with their orthogonalized versions, are closely related, with correlations of 0.87 and 0.89, respectively. Similarly, ESI and the spread are also closely related to their orthogonalized versions, with correlations of 0.71 and 0.69. The most significant difference between the raw and orthogonalized versions of ESI is observed in 2020, where ESI experiences a drastic decrease, while the orthogonalized version does not exhibit such a pronounced decrease in level. Upon examination of the macroeconomic variables regressed against, which are provided in the appendix, it seems like there is a correlation with the large drop in the industrial production index, which must have been captured in the orthogonalization process.

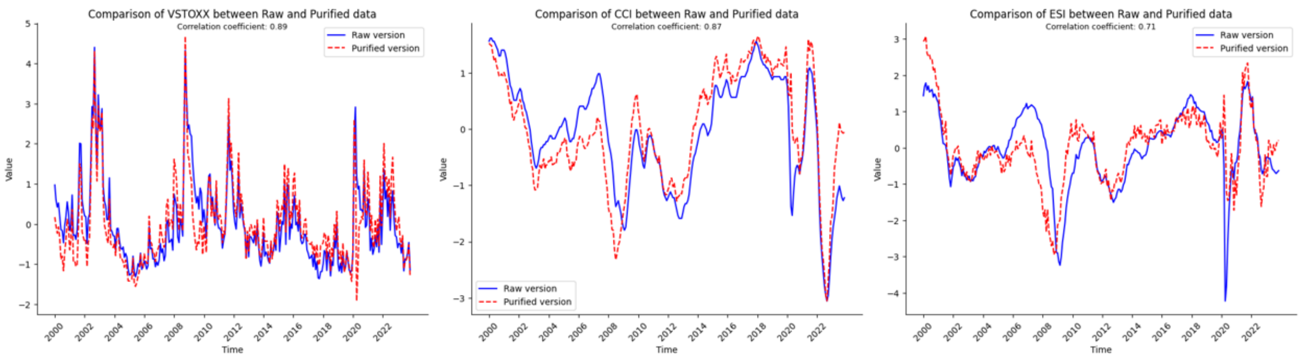

Figure 8 - Graph showing the relation between VSTOXX, ESI and CCI and their orthogonalized versions.

The price of gold exhibits the lowest correlation with its orthogonalized version, at only 0.36. This relative weak correlation is clearly illustrated in the graph, where the orthogonalized version shows no trend while the raw price data indicates a positive trend in gold prices. This disparity strongly suggests that gold prices are significantly influenced by macroeconomic factors that are captured by the three chosen macroeconomic indicators for orthogonalization. This observation makes sense, considering that gold is a traded asset and commodity, unlike the other proxies, and may be a less directly measure of investor sentiment.

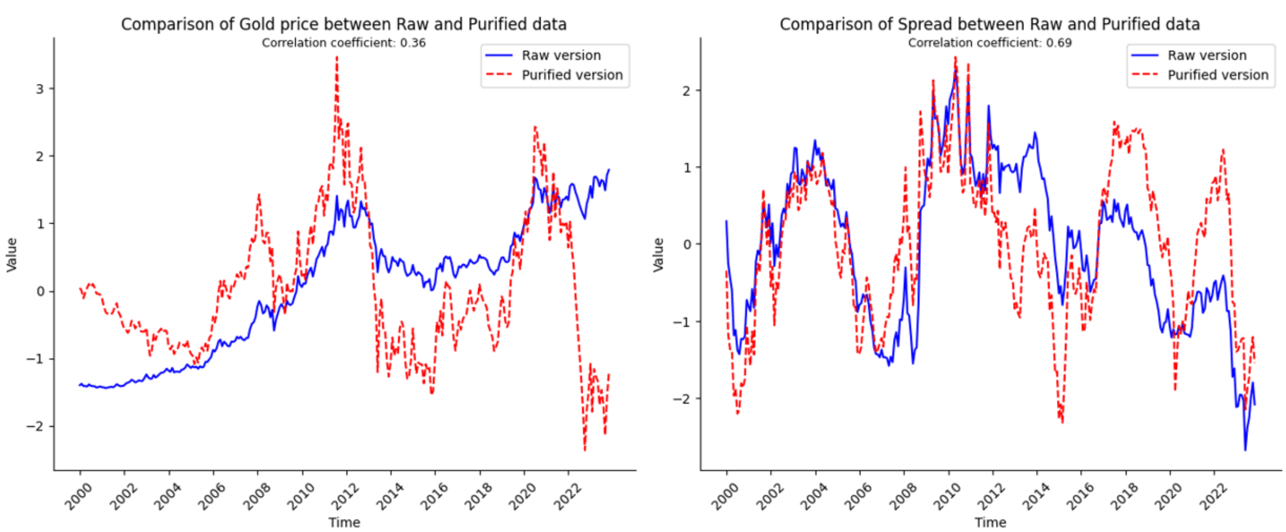

Figure 9 - Graph showing the relation between gold price, spread and their orthogonalized versions.

Stationarity

Stationarity is tested using the Augmented Dickey–Fuller (ADF) test. All five of the orthogonalized proxies reject the null hypothesis and are therefore stationary. This test result is supported by the Figures 10,11 and 12, which shows no visible trend in VSTOXX, ESI, CCI, as well as the spread and the gold price. As discussed earlier, the spread was expected to be stationary due to its constructed as a spread has natural boundaries. The change in result indicates that the non-stationarity in the spread we observed earlier, with a downward trend, was caused by macroeconomic fundamentals. Now, the graph shows no downward trend after removing business cycle components, and it appears stationary.

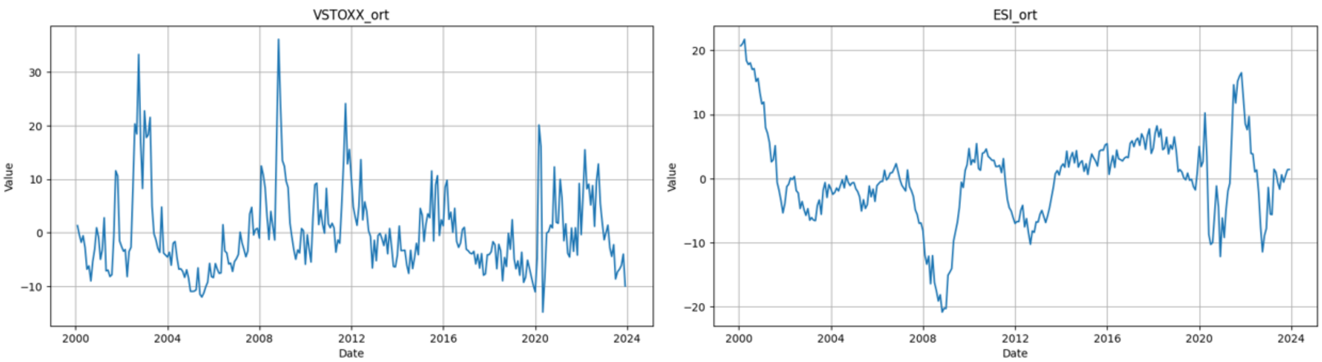

Figure 10 - Graph showing the orthogonalized versions of the investor sentiment proxies VSTOXX and ESI.

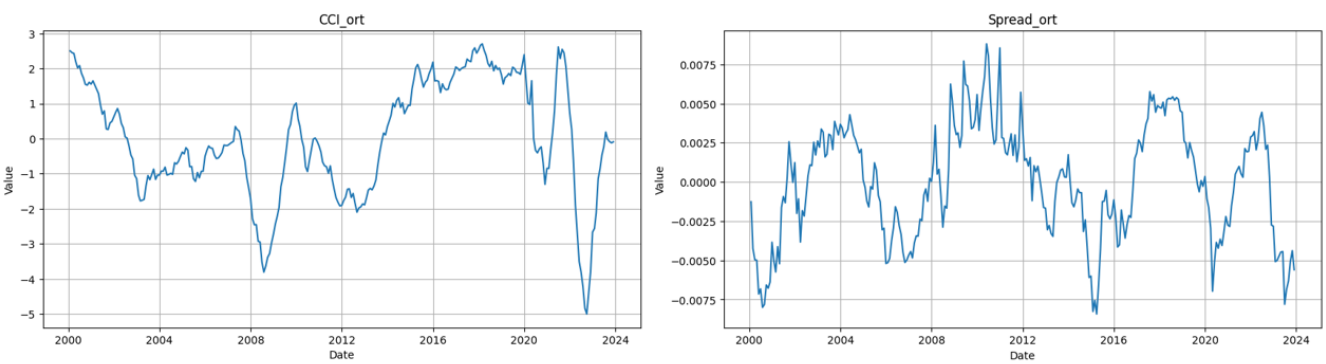

Figure 11 - Graph showing the orthogonalized versions of the investor sentiment proxies CCI and spread.

Interestingly, the price of gold becomes stationary after it is regressed against macroeconomic indicators. Its graph and development over time look significantly different from before. Prior to orthogonalization, there was a clear upward trend, as expected for the price of gold. However, after removing the effects of the chosen macroeconomic indicators, this trend is nowhere to be seen. This suggests that the development and trend in the gold price are to a high degree influenced by the macroeconomic environment, which effect has now been removed from the data.

Figure 12 - - Graph showing the orthogonalized versions of the investor sentiment proxi Gold price.

5.2 PSENT and PSENT_L

The model for the investor sentiment index purified for the chosen macroeconomic factors written in equation 14, remains very similar to the ones using the raw proxies. The sentiment proxies ESI and CCI still have the highest values and a positive impact on the investor sentiment index after orthogonalization. Similarly, VSTOXX, spread, and gold price also continue to have a negative impact on the level of investor sentiment. This relatively similar result after orthogonalization aligns well with Baker and Wurgler's findings, as they also observed that the raw investor sentiment index looked and performed very similarly to the orthogonalized investor sentiment index (Baker & Wurgler, 2006).

PSENT

There is a slight change in the interpreting of the investor sentiment proxy variables, gold price and spread, as it now relies on their actual values rather than changes in these values. Generally, interpreting this sentiment index based on orthogonalized proxies is more challenging because even though the price of gold is increasing, its orthogonalized version can be decreasing and therefore have the opposite effect on the investor sentiment index. This applies to all the orthogonalized proxies but seems to be most pronounced for gold, as there are the most drastic changes in the graph and its movements.

$$PSENT = 0{,}581 ortESI_t + 0{,}574 ortCCI_t - 0{,}452 ortVSTOXX_t - 0{,}256 ortSpread_t - 0{,}252 ortGold_t \quad (14)$$

The explained variance in the PCA first principal component is 43.23%, slightly higher than the common variance in both SENT and SENT_L and approaching Reis and Pinho's retained variance of 46% on the European market. Since Reis and Pinho also created their investor sentiment index using orthogonalized investor sentiment proxies, this result is anticipated because employing the same method would naturally lead to more similar outcomes (Reis & Pinho, 2020). The small increase in explained variance relative to the raw method also aligns with the findings of Baker and Wurgler, who observed an increase from 49% to 53%. They argue that this result suggests some robustness of the investor sentiment index, as one would expect the opposite if the raw variables were driven by common macroeconomic conditions (Baker & Wurgler, 2006).

PSENT_L

For the construction of the investor sentiment PSENT_L is lagged versions of the orthogonalized proxies included and the versions with the highest correlation with the first-stage index is selected. The figure below illustrates that, similar to SENT_L, CCI and ESI are used without a lag. The overall difference between the lagged and non-lagged versions is smaller after controlling for macroeconomic factors, except for gold price. Gold price was also the proxy that changed the most after being regressed against the chosen macroeconomic factors.

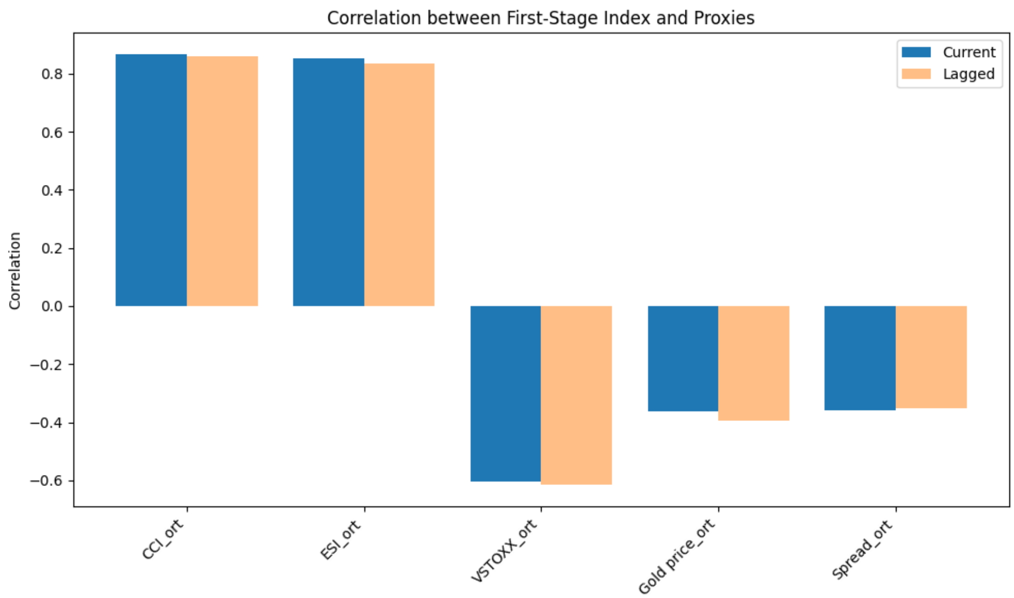

Figure 13 - Correlations with first stage index.

Applying the highest correlated versions to the PCA results in a very small increase in retained variance to 43.39%, indicating an increase of only 0.16%. This suggests, as the figure also shows, that in the orthogonalized version, there only is a slight difference between the lagged and non-lagged versions. The model for PSENT_L in equation 15 shows the direction the different proxies affect the investor sentiment index is similar to results of both SENT, SENT_L, and PSENT, as well as the findings of Reis and Pinho (Reis & Pinho, 2020).

$$PSENT_L = 0{,}581 ortESI_t + 0{,}563 ortCCI_t - 0{,}451 ortVSTOXX_{t-1} - 0{,}283 ortSpread_t - 0{,}249 ortGold_{t-1} \quad (15)$$

PSENT and PSENT_L correlation with Fama French factors

The correlation matrix in Figure 14 shows that PSENT and PSENT_L are very closely correlated, and similar to SENT and SENT_L are they only slightly correlated with the Fama French five factors. Suggesting that both PSENT and PSENT_L provide some new information to the Fama French five factor model. However, tests must be applied to determine whether this new information can improve the explanatory power of the Fama-French five-factor model.

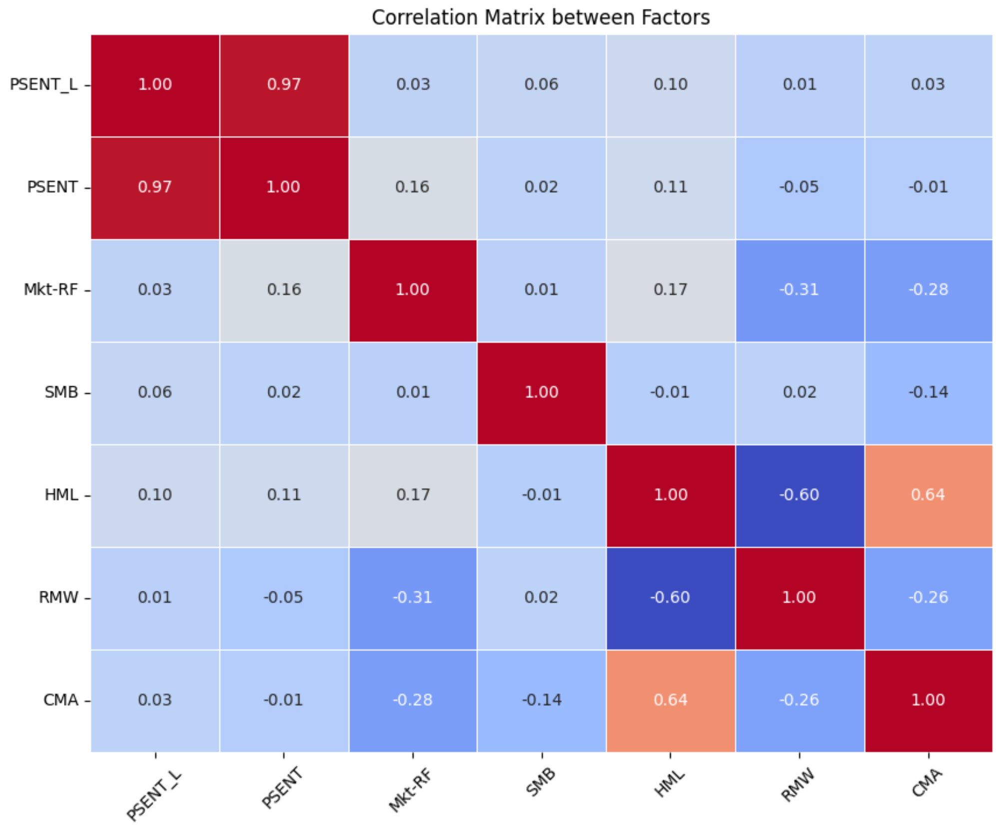

Figure 14 - Correlation matrix with PSENT, PSENT_L and the Fama French five factors.

6. Correlations SENT and PSENT

Investor sentiment indexes SENT and PSENT, showed very close relation to their lagged counterparts and SENT and PSENT are the ones that will be focused on in the rest of this paper. The use of the non-lagged versions makes the interpretation and use of the index simpler and keep the focus on explaining and not predicting. To get initial insights into the two investor sentiments constructed are the correlations between them calculated and plotted. Furthermore, these indicators are plotted against the market index EURO STOXX 600 to determine if there is any correlation with the market. This correlation might indicate that they can be used as a factor to capture some of the movements in stock returns. They will also be compared to the US investor sentiment measure constructed by Baker and Wurgler, and these results will be used to validate the measures of investor sentiment.

Correlation SENT and PSENT

PSENT is visualized alongside SENT in figure 15, illustrating the close relationship between the "raw" investor sentiment index and the "purified" investor sentiment index. They are highly correlated with a coefficient of 0.78, indicating a slight difference but very close relation. The graph shows that the PSENT in most cases have the same max and minimums as the SENT. PSENT's level is however significantly lower than SENT's in 2008 and early 2009, during the peak of the financial crisis, and conversely higher during the stock market crash in 2020.

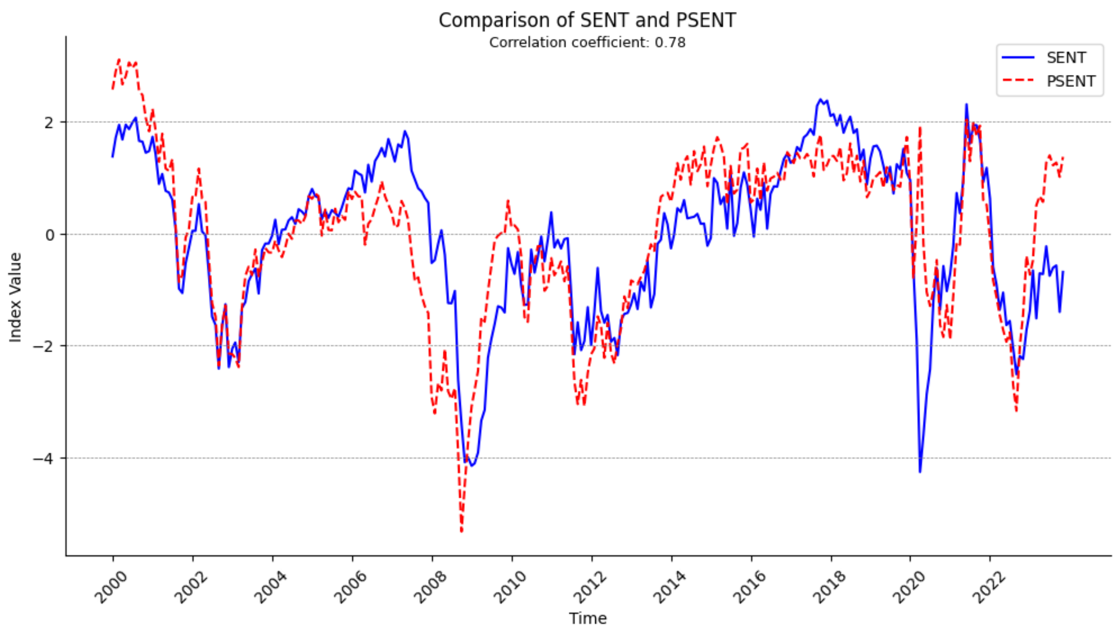

Figure 15 - Plot of the investor sentiment indexes SENT and PSENT and their correlation.

This suggests that the macroeconomic indicators used to cleanse the investor sentiment index have been more effective in explaining the crash in 2020 than in 2008. The macroeconomic data plotted in the appendix indicates that this is likely due to a significant, short-term decrease in the industrial production index during this period. The development of the industrial production index is very similar to the development of in SENT in 2020, and this is therefore captured in the orthogonalization of the investment proxies.

SENT and PSENT correlation with market index.

SENT and PSENT correlations with the market index is shown in figure 16. Both investor sentiment indexes have a correlation of 0,51 with the market index (EURO STOXX 600). PSENT exhibits a tendency to move more than the market index, similar to SENT. This aligns with the rational that the investor sentiment is expected to best at explaining the more uncertain, volatile, hard to value stocks. It is at this point hard to say which version of the investor sentiment index will perform best in the coming tests, as they are so closely correlated. Therefore, it is not yet possible to exclude one due to the superiority of the others.

SENT and PSENT also shows correlation with the log returns of EURO STOXX 600 of 0.24 and 0.16, respectively. These correlations fall within the same range as both Reis and Pinho's EURsent and Baker and Wurgler's Investor Sentiment, which, depending on the different periods, experience correlations of -0.3 to -0.16 and 0.28 with EURO STOXX and S&P 500 (Baker & Wurgler, 2007; Reis & Pinho, 2020). This provides validation of the measure constructed in this paper, indicating the potential explanatory power of the investor sentiment index. It may also offer an initial indication of the strength of PSENT relative to SENT.

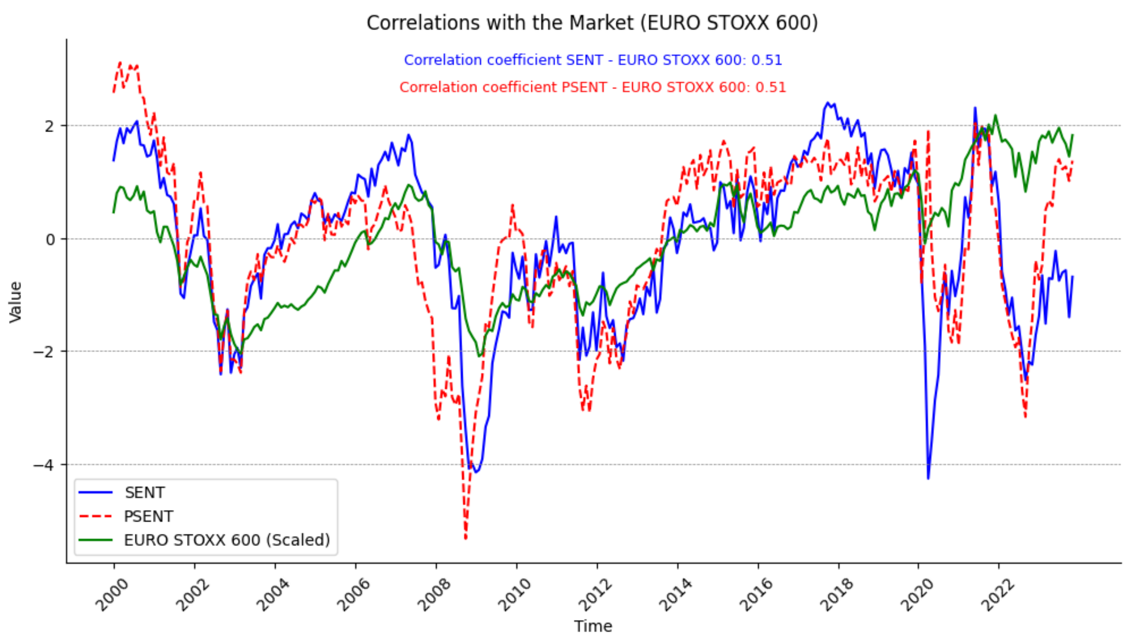

Figure 16 - Plot of the SENT, PSENT and the EURO STOXX 600 also reporting the correlations with EURO STOXX 600.

SENT and PSENT correlation with Baker and Wurgler's investor sentiment index.

Figure 17 illustrates SENT and PSENT correlations with Baker and Wurgler's investor sentiment index of 0.31. This is slightly lower than the correlation Reis and Pinho's EURsent experiences for their entire period (0.49) (Baker & Wurgler, 2006; Reis & Pinho, 2020). However, similar to the different results when comparing to the EURO STOXX 600, this discrepancy is expected to be mainly driven by the difference in time periods. Reis and Pinho's EURsent only had a correlation of 0.24 with Baker and Wurgler's investor sentiment index in the period 2009-2019, which is a large part of the period used in this study. Furthermore, Reis and Pinho's EURsent also exhibits a very weak correlation with Baker and Wurgler's index during the crisis of 2008 (0.09), as their EURsent also demonstrates significantly more movement than Baker and Wurgler's index (Baker & Wurgler, 2006; Reis & Pinho, 2020).

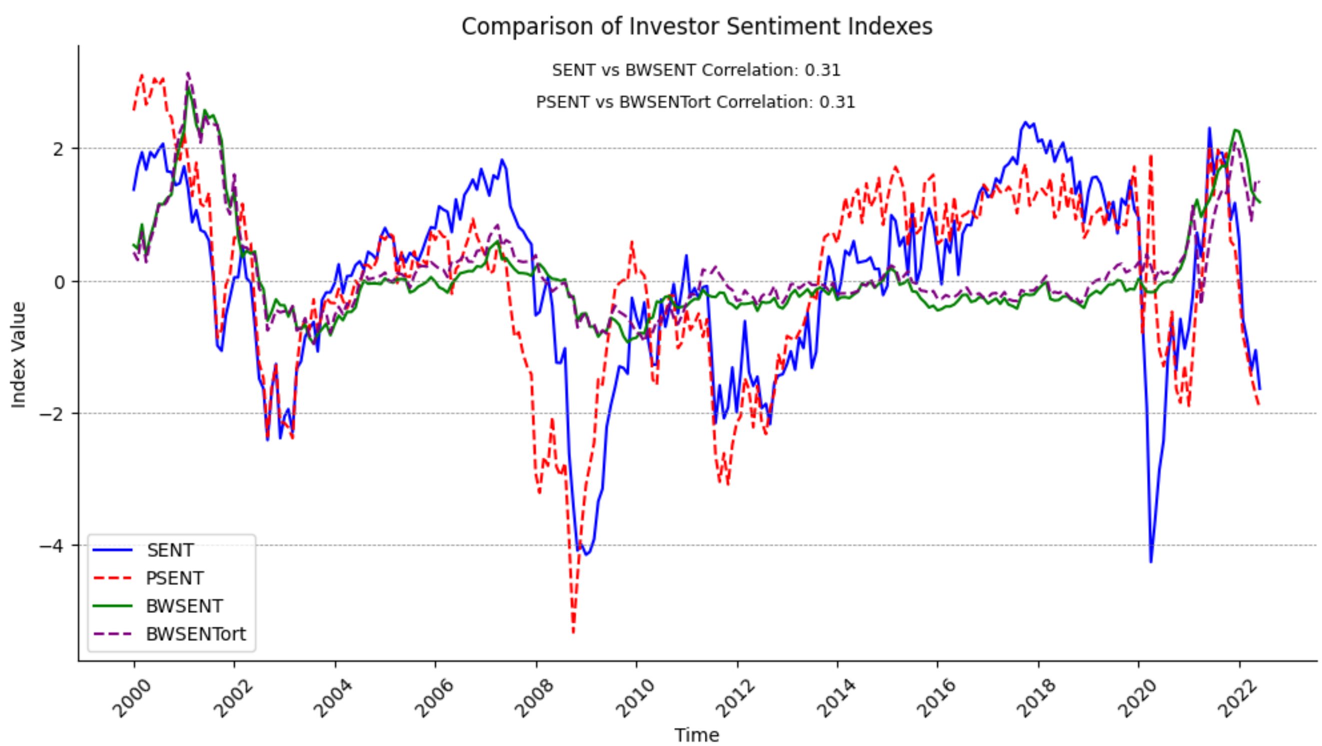

Figure 17 - Plot of SENT, PSENT and Baker and Wurgler's investor sentiment index also reporting the correlations with Baker and Wurgler's investor sentiment index.

7. Times-series test SENT and PSENT

The coming sections will test the capabilities of the investor sentiments SENT and PSENT in an asset pricing context. The non-lagged versions of the sentiment index are chosen, as their results showed that they are very closely related to their lagged version and almost indifferent. Furthermore, will the focus of this paper be the investor sentiment indexes explanatory power and not on their predictive power. The use of the non-lagged versions also makes the interpretation and use of the index simpler, which is worth considering, when the differences between the versions are as small as they are. Therefore, the models to be tested will include the Fama-French five-factor model equation 16 and the revised models incorporating one of the investor sentiment factors equations 17 and 18.

$$R_{it} - R_{Ft} = a_i + b_i(Mkt_t - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it} \quad (16)$$

$$R_{it} - R_{Ft} = a_i + b_i(Mkt_t - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + i_i SENT_t + \varepsilon_{it} \quad (17)$$

$$R_{it} - R_{Ft} = a_i + b_i(Mkt_t - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + p_i PSENT_t + \varepsilon_{it} \quad (18)$$

The three asset pricing models will first be tested using OLS for timeseries regression on individual stocks. Afterwards will six sets of portfolios with different combinations of characteristics be used to test the three models.

7.1 Test on Stocks

The three different asset pricing models detailed in equations 16, 17, and 18 will be applied to 19 non-financial stocks selected from the EURO STOXX 600, using OLS for time series regression. The 19 stocks chosen are those with the largest market value at the end of the data period, specifically November 2023. his test, using the 19 largest stocks in the European market, is meant to be though test of the explanatory power of the indexes. The main reason for this is expected to be a tough test is that the investor sentiment is expected to have the biggest impact on opaque companies that hard to value with characteristics such as being small, volatile and a significant amount of intangible assets, and these characteristics are not expected to be the main characteristics of the 19 largest stocks in Europe (Berger & Turtle, 2012).

Even though the results from testing on individual stocks are not as generalizable as those from portfolio testing, this approach is still used by researchers (Allen, McAleer, & Singh, 2019; Liew & Budavari, 2017). In this paper it has the purpose of providing insights into if investor sentiment affects the largest and likely most closely analyzed and highly traded individual stocks in Europe. The test will include the % change in $R^2$and adjusted R^2, to assess if the addition of SENT or PSENT can improves the Fama French five factor models' ability to explain excess returns of the chosen stocks. Furthermore, there will also be a focus on the intercepts (alphas) from the time series regressions by measuring the average absolute alpha and the number of significant alphas. These measures provide an indication of whether the stocks have shown abnormal returns after adjusted for the factors and which model best captures the excess returns, leaving the least unexplained excess return.

7.1.1 Stock data

The stock data is picked from the FactSet platform, taking the price data for the 19 largest non-financial stocks measured by market value from EURO STOXX 600 in the end of the data period November 2023. The stock data is for the period of 31-01-1999 to 30-11-2023, meaning similar to the data period of the investor sentiment proxies in Section 4.1. The prices are reported in the local currency. As this paper is focusing on the ability to explain excess returns, are the log-returns of the stocks calculated and withdrawn the risk-free rate. The risk-free rate used is the US one month T-bill that is reported with European five factors in the Kennth R. French data library and used for the factor Mkt- RF. The construction of the excess returns results in a total of 298 observations. However, only the observations from January 2000 to November 2023 will be used, as this matches the period of the investor sentiment factor PSENT. This period is slightly shorter due to missing unemployment data. Consequently, the stock testing will be conducted using 287 observations of monthly excess returns and factors.

7.1.2 Factor data

Figure 18 shows the summary statistics for the factors used in the three different asset pricing models. SENT and PSENT are the investor sentiment factors constructed in this paper, the European Fama French five factors are picked from the Kennth R. French data library. The European five-factor data in the Kenneth R. French library is constructed using returns in U.S. dollars (French, 2024). SENT and PSENT has by construction an approximately 0 mean, as they are created using standardized proxies all with a zero mean.

	SENT	PSENT_	Mkt-RF	SMB	HML	RMW	CMA
count	287.0	287.0	287.0	287.0	287.0	287.0	287.0
mean	-0.04	-0.0	0.4	0.16	0.38	0.29	0.23
std	1.42	1.47	5.37	2.02	2.91	1.72	1.9
min	-4.26	-5.32	-22.02	-7.33	-11.3	-5.4	-7.3
25%	-1.05	-0.87	-2.7	-1.02	-1.23	-0.66	-0.72
50%	0.08	0.24	0.61	0.2	0.37	0.38	0.12
75%	1.08	1.09	4.08	1.46	1.76	1.38	1.04
max	2.4	3.11	16.62	8.83	12.09	6.4	8.77

Figure 18 - Summary statistics of the seven factors.

As shown in the figure 19 is SENT and PSENT only to a very little degree correlated with any of the other factors. The highest correlation is between PSENT and Mkt-RF at 0,15. This is significantly lower than most of the correlations between the existing factors in the Fama French five factor model. Especially is the HML factor closely correlated with both RMW and CMA with correlation of respectively -0,6 and 0,65. The results shows signs of that in the addition of the RMW and CMA factors the HML might have lost its eligibility, as it shares much information with the RMW and CMA factors. Eugene F. Fama and Kenneth R. French already discussed the possibility that the HML factor might have become redundant in their article introducing the five-factor model (Fama & French, 2015).

That PSENT and SENT both exhibit very low correlations with the other factors suggests they are introducing new information not captured by existing factors. Whether this new information helps explain excess returns remains to be tested. The close relationship between the two sentiment indices suggests some closely related outcomes, but also leaves room for one to potentially be superior to the other.

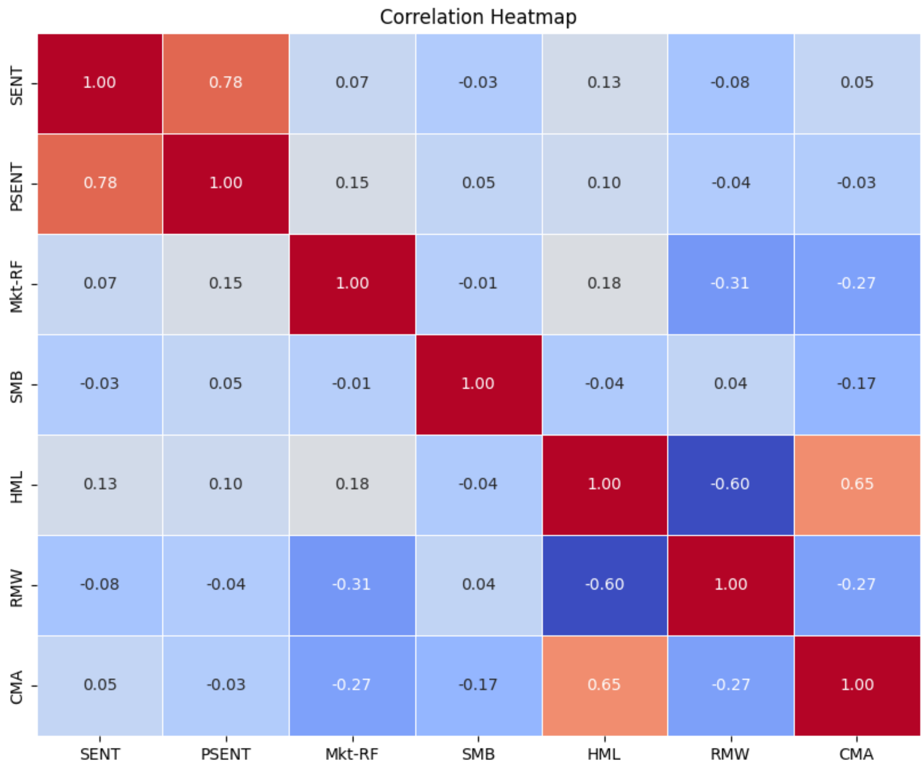

Figure 19 - Correlation matrix of the seven factors.

7.1.2 Stock testing

The regression results in table 20, shows to some degree that this is a tough test of the sentiment indexes. The mean of the beta of Mkt-RF is 0,73 indicating the stocks tested tend to move less than the market, furthermore, are the excess returns of the stocks on average negative affected by the SMB factor. This gives an indication of the stocks are less volatile relative to the market, and also large stocks, which is not kind of characteristics that is expected for a sentiment prone stock. The negative slope for HML showing that the stocks do not shows signs of being value stocks but seems on average to perform more like growth stocks. RMW and CMA also have negative average slopes meaning the stocks excess returns is therefore on average negative affected when companies with high operating profit and conservative investment policies beating the returns of their counterparts. This is somewhat unexpected when analyzing the 19 largest non-financial stocks in Europe. An explanation could be that although they are the largest at the end of the period, the characteristics of these stocks may have changed over the nearly 24-year period. They might have secured their positions by focusing on investment and growth. The average absolute alpha is having a slight increase when including an investor sentiment as it increases from 0,68 to 0,7 with the inclusion of SENT and 0,71 with PSENT. This suggest that the addition of the investor sentiment factor is making the Fama French five factor model capture less of the excess returns, even though the increase relatively small.

Except for on the HM. B-OME stock, the PSENT and SENT factors show positive betas. This suggests that the excess returns of most of the selected stocks are positively affected during periods of high investor sentiment, consistent with the correlations observed with the EURO STOXX 600. This positive effect aligns with expectations, as behavioral theory suggests that when investor sentiment increases, investors' risk aversion decreases, potentially leading them to allocate a larger portion of their wealth to stocks, thereby driving up price. Consequently, a general increase in stock prices would be anticipated, with some stocks being more sensitive to this rise in investor sentiment (Baker & Wurgler, 2006). Conversely, it is also expected that when sentiment levels decrease, investors will tend to invest less, thus driving down the general price level.

It is clear that some of the 19 stocks are significantly more prone to sentiment than others, as the absolute average betas of SENT and PSENT respectively is 0,3 and 0,41, while VWS-DK is having betas of 1,3 and 1,69. The absolute average beta of especially PSENT shows that it is on average having a slightly higher impact on the expected returns than the CMA Factor (0,4) and close to the level of the other factors. Additionally, the average absolute beta shows that PSENT generally outperforms the investor sentiment factor SENT in terms of its effect on expected returns. When examining the individual beta, PSENT also exhibits a higher beta on almost every stock, with only three exceptions in favor for SENT.

Stock	Begin Date	End Date	Observation	Coefficients											
				a	b	s	h	r	c	i	p	R^2	% Change	Adj- R^2	% Change
ASML-NL	31-01-2000	30-11-2023	287	1,78	0,95	-0,70	-1,34	-1,95	-0,59			0,39		0,38	
ASML-NL	31-01-2000	30-11-2023	287	1,79	0,95	-0,70	-1,36	-1,96	-0,58	0,27		0,39	0,29%	0,38	-0,27%
ASML-NL	31-01-2000	30-11-2023	287	1,80	0,94	-0,71	-1,37	-1,98	-0,57		0,32	0,39	0,44%	0,38	-0,12%
ASSA.B-SE	31-01-2000	30-11-2023	287	0,64	0,65	-0,51	-0,46	-0,21	-0,20			0,27		0,26	
ASSA.B-SE	31-01-2000	30-11-2023	287	0,65	0,65	-0,51	-0,48	-0,21	-0,19	0,26		0,27	0,86%	0,26	-0,10%
ASSA.B-SE	31-01-2000	30-11-2023	287	0,66	0,64	-0,53	-0,50	-0,24	-0,17		0,41	0,28	2,28%	0,26	1,42%
ATCO.A-SE	31-01-2000	30-11-2023	287	0,94	0,81	-0,50	-0,16	-0,12	-0,28			0,32		0,30	
ATCO.A-SE	31-01-2000	30-11-2023	287	0,95	0,81	-0,49	-0,17	-0,12	-0,28	0,09		0,32	0,07%	0,30	-0,74%
ATCO.A-SE	31-01-2000	30-11-2023	287	0,95	0,80	-0,50	-0,18	-0,13	-0,27		0,22	0,32	0,48%	0,30	-0,30%
COLO.B-DK	31-01-2000	30-11-2023	287	0,73	0,30	-0,07	-0,41	0,50	0,55			0,07		0,05	
COLO.B-DK	31-01-2000	30-11-2023	287	0,74	0,30	-0,07	-0,42	0,50	0,55	0,15		0,07	1,63%	0,05	-4,35%
COLO.B-DK	31-01-2000	30-11-2023	287	0,76	0,29	-0,08	-0,44	0,47	0,57		0,35	0,07	9,79%	0,06	6,65%
DNB-NO	31-01-2000	30-11-2023	287	0,06	0,79	0,22	0,97	-0,21	-0,84			0,49		0,48	
DNB-NO	31-01-2000	30-11-2023	287	0,06	0,79	0,23	0,96	-0,21	-0,83	0,13		0,49	0,11%	0,48	-0,27%
DNB-NO	31-01-2000	30-11-2023	287	0,08	0,77	0,21	0,94	-0,23	-0,82		0,34	0,49	0,73%	0,48	0,37%
DSV-DK	31-01-2000	30-11-2023	287	0,92	0,90	0,35	0,25	0,44	-0,86			0,37		0,36	
DSV-DK	31-01-2000	30-11-2023	287	0,96	0,89	0,36	0,19	0,44	-0,84	0,72		0,38	3,43%	0,37	2,96%
DSV-DK	31-01-2000	30-11-2023	287	0,96	0,88	0,33	0,18	0,39	-0,82		0,73	0,38	3,73%	0,37	3,29%
ERIC.B-OME	31-01-2000	30-11-2023	287	1,01	0,64	-0,79	-2,26	-3,78	-0,43			0,35		0,34	
ERIC.B-OME	31-01-2000	30-11-2023	287	1,03	0,63	-0,79	-2,28	-3,79	-0,42	0,27		0,35	0,23%	0,34	-0,45%
ERIC.B-OME	31-01-2000	30-11-2023	287	1,03	0,63	-0,80	-2,28	-3,80	-0,41		0,26	0,35	0,23%	0,34	-0,45%
HEXA.B-SE	31-01-2000	30-11-2023	287	0,60	1,06	0,69	0,13	0,79	-0,27			0,36		0,34	
HEXA.B-SE	31-01-2000	30-11-2023	287	0,63	1,06	0,70	0,10	0,79	-0,25	0,43		0,36	1,09%	0,35	0,47%
HEXA.B-SE	31-01-2000	30-11-2023	287	0,63	1,04	0,68	0,08	0,75	-0,23		0,57	0,36	1,99%	0,35	1,42%
HM.B-OME	31-01-2000	30-11-2023	287	-0,40	0,64	-0,13	-0,01	0,32	0,00			0,16		0,14	
HM.B-OME	31-01-2000	30-11-2023	287	-0,42	0,64	-0,14	0,01	0,32	-0,01	-0,32		0,16	1,92%	0,14	0,00%
HM.B-OME	31-01-2000	30-11-2023	287	-0,42	0,65	-0,12	0,02	0,35	-0,02		-0,35	0,16	2,41%	0,14	0,55%
MAERSK.B-DK	31-01-2000	30-11-2023	287	-0,37	0,81	0,92	0,18	-0,06	-0,22			0,28		0,26	
MAERSK.B-DK	31-01-2000	30-11-2023	287	-0,37	0,81	0,92	0,18	-0,06	-0,22	0,02		0,28	0,00%	0,26	-0,99%
MAERSK.B-DK	31-01-2000	30-11-2023	287	-0,36	0,81	0,91	0,17	-0,06	-0,21		0,10	0,28	0,08%	0,26	-0,91%
MC-FR	31-01-2000	30-11-2023	287	0,58	0,88	-0,46	-0,22	-0,23	-0,37			0,45		0,44	
MC-FR	31-01-2000	30-11-2023	287	0,59	0,88	-0,46	-0,23	-0,24	-0,37	0,17		0,46	0,21%	0,44	-0,23%
MC-FR	31-01-2000	30-11-2023	287	0,59	0,87	-0,47	-0,23	-0,25	-0,36		0,16	0,46	0,20%	0,44	-0,24%
NESN-CH	31-01-2000	30-11-2023	287	0,12	0,31	-0,23	-0,31	0,36	0,42			0,17		0,15	
NESN-CH	31-01-2000	30-11-2023	287	0,15	0,31	-0,22	-0,34	0,36	0,43	0,45		0,20	16,19%	0,18	16,16%
NESN-CH	31-01-2000	30-11-2023	287	0,15	0,29	-0,25	-0,35	0,33	0,45		0,46	0,20	17,70%	0,18	17,85%
NOVO.B-DK	31-01-2000	30-11-2023	287	1,50	0,26	-0,52	-0,42	-0,04	0,01			0,08		0,06	
NOVO.B-DK	31-01-2000	30-11-2023	287	1,52	0,26	-0,51	-0,45	-0,05	0,02	0,37		0,08	7,17%	0,06	3,81%
NOVO.B-DK	31-01-2000	30-11-2023	287	1,53	0,24	-0,53	-0,47	-0,08	0,04		0,49	0,09	12,92%	0,07	11,26%
OR-FR	31-01-2000	30-11-2023	287	0,21	0,59	-0,78	-0,18	0,52	0,23			0,35		0,33	
OR-FR	31-01-2000	30-11-2023	287	0,22	0,59	-0,77	-0,19	0,52	0,24	0,17		0,35	0,51%	0,33	-0,17%
OR-FR	31-01-2000	30-11-2023	287	0,23	0,57	-0,79	-0,21	0,49	0,26		0,43	0,36	3,50%	0,34	2,99%
RMS-PAR	31-01-2000	30-11-2023	287	1,16	0,55	-0,60	-0,18	0,17	-0,59			0,21		0,20	
RMS-PAR	31-01-2000	30-11-2023	287	1,17	0,55	-0,60	-0,19	0,17	-0,59	0,13		0,21	0,25%	0,20	-1,15%
RMS-PAR	31-01-2000	30-11-2023	287	1,17	0,55	-0,60	-0,19	0,17	-0,59		0,09	0,21	0,12%	0,20	-1,30%
SAND-SE	31-01-2000	30-11-2023	287	-0,36	0,93	0,08	0,42	0,89	-0,34			0,37		0,36	
SAND-SE	31-01-2000	30-11-2023	287	-0,35	0,92	0,08	0,41	0,89	-0,34	0,20		0,37	0,31%	0,36	-0,31%
SAND-SE	31-01-2000	30-11-2023	287	-0,35	0,92	0,07	0,40	0,87	-0,33		0,28	0,37	0,63%	0,36	0,02%
SAP-DE	31-01-2000	30-11-2023	287	1,16	0,85	-0,47	-1,24	-1,74	-0,60			0,41		0,40	
SAP-DE	31-01-2000	30-11-2023	287	1,18	0,84	-0,47	-1,26	-1,75	-0,59	0,26		0,41	0,33%	0,40	-0,19%
SAP-DE	31-01-2000	30-11-2023	287	1,19	0,83	-0,48	-1,28	-1,77	-0,58		0,38	0,41	0,76%	0,40	0,26%
VOLV.B-SE	31-01-2000	30-11-2023	287	0,01	1,02	0,35	0,14	-0,06	-0,05			0,41		0,40	
VOLV.B-SE	31-01-2000	30-11-2023	287	0,01	1,02	0,35	0,13	-0,06	-0,04	0,05		0,41	0,01%	0,39	-0,53%
VOLV.B-SE	31-01-2000	30-11-2023	287	0,02	1,01	0,35	0,12	-0,07	-0,04		0,19	0,41	0,25%	0,40	-0,28%
VWS-DK	31-01-2000	30-11-2023	287	0,43	0,98	1,18	-0,15	-0,62	-0,80			0,21		0,19	
VWS-DK	31-01-2000	30-11-2023	287	0,51	0,96	1,21	-0,25	-0,63	-0,76	1,30		0,22	7,53%	0,20	6,76%
VWS-DK	31-01-2000	30-11-2023	287	0,53	0,92	1,13	-0,30	-0,74	-0,70		1,69	0,23	13,63%	0,22	13,44%
Mean			287	0,58	0,73	-0,11	-0,30	-0,27	-0,26	0,27	0,37	0,30	3,00%	0,29	2,01%
Median			287	0,63	0,81	-0,23	-0,19	-0,06	-0,28	0,20	0,34	0,35	0,68%	0,33	-0,11%
Absolute mean				0,70	0,73	0,50	0,50	0,69	0,40	0,30	0,41				
				(absolute)											
Mean FFFFM			287	0,68	0,73	-0,10	-0,28	-0,26	-0,27	0,00	0,00	0,30	0,00%	0,29	0,00%
Mean SENT			287	0,70	0,73	-0,10	-0,30	-0,27	-0,27	0,27	0,00	0,30	2,22%	0,29	1,07%
Mean PSENT			287	0,71	0,72	-0,12	-0,31	-0,29	-0,25	0,00	0,37	0,31	3,78%	0,29	2,94%

Figure 20 - Regression results on the 19 largest non-financial stocks in EURO STOXX 600 including coefficients, R^2 and $adj\ R^2$.

R^2 *and* $adj\ R^2$

The addition of an investor sentiment factor increases the R^2 for all stocks, regardless of which of the revised Fama French models applied. The average percentage increase in R^2 is 3%, with an average increase of 2.22% when applying the SENT factor and 3.78% when using the PSENT factor. This increase in explanatory power of the model is primarily driven by a small part of the sample that is experiencing large increases in R^2. The most notable percentage increases are seen in COLO.B-DK, NOVO.B-DK, and VWS-DK. The main reason for the substantial percentage increases in COLO.B-DK, NOVO.B-DK is largely due to their initially low levels of R^2, meaning that even small increase in R^2 result in large percentage change. The average increase in R^2 indicates that investor sentiment, especially when "purified" for macro factors, enhances the explanatory power of the Fama-French five-factor model on the excess returns of individual stocks.

Focusing on the adj R^2, which imposes a penalty for adding additional factors, the addition of an investor sentiment factor is still having a positive effect on average. The average increase in $adj\ R^2$ is 2.01%, with respective increases of 1.07% for the model including SENT and 2.94% for PSENT. The effect of the imposed penalty is clear, as stocks that previously showed only a slight increase in R^2 are now, in most cases, experiencing a negative change in adj R^2. The median of the percentage change in adj R^2 is -0.11, indicating that the positive average percentage increase is primarily due to a few large increases in adj R^2. The performance difference between the two sentiment factors has also widened when measured by adj R^2. The difference is especially pronounced for COLO.B-DK, NOVO.B-DK, and VWS-DK. In the case of COLO.B-DK, the change in adj R^2 shifts from -4.35% with SENT to an increase of 6.65% with PSENT. This suggests that the revised model using the PSENT is better at explaining the excess returns of individual stocks. Furthermore, the explanatory power of the Fama-French five-factor model, as measured by average adj R^2, increases when PSENT is included, indicating that this model is better at explaining the excess returns of individual stocks.

Even though this was a tough test the average results of R^2 and $adj\ R^2$ indicate that the investor sentiment factors, particularly PSENT, enhanced the explanatory power of the Fama-French five-factor model.

T-statistics and p-values

The t-statistics in Figure 21 gives a further understanding of the betas in Figure 20. Across all three models are the same six stocks having significant positive alpha at a 0.05 significance level. This indicates that, after controlling for the Fama-French five factors and additional investor sentiment factors, these stocks have performed better than expected, with t-statistics ranging from 2.17 (ACTO.A-SE) to 3.56 (NOVO.B-DK) and alphas between 0.92 and 1.53. This really shows that these stocks have outperformed and given abnormal returns over a long period of time. This makes sense as the stock picking method might tend to favor exceptional performers. As the largest 19 stocks by market value today may have earned their positions due to extraordinary performance over the last 24 years.

The T-statistic of the individual stocks is also further supporting the past results showing that PSENT are more significant than SENT, when applied to the Fama French factor model, with the goal of explaining the excess returns of individual stocks. PSENT is significant on four stocks measured by a significance level 0,05 and additional two more if measured with a significance level of 0,1. The investor sentiment factor SENT is only significant on three stocks with a significance level of 0,05, and this does not change if the significance level is set to 0,1. Furthermore is the absolute mean of the t-statistics of PSENT also higher compared to SENT and also the CMA Factor indicating that PSENT on average is more likely to be significant

These results therefore suggest that PSENT has more significant explanatory power on the excess returns of the 19 largest non-financial European stocks compared to SENT. The t-statistics further support the findings presented in Table 20, measuring performance by the slopes, R^2, and adjusted R^2.

Stock	Begin Date	End Date	Observation	t-stat(a)	t-stat(b)	t-stat(s)	t-stat(h)	t-stat(r)	t-stat(c)	t-stat(p)	t-stat(i)
MAERSK.B-DK	31-01-2000	30-11-2023	287	-0,73	7,56***	3,79***	0,63	-0,16	-0,55		
MAERSK.B-DK	31-01-2000	30-11-2023	287	-0,72	7,54***	3,78***	0,62	-0,16	-0,55		0,06
MAERSK.B-DK	31-01-2000	30-11-2023	287	-0,71	7,47***	3,77***	0,6	-0,17	-0,53	0,29	
ASML-NL	31-01-2000	30-11-2023	287	3,18***	8,05***	-2,64***	-4,34***	-4,92***	-1,36		
ASML-NL	31-01-2000	30-11-2023	287	3,2***	8,01***	-2,62***	-4,39***	-4,92***	-1,34		0,73
ASML-NL	31-01-2000	30-11-2023	287	3,21***	7,9***	-2,67***	-4,41***	-4,97***	-1,32	0,89	
ASSA.B-SE	31-01-2000	30-11-2023	287	1,57	7,63***	-2,67***	-2,06**	-0,73	-0,63		
ASSA.B-SE	31-01-2000	30-11-2023	287	1,61	7,59***	-2,63***	-2,13**	-0,74	-0,6		0,95
ASSA.B-SE	31-01-2000	30-11-2023	287	1,64	7,43	-2,73	-2,21	-0,83	-0,55	1,55	
ATCO.A-SE	31-01-2000	30-11-2023	287	2,17**	8,85***	-2,41**	-0,68	-0,38	-0,83		
ATCO.A-SE	31-01-2000	30-11-2023	287	2,18**	8,82***	-2,4**	-0,7	-0,38	-0,82		0,3
ATCO.A-SE	31-01-2000	30-11-2023	287	2,2**	8,7***	-2,44**	-0,76	-0,43	-0,79	0,79	
COLO.B-DK	31-01-2000	30-11-2023	287	1,92*	3,76***	-0,4	-1,96*	1,85*	1,86*		
COLO.B-DK	31-01-2000	30-11-2023	287	1,94*	3,73***	-0,39	-2**	1,84*	1,87*		0,58
COLO.B-DK	31-01-2000	30-11-2023	287	1,98*	3,58***	-0,46	-2,09**	1,75*	1,93*	1,42	
DNB-NO	31-01-2000	30-11-2023	287	0,15	10,06***	1,26	4,71***	-0,78	-2,92***		
DNB-NO	31-01-2000	30-11-2023	287	0,17	10,03***	1,27	4,64***	-0,79	-2,9***		0,54
DNB-NO	31-01-2000	30-11-2023	287	0,21	9,86***	1,21	4,55***	-0,88	-2,86***	1,4	
DSV-DK	31-01-2000	30-11-2023	287	2,01**	9,39***	1,6	0,98	1,37	-2,44**		
DSV-DK	31-01-2000	30-11-2023	287	2,13**	9,39***	1,69*	0,77	1,36	-2,41**		2,38**
DSV-DK	31-01-2000	30-11-2023	287	2,13**	9,15***	1,52	0,73	1,21	-2,35**	2,49**	
HM.B-OME	31-01-2000	30-11-2023	287	-0,82	6,2***	-0,57	-0,05	0,92	0		
HM.B-OME	31-01-2000	30-11-2023	287	-0,86	6,23***	-0,6	0,04	0,93	-0,02		-1
HM.B-OME	31-01-2000	30-11-2023	287	-0,86	6,28***	-0,53	0,06	1	-0,05	-1,12	
RMS-PAR	31-01-2000	30-11-2023	287	2,62***	5,91***	-2,85***	-0,74	0,55	-1,73*		
RMS-PAR	31-01-2000	30-11-2023	287	2,63***	5,88***	-2,83***	-0,77	0,54	-1,72*		0,44
RMS-PAR	31-01-2000	30-11-2023	287	2,62***	5,83***	-2,86***	-0,76	0,52	-1,71*	0,3	
HEXA.B-SE	31-01-2000	30-11-2023	287	1,2	10,11***	2,92***	0,46	2,24**	-0,69		
HEXA.B-SE	31-01-2000	30-11-2023	287	1,26	10,07***	2,96***	0,34	2,23**	-0,66		1,3
HEXA.B-SE	31-01-2000	30-11-2023	287	1,27	9,89***	2,86***	0,28	2,12**	-0,61	1,76*	
OR-FR	31-01-2000	30-11-2023	287	0,71	9,71***	-5,65***	-1,11	2,53**	1,04		
OR-FR	31-01-2000	30-11-2023	287	0,75	9,67***	-5,62***	-1,18	2,52**	1,06		0,87
OR-FR	31-01-2000	30-11-2023	287	0,81	9,47***	-5,78***	-1,34	2,39**	1,15	2,3**	
MC-FR	31-01-2000	30-11-2023	287	1,63	11,7***	-2,75***	-1,11	-0,93	-1,35		
MC-FR	31-01-2000	30-11-2023	287	1,66*	11,66***	-2,72***	-1,17	-0,93	-1,33		0,7
MC-FR	31-01-2000	30-11-2023	287	1,66*	11,54***	-2,77***	-1,17	-0,97	-1,32	0,69	
NESN-CH	31-01-2000	30-11-2023	287	0,54	6,58***	-2,19**	-2,46**	2,26**	2,42**		
NESN-CH	31-01-2000	30-11-2023	287	0,67	6,57***	-2,12**	-2,76***	2,27**	2,53**		3,07***
NESN-CH	31-01-2000	30-11-2023	287	0,67	6,29***	-2,35**	-2,82***	2,08**	2,61***	3,22***	
NOVO.B-DK	31-01-2000	30-11-2023	287	3,48***	2,89***	-2,53**	-1,78*	-0,14	0,03		
NOVO.B-DK	31-01-2000	30-11-2023	287	3,54***	2,85***	-2,49**	-1,9*	-0,15	0,07		1,3
NOVO.B-DK	31-01-2000	30-11-2023	287	3,56***	2,69***	-2,6***	-1,96*	-0,25	0,12	1,76*	
SAND-SE	31-01-2000	30-11-2023	287	-0,86	10,45***	0,38	1,83*	2,99***	-1,05		
SAND-SE	31-01-2000	30-11-2023	287	-0,83	10,41***	0,4	1,75*	2,98***	-1,03		0,71
SAND-SE	31-01-2000	30-11-2023	287	-0,82	10,27***	0,34	1,71*	2,92***	-1	1,02	
SAP-DE	31-01-2000	30-11-2023	287	2,39**	8,25***	-2,04**	-4,62***	-5,05***	-1,59		
SAP-DE	31-01-2000	30-11-2023	287	2,42**	8,22***	-2,01**	-4,67***	-5,06***	-1,57		0,81
SAP-DE	31-01-2000	30-11-2023	287	2,44**	8,08***	-2,08**	-4,72***	-5,13***	-1,53	1,22	
ERIC.B-OME	31-01-2000	30-11-2023	287	1,51	4,5***	-2,49**	-6,08***	-7,94***	-0,83		
ERIC.B-OME	31-01-2000	30-11-2023	287	1,53	4,47***	-2,46**	-6,11***	-7,94***	-0,81		0,59
ERIC.B-OME	31-01-2000	30-11-2023	287	1,53	4,4***	-2,5**	-6,11***	-7,96***	-0,8	0,59	
VWS-DK	31-01-2000	30-11-2023	287	0,52	5,6***	2,99***	-0,33	-1,05	-1,24		
VWS-DK	31-01-2000	30-11-2023	287	0,62	5,56***	3,09***	-0,54	-1,08	-1,2		2,36**
VWS-DK	31-01-2000	30-11-2023	287	0,65	5,3***	2,91***	-0,66	-1,28	-1,11	3,2***	
VOLV.B-SE	31-01-2000	30-11-2023	287	0,02	11,14***	1,71*	0,57	-0,2	-0,14		
VOLV.B-SE	31-01-2000	30-11-2023	287	0,03	11,11***	1,72*	0,55	-0,2	-0,13		0,17
VOLV.B-SE	31-01-2000	30-11-2023	287	0,05	10,99***	1,68*	0,49	-0,24	-0,11	0,69	
Mean			287	1,25	7,74	-0,77	-1,02	-0,43	-0,60	1,29	0,89
Absolute mean			287	1,51	7,74	2,31	1,95	1,95	1,19	1,41	0,99
Median			287	1,53	8,01	-2,04	-0,76	-0,17	-0,80	1,22	0,71
Mean FFFFM			287	1,22	7,81	-0,76	-0,95	-0,40	-0,63		
Mean SENT			287	1,26	7,78	-0,74	-1,03	-0,40	-0,61		
Mean PSENT			287	1,28	7,64	-0,82	-1,08	-0,48	-0,57		

*Figure 21- T-statistics from the regression on the 19 largest non-financial stocks in EURO STOXX 600. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.*

7.1.3 Conclusion Stock testing

The in-sample test on the 19 non-financial stocks showed that the investor sentiment indexes helped increase the explanatory power of the Fama-French five-factor model measured by R^2 and adj R^2. This means that SENT and PSENT provided the model with new information that could be used to explain the excess returns of individual stocks. However, was the average increase in explanatory power measured by R^2 and $adj\ R^2$ relatively small, and highest including the PSENT factor. The modest average increase in explanatory power was primarily driven by a few sentiments' prone stocks, which exhibited significantly % increase in R^2 and $adj\ R^2$. In these cases, there was a notable improvement in the Fama-French five-factor model. The test also showed an increase in average absolute alpha when including an investor sentiment factor, indicating the revised models captures less of the excess return. However, was the number of significant alphas using a 0,05-significance level the same across all the models. The results regarding the investor sentiment factors ability to improve the Fama French five factor is therefore mixed but with some indications of they might improve the Fama French five factor model.

7.2 Test on Portfolios

Six set of portfolios will be used to evaluate the asset pricing models presented in Section 7, with a focus on determining whether the additional investor sentiment factor can enhance the performance of the Fama French five-factor model by incorporating new information. The portfolio combinations selected are the same as those used by Eugene F. Fama and Kenneth R. French in their paper introducing the Fama-French five-factor model. This selection aims to test whether investor sentiment can enhance the model by addressing some of the challenges the Fama-French five-factor model encountered with these portfolios (Fama & French, 2015).

The results from portfolio testing will be more generalizable compared to the results of individual stocks, as the use of portfolios reduces noise and idiosyncratic risk. First step in the portfolio testing will be using GRS test to test if the asset pricing models are able to fully explain the excess returns, which is not expected, the GRS test will more likely reject this. The GRS score as well as other statistics will be used to evaluate the asset pricing models relative performance. For a more detailed analysis of these results, the portfolio sets OLS timeseries regression results are analyzed. This approach provides the opportunity to identify which portfolios are causing issues for the asset pricing model and to determine whether the addition of an investor sentiment factor resolves some of these issues (Fama & French, 2015).

7.2.1 Portfolios data

The portfolio sets are picked from the Kenneth R. French data library similar to the European Fama French five factors. The six European portfolio sets chosen are all constructed using returns in U.S dollars including dividends and capital gains. The European Fama French five factors are also constructed using U.S dollars (French, 2024). The portfolios returns are constructed as monthly average value weighted returns. The risk-free rate is withdrawn to get the excess returns. The risk-free rate is US one month T-bill that reported with the Fama French five factors and used for the factor Mkt- RF (French, 2024). All the portfolios are constructed annually by the end of June using different sorts of Size, B/M, OP and INV, which all are defined below.

Size is determined by the market capitalization at the end of June, with classifications made annually by the end of June.
B/M is calculated using the book equity(B) and market equity(M) and is calculated by taking the book value at the last fiscal year end of the prior calendar year divided by market equity as of 6 months before formation in end of June. Firms with negative book equity are excluded from the portfolios, a criterion applied consistently across all portfolio sets.
OP is determined by subtracting the cost of goods sold, interest expense, and selling, general, and administrative expenses from the annual revenue, and then dividing by the book equity for the last fiscal year.
INV is calculated as the change in total assets from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by the total assets in year t-2 (French, 2024).

The portfolio sets used in this paper are divided into two groups: three portfolios formed based on two characteristics, and three portfolios formed based on three characteristics.

Portfolios formed on two characteristics.

Three sets of portfolios formed on two characteristics are selected, all based on Size. Each set incorporating one of three characteristics: book-to-market equity (B/M), profitability (OP), and investments (INV). These characteristics are divided into five categories, such as Small, 2, 3, 4, and Big, resulting in a total of 25 portfolios within each set.

The Size characteristic is divided into five groups from small to big, with break points set at the 3rd, 7th, 13th, and 25th percentiles of market capitalization. This means that 75% of the market capitalization falls within the big size category. The B/M breakpoints are set at the 20th, 40th, 60th, and 80th percentiles of the B/M for the top 90% of market capitalization stocks. The top 90% of the market serves as the breakpoint when size is split into two groups, which means that the B/M breakpoints are created using this definition of big stocks. Similarly, OP and INV are divided into groups using the same breakpoints as B/M but measured in terms of OP or INV for the top 90% of market capitalization stocks.

Figure 22 present the average excess returns for each portfolio set, representing every combination of characteristics that later will be used for testing the asset pricing models. In the matrix with the 25 Size and B/M portfolios, the size effect was expected to be clear, which it also is in the column with the highest B/M. However, in the first four groups of B/M, the size effect is not visible, and there is actually an opposite size effect in the two groups with the lowest B/M. In these groups, excess returns increase from small to big, contrary to the expected relationship. The reverse size effect visible in the portfolios with the lowest B/M portfolios align with the results reported by Fama and French when testing their five-factor model, but their findings showed a clear size effect in the other B/M groups(Fama & French, 2015).

The relationship between excess returns and B/M, also known as the value effect, is much more consistent, with excess returns increasing in most portfolios as B/M increases. This relationship is strongest among small stocks and decreases as size increases. These results are consistent with past research indicating that the value effect is strongest among small stock (Fama & French, 2015).

The patterns regarding excess returns and size in the 25 Size-OP portfolios show similarities to those observed in the 25 Size-INV portfolios. Once again, it is not as clear as expected, but now it is more visible in the four groups with the highest OP. Although it is not a perfect pattern where excess returns decrease each time size increases, there is a clear difference observed from the excess returns of small stocks to large stocks, with less pronounced differences in the portfolios in between. The profitability effect also appears evident, with a clear increase in excess return from low OP to high OP, although the development in between is somewhat mixed. Despite the pattern not being perfect across the different OP groups, a clear relation can be observed, and therefore the presence of the profitability effect.

When focusing on the 25 Size-INV portfolios, the size effect is visible in all groups except the high inv groups, where there is a negative relation with size, meaning the excess returns is increasing as the size of the firms increases. The other four groups show a clear decrease in excess returns from small to big, but with a more mixed pattern in between. The investment effect is more visible, as the average excess returns are much lower for the high investment groups relative to the low investment groups, except for the big stocks. In this case, the change is not as visible, even though the excess returns are still decreasing.

	LOW	**2**	**3**	**4**	**High**
Size - B/M portfolios					
Small	-0,23	0,21	0,39	0,56	0,78
2	0,17	0,51	0,57	0,69	0,84
3	0,34	0,55	0,62	0,69	0,79
4	0,46	0,64	0,58	0,65	0,62
Big	0,28	0,44	0,38	0,48	0,40
Size - OP portfolios					
Small	0,03	0,66	0,75	0,93	0,66
2	0,26	0,61	0,70	0,79	0,87
3	0,31	0,72	0,73	0,64	0,84
4	0,34	0,56	0,64	0,77	0,61
Big	0,10	0,49	0,40	0,29	0,44
Size - INV portfolios					
Small	0,47	0,70	0,71	0,60	0,01
2	0,62	0,78	0,78	0,69	0,25
3	0,72	0,71	0,77	0,60	0,27
4	0,63	0,61	0,67	0,67	0,30
Big	0,39	0,48	0,35	0,29	0,33

Figure 22 - Average excess returns two split portfolios.

Portfolios three splits

Three sets of portfolios are based on Size, with two of the three characteristics B/M, OP, and investments (INV) included. Stocks are categorized in terms of size as either Big or Small, while the other three characteristics are now divided into four groups. For example, Low INV, 2, 3, and High INV represent the four categories of INV. This results in the portfolios being sorted into a 2x4x4 configuration, totaling 32 portfolios (French, 2024). Since these portfolios include an additional characteristic compared to the first three sets, they offer the opportunity to unfold more detailed combinations of characteristics and potential patterns.

The three sets of portfolios are Size-B/M-INV, Size-B/M-OP, and Size-INV-OP, with the average excess returns of these combinations presented in Figure 23. The categories are split into two Size groups, four B/M groups, four INV groups, and four OP groups. With Size included in each set of portfolios, this results in 32 portfolios in each set. Big stocks are those in the top 90% of the market capitalization in June, while small stocks are those in the bottom 10% of the market capitalization. The stocks in each Size group are allocated to the four B/M, OP, or INV groups based on the quartiles for the specific size group (French, 2024).

In the test of the three asset pricing models are one of the most challenging combinations of characteristics the small stocks with low OP and low B/M. Additionally, as discussed by Fama and French are small stocks that invest a lot despite low profitability are a big issue for the five-factor model (Fama & French, 2015). The average excess returns of these portfolios are only captured to a very limited degree by the five-factor model and the investor sentiment factor, as will be evident in the test results later in the report.

	Small				Big			
	LOW	2	3	High	LOW	2	3	High
B/M ->								
Size - B/M - INV portfolios								
Low INV	0,23	0,60	0,77	0,83	0,36	0,40	0,51	0,51
2	0,48	0,69	0,86	0,94	0,25	0,66	0,63	0,65
3	0,54	0,74	0,75	0,95	0,30	0,42	0,44	0,56
High INV	-0,07	0,22	0,37	0,65	0,39	0,26	0,41	0,42
Size - B/M - OP portfolios								
Low OP	-0,78	-0,49	0,21	0,29	0,02	0,12	0,50	0,37
2	-0,38	0,25	0,56	0,80	0,37	0,51	0,47	0,72
3	0,26	0,68	0,81	1,18	0,21	0,43	0,46	0,57
High OP	0,58	0,82	1,10	1,17	0,37	0,41	0,63	0,68
OP ->								
Size - INV - OP portfolios								
Low INV	-0,03	0,63	0,84	0,88	0,33	0,55	0,45	0,51
2	0,13	0,76	0,80	0,88	0,39	0,57	0,61	0,50
3	-0,02	0,50	0,80	0,83	0,36	0,41	0,30	0,48
High INV	-0,81	-0,11	0,28	0,49	0,06	0,43	0,35	0,37

Figure 23 - Average excess returns three split portfolios.

7.2.1 GRS statistics

To test the performance of three asset pricing models presented in Section 7. are the models applied to the excess returns on the six different sets of portfolios described in Section 7.2.1. If the asset pricing models are completely able to capture the excess returns, then the intercept is indistinguishable from zero. To test this is the GRS test, developed by Gibbons, Ross, and Shanken used. The GRS test is a hypothesis test that will be applied to each portfolio set to determine whether the excess returns are jointly indistinguishable from zero. If the null hypothesis is not rejected, it indicates that the excess returns are indeed indistinguishable from zero. However, if the null hypothesis is rejected, it cannot be concluded that the excess returns are indistinguishable from zero (Linton, 2019).

GRS test-results

Not surprisingly, the GRS test-results in Figure 24 shows that none of the models tested are fully able to capture the excess returns as they all reject the null-hypothesis. For all portfolio sets and models, the p-values round to 0 when rounded to two decimals, except for the Size-Inv portfolios. This suggests that the models perform best at explaining the 25 Size-Inv portfolios. However, the p-value is still below 0.05, leading to rejection of the null hypothesis and indicating that the models are not fully able to capture the excess returns. Interestingly, the Fama-French five-factor model without any investor sentiment factor appears to perform best on the Size-Inv portfolios, as both the GRS-statistic and the p-value are lowest without the addition of an investor sentiment factor. The observation that the Fama-French five-factor model without an investor sentiment factor performs better on the 25 Size-INV portfolios, indicates that the investor sentiment factor may not significantly improve the model, when applied to portfolios.

The rejection of the asset pricing models was able to fully capture the excess returns is not the most important results of this test, as this was expected, and similar to the results of past research. More interestingly is the model's relative performance, assessed using the GRS-statistics, p-values, average R^2 (AR^2) and the average absolute alpha ($A|ai|$) (Fama & French, 2015).

For four of the six portfolio sets, the Fama-French five-factor model including an investor sentiment factor exhibits a lower GRS statistic compared to the original model. However, the decrease in GRS is minimal and in the range of (0.01 and 0.03). In the Size-Inv portfolio, the GRS statistic even increases with the addition of an investor sentiment factor. Across all six portfolio sets, the model including the investor sentiment factor SENT performs as well as or better than the model including PSENT. However, this slight improvement in model performance can only be observed through the GRS statistics, as changes with two decimal places are not evident in the p-values, the AR^2, and the average absolute alpha. In general, changes in performance cannot be measured by observing the AR^2 and the ($A|ai|$, as they with two decimals are the same for all three asset pricing models.

	GRS	P(GRS)	AR^ 2	A|ai|
Size - B/M portfolios				
FFF Factors	2,56	0,00	0,96	0,09
FFF Factors + SENT	2,53	0,00	0,96	0,09
FFF Factors + PSENT	2,55	0,00	0,96	0,09
Size - OP portfolios				
FFF Factors	5,03	0,00	0,96	0,12
FFF Factors + SENT	5,01	0,00	0,96	0,12
FFF Factors + PSENT	5,02	0,00	0,96	0,12
Size- INV portfolios				
FFF Factors	1,67	0,03	0,96	0,08
FFF Factors + SENT	1,69	0,02	0,96	0,08
FFF Factors + PSENT	1,75	0,02	0,96	0,08
Size - BM - INV portfolios				
FFF Factors	2,54	0,00	0,92	0,12
FFF Factors + SENT	2,52	0,00	0,92	0,12
FFF Factors + PSENT	2,52	0,00	0,92	0,12
Size - BM - OP portfolios				
FFF Factors	2,37	0,00	0,89	0,18
FFF Factors + SENT	2,35	0,00	0,89	0,18
FFF Factors + PSENT	2,37	0,00	0,89	0,18
Size - OP - INV portfolios				
FFF Factors	3,61	0,00	0,91	0,15
FFF Factors + SENT	3,58	0,00	0,91	0,15
FFF Factors + PSENT	3,59	0,00	0,91	0,15

Figure 24 - GRS test results from all six sets portfolios including GRS-statistics, the p-value, average R^2 and average absolute alpha.

7.2.2 Regression portfolios

To gain insights into the models' performance, the regressions details are examined, with a focus on the intercepts, and particularly interesting betas mainly the beta of the SENT. The purpose is to reveal eventual patterns, and the different portfolios' exposure to the factors. For simplicity and to save space, is there only focused on the regressions of the Fama French five-factor model and the five factor-model including SENT. PSENT is excluded from this section to save space and because, despite demonstrating the best results when applied to individual stocks, the findings from the GRS section indicate that it exhibits lower explanatory power compared to SENT when applied to portfolios. Therefore, only the results of the models listed in equation 19 and 20 below will be discussed in the sections analyzing the regression on portfolios.

$$R_{it} - R_{Ft} = a_i + b_i(Mkt_t - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_{it} \quad (19)$$

$$R_{it} - R_{Ft} = a_i + b_i(Mkt_t - RF_t) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + i_i SENT_t + \varepsilon_{it} \quad (20)$$

The regression results of the models will be discussed for all six sets of portfolios, which are the same portfolios that Fama and French focused on in their test of the Fama-French five-factor model. The same sets of portfolios are chosen with the goal of identifying whether the same weaknesses they discuss can be observed in our results and if the investor sentiment factor SENT might address these weaknesses (Fama & French, 2015). This despite of the seemingly weak results of adding the investor sentiment as an additional factor, as measured by the GRS statistics. The regression results of PSENT, which is excluded in the following sections, can be found in the appendix.

7.2.3 Two sort portfolios

25 Size - B/M portfolios

Figure 25 shows the intercepts and betas for the Fama-French five-factor regression for the 25 Size B/M portfolios. The intercept exhibits a similar problem to what Fama and French have encountered with the small extreme growth stocks in the left corner of the intercept matrix. These are producing a negative intercept of 0,37% per month (t=-3,71). The extreme growth column in the intercept also poses a challenge for the model, with small stocks generating a negative intercept and large stocks a positive intercept, accompanied by relatively high t-statistics. Furthermore, are there also some challenges with the small value stocks.

These results clearly demonstrate why the GRS test rejected the null hypotheses, as there are multiple portfolios whose excess returns cannot be fully explained. The Fama-French model, including the investor sentiment factor SENT, shows no sign of resolving any of these issues regarding the intercepts. The results remain largely unchanged, with only minor changes in t-statistics. Therefore, the inclusion of the additional factor does not seem to enhance the Fama-French five-factor model's ability to explain the excess returns on portfolios sorted by Size and B/M.

Focusing on the betas of the investor sentiment factor SENT, they appear very weak, suggesting that the factor may be redundant as it has minimal effect on the expected returns. However, it seems to have some significance in explaining the excess returns on large value stocks, as indicated by the relatively high t-statistic of -2.56. The large value stocks seem to have a negative exposure to SENT, which aligns with the theory suggesting that during periods of high sentiment, investors become less risk-averse and therefore seek riskier assets in pursuit of abnormal returns a behavior that contradicts the characteristics of large value stocks (Baker & Wurgler, 2006). However, except for this is there no clear pattern supporting this observation when examining the betas of SENT.

The betas of the other factors do not change significantly when applying the sentiment factor as an additional factor. This outcome was anticipated because the SENT factor exhibits very little correlation with the other factors, resulting in minimal shared information. The remaining betas will not be further analyzed as these are not the main objectives of this research paper.

B/M ->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,37	-0,08	0,02	0,01	0,15	-3,71	-1,01	0,32	0,18	2,47
2	-0,05	0,14	-0,01	-0,03	0,08	-0,56	1,84	-0,21	-0,52	1,35
3	0,21	0,08	-0,05	-0,02	0,06	2,19	0,97	-0,63	-0,23	0,75
4	0,29	0,21	-0,01	-0,01	-0,12	3,36	2,27	-0,10	-0,10	-1,32
BIG	0,17	0,03	-0,02	0,01	-0,04	2,22	0,53	-0,22	0,10	-0,46
			b					t(b)		
Small	0,96	0,95	0,94	0,93	0,88	45,23	55,00	59,79	71,91	70,23
2	1,06	1,03	1,01	1,00	0,99	58,98	65,72	77,58	77,07	78,75
3	1,08	1,07	1,04	1,03	1,02	53,22	65,17	59,98	62,53	60,65
4	1,04	1,04	1,03	1,05	1,05	56,58	53,75	63,06	59,47	53,63
BIG	0,93	0,99	1,04	1,00	1,04	55,95	72,55	70,34	56,58	53,31
			s					t(s)		
Small	1,10	1,02	0,95	0,94	0,93	22,99	26,04	26,96	32,18	32,80
2	1,03	0,87	0,95	0,86	0,86	25,39	24,65	32,44	29,40	30,33
3	0,70	0,71	0,67	0,65	0,64	15,24	19,20	17,17	17,40	16,83
4	0,32	0,36	0,34	0,43	0,41	7,60	8,34	9,34	10,91	9,15
BIG	-0,31	-0,24	-0,16	-0,20	-0,21	-8,42	-7,61	-4,74	-5,07	-4,68
			h					t(h)		
Small	-0,47	-0,25	-0,13	0,05	0,29	-8,54	-5,54	-3,10	1,39	8,81
2	-0,55	-0,26	0,00	0,30	0,43	-11,72	-6,43	0,02	8,86	13,14
3	-0,51	-0,22	0,17	0,28	0,51	-9,61	-5,03	3,74	6,51	11,51
4	-0,49	-0,22	0,08	0,29	0,70	-10,25	-4,33	1,78	6,38	13,50
BIG	-0,60	-0,29	-0,07	0,33	0,82	-13,92	-7,95	-1,79	7,05	16,16
			r					t(r)		
Small	-0,58	-0,36	-0,30	-0,05	-0,04	-8,20	-6,12	-5,63	-1,22	-0,98
2	-0,34	-0,16	0,01	0,19	0,07	-5,60	-3,09	0,26	4,36	1,63
3	-0,34	0,04	0,25	0,23	0,01	-4,94	0,67	4,21	4,11	0,12
4	-0,18	0,03	0,20	0,12	0,06	-2,92	0,44	3,61	2,08	0,92
BIG	0,02	0,27	-0,05	-0,02	-0,49	0,43	5,90	-1,07	-0,41	-7,52
			c					t(c)		
Small	-0,27	-0,21	-0,14	0,10	0,15	-3,55	-3,31	-2,36	2,04	3,16
2	-0,26	-0,14	0,08	0,06	0,20	-4,02	-2,38	1,78	1,25	4,30
3	-0,51	0,02	0,05	0,08	0,10	-6,95	0,31	0,74	1,29	1,60
4	-0,26	0,13	0,14	0,08	-0,11	-3,92	1,81	2,35	1,30	-1,54
BIG	0,02	0,32	0,20	-0,03	-0,48	0,25	6,44	3,61	-0,52	-6,73

Figure 25 - Regression results Fama French five factor model, 25 Size B/M portfolios.

B/M ->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,37	-0,08	0,03	0,02	0,15	-3,71	-0,95	0,38	0,27	2,50
2	-0,05	0,14	-0,01	-0,03	0,08	-0,64	1,82	-0,14	-0,45	1,38
3	0,21	0,07	-0,05	-0,02	0,06	2,20	0,92	-0,63	-0,29	0,70
4	0,29	0,21	-0,01	-0,01	-0,12	3,34	2,27	-0,08	-0,13	-1,31
BIG	0,17	0,04	-0,01	0,01	-0,05	2,19	0,57	-0,21	0,10	-0,57
			b					t(b)		
Small	0,96	0,95	0,94	0,93	0,88	45,14	55,00	59,80	72,26	70,12
2	1,06	1,03	1,01	1,00	0,99	59,25	65,59	77,79	77,31	78,62
3	1,08	1,07	1,04	1,03	1,02	53,09	65,20	59,85	62,60	60,72
4	1,04	1,04	1,02	1,05	1,05	56,47	53,62	62,93	59,40	53,50
BIG	0,93	0,99	1,04	1,00	1,04	55,87	72,51	70,17	56,44	53,88
			s					t(s)		
Small	1,10	1,02	0,96	0,94	0,93	22,93	26,10	27,03	32,43	32,79
2	1,02	0,87	0,95	0,86	0,86	25,42	24,59	32,62	29,58	30,31
3	0,70	0,71	0,67	0,65	0,64	15,21	19,17	17,12	17,37	16,80
4	0,32	0,36	0,34	0,43	0,41	7,58	8,33	9,34	10,87	9,14
BIG	-0,32	-0,23	-0,16	-0,20	-0,21	-8,43	-7,58	-4,73	-5,05	-4,81
			h					t(h)		
Small	-0,47	-0,26	-0,13	0,04	0,29	-8,47	-5,65	-3,22	1,20	8,69
2	-0,54	-0,26	0,00	0,30	0,43	-11,56	-6,36	-0,14	8,70	13,01
3	-0,51	-0,21	0,17	0,29	0,51	-9,58	-4,91	3,73	6,61	11,59
4	-0,49	-0,22	0,07	0,30	0,70	-10,16	-4,31	1,73	6,41	13,40
BIG	-0,60	-0,29	-0,07	0,33	0,84	-13,80	-8,03	-1,80	7,00	16,48
			r					t(r)		
Small	-0,58	-0,36	-0,30	-0,05	-0,04	-8,19	-6,14	-5,65	-1,25	-0,99
2	-0,34	-0,16	0,01	0,19	0,07	-5,61	-3,08	0,24	4,36	1,62
3	-0,34	0,04	0,25	0,23	0,01	-4,93	0,68	4,20	4,12	0,13
4	-0,18	0,03	0,20	0,12	0,06	-2,92	0,43	3,60	2,09	0,92
BIG	0,02	0,27	-0,05	-0,02	-0,49	0,44	5,89	-1,07	-0,41	-7,57
			c					t(c)		
Small	-0,28	-0,21	-0,13	0,10	0,15	-3,55	-3,28	-2,33	2,10	3,18
2	-0,27	-0,14	0,09	0,06	0,20	-4,07	-2,39	1,83	1,30	4,31
3	-0,51	0,02	0,05	0,08	0,10	-6,93	0,28	0,73	1,27	1,57
4	-0,26	0,13	0,14	0,08	-0,11	-3,92	1,80	2,36	1,28	-1,54
BIG	0,01	0,32	0,20	-0,03	-0,48	0,24	6,46	3,61	-0,52	-6,85
			i					t(i)		
Small	-0,02	0,07	0,07	0,09	0,03	-0,29	1,34	1,36	2,14	0,85
2	-0,10	-0,02	0,07	0,08	0,03	-1,81	-0,36	1,83	1,89	0,73
3	0,02	-0,06	-0,01	-0,07	-0,07	0,29	-1,11	-0,18	-1,25	-1,24
4	-0,02	0,00	0,03	-0,04	0,02	-0,34	0,05	0,53	-0,68	0,26
BIG	-0,03	0,05	0,01	0,01	-0,16	-0,55	1,15	0,22	0,15	-2,56

Figure 26 - Regression results Fama French five factor model + SENT, 25 Size B/M portfolios.

25 Size - OP portfolios

The GRS test, as well as the other statistics in Section 7.2.1, indicated that the performance of the Fama-French five-factor model was almost identical to the models including the investor sentiment factors on the 25 Size-OP portfolios. The regression results are presented in Figure 27 and 28.

The Fama-French factor model encounters issues in explaining the excess returns of small companies across their various operating profitability sorts. Particularly, small stocks with low profitability produce a negative intercept of -0.27% (t = -3.79), while small stocks in the second-highest quintile of profitability present an issue with a positive intercept of 0.35% (t = 5.58). From a broader perspective, this second-highest quintile of profitability appears to be a problem for the model, as small stocks exhibit positive intercepts while large stocks have negative intercepts with high t-statistics. These results differ slightly from those observed by Fama and French when proposing the five-factor model. They reported relatively low intercepts for the 25 Size-OP portfolios compared to the rest of the sets of portfolios (Fama & French, 2015). However, it is not surprising that these results differ from their original findings, as this test is applied to a different time period and market compared to their study.

The betas of the investor sentiment factor SENT on the Size - OP portfolios, is similar to the betas on 25 Size - B/M portfolios, mostly very low across the portfolios showing low explanatory power. The highest slope observed is -0.18% (t = -3.19) on the medium-sized stocks with high operating profits, showing a negative exposure to the investor sentiment index. Another noteworthy observation from the beta matrix of SENT is that all the small stocks have a positive exposure to the investor sentiment index. This aligns with the rationale behind the sentiment index, which suggests that when investor sentiment is high, investors become more risk-averse and may seek increasing risk by investing in small stocks, generally known as riskier (Baker & Wurgler, 2006). However, aside from this pattern, it is difficult to observe any clear patterns in SENTs betas, which are generally very low. This is similar to the results of the 25 Size-B/M portfolios suggesting that the investor sentiment factor may be redundant.

OP ->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,27	0,13	0,16	0,35	0,10	-3,79	2,08	2,43	5,58	1,23
2	-0,12	0,02	0,01	0,12	0,22	-1,80	0,40	0,22	1,66	2,90
3	-0,04	0,13	0,09	0,00	0,18	-0,50	1,92	1,21	0,05	2,10
4	0,02	0,03	-0,01	0,23	0,12	0,17	0,36	-0,07	2,78	1,48
BIG	0,05	0,17	0,09	-0,22	0,01	0,54	2,41	1,17	-3,52	0,22
			b					t(b)		
Small	0,93	0,89	0,93	0,96	0,94	60,86	65,24	68,59	71,74	56,64
2	1,00	0,97	1,03	1,04	1,06	70,40	76,95	73,86	70,21	65,83
3	1,04	1,04	1,01	1,06	1,08	61,63	70,20	63,99	62,15	60,65
4	1,06	0,97	1,08	1,04	1,05	49,73	53,52	63,39	59,97	61,47
BIG	1,04	1,01	1,02	1,02	0,92	49,49	69,08	62,37	76,43	71,25
			s					t(s)		
Small	1,05	0,89	0,97	0,94	1,01	30,49	28,99	31,60	31,13	26,83
2	0,91	0,87	0,94	0,91	0,99	28,40	30,52	29,63	27,40	27,24
3	0,68	0,63	0,74	0,68	0,73	17,73	18,86	20,77	17,59	18,15
4	0,39	0,34	0,39	0,40	0,37	8,03	8,37	10,18	10,10	9,48
BIG	-0,23	-0,22	-0,26	-0,12	-0,27	-4,91	-6,77	-7,12	-4,07	-9,18
			h					t(h)		
Small	-0,17	0,07	0,10	0,04	0,03	-4,13	2,07	2,91	1,18	0,58
2	-0,03	0,11	0,09	0,07	0,02	-0,83	3,20	2,38	1,85	0,55
3	-0,05	0,12	0,13	0,07	0,15	-1,07	3,03	3,16	1,56	3,21
4	-0,05	0,25	0,19	0,00	-0,09	-0,98	5,25	4,16	0,02	-2,08
BIG	0,16	0,16	-0,19	0,07	-0,16	2,94	4,13	-4,49	2,13	-4,61
			r					t(r)		
Small	-0,53	-0,08	0,07	0,07	0,07	-10,28	-1,82	1,62	1,63	1,17
2	-0,41	-0,03	0,16	0,27	0,22	-8,48	-0,72	3,33	5,43	4,13
3	-0,48	0,03	0,26	0,27	0,36	-8,49	0,60	5,00	4,73	6,06
4	-0,55	0,02	0,29	0,20	0,19	-7,60	0,34	4,99	3,47	3,36
BIG	-1,09	-0,37	-0,12	0,43	0,51	-15,46	-7,50	-2,25	9,57	11,59
			c					t(c)		
Small	-0,10	0,10	0,04	0,03	-0,03	-1,82	1,97	0,82	0,59	-0,51
2	-0,14	0,10	0,18	0,05	-0,07	-2,70	2,17	3,56	0,90	-1,11
3	-0,07	0,09	-0,04	-0,01	-0,23	-1,20	1,62	-0,77	-0,19	-3,50
4	0,09	-0,05	0,00	0,00	-0,04	1,09	-0,70	0,07	0,05	-0,69
BIG	-0,33	0,00	0,21	-0,11	0,07	-4,32	0,03	3,49	-2,23	1,45

Figure 27 - Regression results Fama French five factor model, 25 Size OP portfolios.

OP ->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,27	0,14	0,16	0,36	0,10	-3,77	2,17	2,46	5,69	1,31
2	-0,12	0,03	0,01	0,11	0,22	-1,75	0,49	0,21	1,62	2,84
3	-0,04	0,13	0,10	0,00	0,17	-0,50	1,85	1,28	0,04	2,00
4	0,02	0,03	-0,01	0,23	0,12	0,15	0,36	-0,06	2,75	1,49
BIG	0,05	0,16	0,09	-0,21	0,01	0,52	2,35	1,18	-3,44	0,19
			b					t(b)		
Small	0,93	0,89	0,93	0,96	0,94	60,72	65,47	68,48	72,01	56,76
2	1,00	0,97	1,03	1,04	1,06	70,37	77,30	73,70	70,17	65,93
3	1,04	1,04	1,01	1,06	1,08	61,49	70,49	64,09	62,03	61,71
4	1,06	0,97	1,08	1,04	1,05	49,65	53,40	63,24	59,88	61,33
BIG	1,04	1,01	1,02	1,02	0,92	49,42	69,36	62,22	77,92	71,22
			s					t(s)		
Small	1,05	0,89	0,97	0,94	1,01	30,42	29,19	31,59	31,34	26,97
2	0,92	0,87	0,94	0,91	0,99	28,44	30,75	29,56	27,35	27,22
3	0,68	0,63	0,74	0,68	0,73	17,68	18,86	20,87	17,54	18,33
4	0,39	0,34	0,39	0,40	0,37	8,00	8,35	10,16	10,06	9,47
BIG	-0,23	-0,23	-0,26	-0,12	-0,27	-4,92	-6,85	-7,09	-4,05	-9,20
			h					t(h)		
Small	-0,17	0,07	0,10	0,04	0,02	-4,11	1,90	2,83	1,00	0,42
2	-0,03	0,10	0,09	0,07	0,03	-0,93	3,01	2,38	1,93	0,67
3	-0,05	0,12	0,12	0,07	0,16	-1,05	3,19	3,01	1,59	3,54
4	-0,05	0,25	0,18	0,00	-0,09	-0,93	5,21	4,12	0,07	-2,09
BIG	0,17	0,16	-0,19	0,06	-0,15	2,98	4,28	-4,49	1,84	-4,51
			r					t(r)		
Small	-0,53	-0,08	0,07	0,07	0,06	-10,26	-1,85	1,62	1,62	1,16
2	-0,41	-0,03	0,16	0,27	0,23	-8,50	-0,74	3,32	5,43	4,15
3	-0,48	0,03	0,26	0,27	0,37	-8,48	0,62	5,00	4,72	6,19
4	-0,55	0,02	0,29	0,20	0,19	-7,58	0,34	4,98	3,47	3,36
BIG	-1,09	-0,37	-0,12	0,43	0,51	-15,43	-7,51	-2,24	9,74	11,59
			c					t(c)		
Small	-0,10	0,10	0,04	0,03	-0,03	-1,82	2,02	0,83	0,64	-0,47
2	-0,14	0,10	0,18	0,05	-0,07	-2,67	2,24	3,55	0,88	-1,15
3	-0,07	0,09	-0,04	-0,01	-0,23	-1,20	1,58	-0,73	-0,20	-3,63
4	0,08	-0,05	0,00	0,00	-0,04	1,08	-0,70	0,07	0,04	-0,69
BIG	-0,33	0,00	0,21	-0,10	0,07	-4,33	-0,01	3,49	-2,19	1,43
			i					t(i)		
Small	0,00	0,08	0,03	0,08	0,09	0,06	1,97	0,79	2,00	1,77
2	0,05	0,08	-0,01	-0,04	-0,07	1,17	2,10	-0,15	-0,89	-1,34
3	-0,01	-0,08	0,08	-0,02	-0,18	-0,16	-1,79	1,62	-0,34	-3,19
4	-0,03	0,00	0,01	-0,03	0,02	-0,47	0,07	0,12	-0,52	0,30
BIG	-0,04	-0,08	0,01	0,15	-0,04	-0,57	-1,75	0,23	3,65	-0,89

Figure 28- Regression results Fama French five factor model + SENT, 25 Size OP portfolios.

25 Size-Inv portfolios

The GRS statistics showed that the asset pricing models approached capturing the excess returns of this set of portfolios. However, despite approaching full capture, the p-value remained below the significance level of 0.05.

Focusing on the intercepts of the 25 Size - Inv portfolios for the Fama-French five-factor model in Figure 30, it is clear to see that the intercepts are significantly lower relative to the results of both the Size-B/M and Size-OP portfolios. The highest absolute intercept is -0.23% (t = -2.72), observed in small stocks with a high level of investments. Small stocks (first row) generally appear to be the main issue for the Fama-French five-factor model on the Size-Inv portfolios. The model also encounters issues with stocks with a medium level of investments. However, overall, the Fama-French five-factor model performs better at explaining the excess returns of the Size-Inv portfolios relative to the other portfolios discussed. This relative strength of the Fama-French five-factor model leaves very little room for the investor sentiment factor to improve. Moreover, combined with the worse GRS results and weak results on the two other portfolios, it does not suggest that adding the investor sentiment factor would increase the explanatory power of the model.

The intercepts in Figure 31 changes only slightly with the inclusion of the investor sentiment factor. In a few cases, the intercept decreases by 1 basis point, and in one instance, it increases by 1 basis point. Therefore, as the GRS results also suggested, there is no evidence that the additional factor improves the model's ability to explain the excess returns of the portfolios.

The betas of the investor sentiment factor SENT are also relatively low, ranging between -0.08 and 0.10. There appears to be a pattern where low investment firms are negatively exposed to SENT, while high investment firms are positively exposed to SENT. However, despite this pattern, the slopes and t-statistics are relatively low, so the significance of this pattern can be discussed. The results are consistent with previous section, indicating that the investor sentiment factor is redundant.

Inv->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,05	0,14	0,13	0,10	-0,23	-0,74	2,25	2,08	1,65	-2,72
2	-0,07	0,09	0,18	0,07	-0,07	-0,94	1,48	2,59	1,06	-1,06
3	0,07	0,03	0,13	0,10	-0,03	0,91	0,32	1,65	1,40	-0,43
4	-0,01	0,00	0,13	0,15	0,07	-0,11	-0,04	1,56	1,94	0,89
BIG	-0,08	0,03	-0,04	0,04	0,00	-1,12	0,50	-0,54	0,54	-0,04
			b					t(b)		
Small	0,95	0,87	0,88	0,91	0,98	65,57	67,69	65,68	68,42	55,59
2	1,06	0,98	0,93	1,02	1,06	71,39	73,20	63,24	78,01	79,38
3	1,08	1,02	0,99	1,01	1,09	62,57	60,62	57,94	66,32	64,31
4	1,06	1,05	0,97	1,04	1,09	55,79	61,86	57,45	61,93	63,10
BIG	1,00	0,98	1,03	1,00	0,98	65,88	68,81	73,49	65,14	56,65
			s					t(s)		
Small	1,04	0,82	0,87	0,91	1,12	31,63	28,23	28,92	30,43	28,23
2	0,92	0,84	0,82	0,90	1,00	27,68	27,88	24,77	30,46	33,33
3	0,72	0,69	0,58	0,62	0,79	18,33	18,18	15,06	17,87	20,73
4	0,40	0,40	0,36	0,31	0,41	9,43	10,48	9,31	8,25	10,46
BIG	-0,13	-0,20	-0,19	-0,26	-0,15	-3,85	-6,16	-5,99	-7,44	-3,91
			h					t(h)		
Small	-0,07	0,09	0,17	0,07	-0,25	-1,74	2,53	4,77	1,93	-5,35
2	0,09	0,14	0,14	0,15	-0,19	2,35	3,92	3,74	4,40	-5,35
3	0,09	0,18	0,22	0,06	-0,11	1,99	4,20	4,88	1,49	-2,45
4	0,11	0,08	0,12	0,10	-0,12	2,30	1,83	2,59	2,26	-2,75
BIG	-0,08	0,02	-0,04	0,00	0,09	-2,08	0,51	-1,01	-0,12	2,06
			r					t(r)		
Small	-0,26	-0,01	0,06	-0,10	-0,48	-5,25	-0,17	1,40	-2,29	-8,09
2	-0,01	0,14	0,06	0,17	-0,31	-0,26	3,10	1,31	3,79	-6,99
3	-0,01	0,10	0,19	0,03	-0,19	-0,24	1,76	3,24	0,65	-3,25
4	0,09	0,05	0,14	0,12	-0,20	1,36	0,82	2,45	2,04	-3,46
BIG	-0,09	0,06	-0,03	0,01	0,20	-1,68	1,33	-0,68	0,28	3,41
			c					t(c)		
Small	0,33	0,24	0,01	-0,03	-0,45	6,15	5,17	0,19	-0,53	-7,02
2	0,39	0,28	0,08	-0,16	-0,45	7,12	5,69	1,55	-3,32	-9,15
3	0,32	0,29	0,06	-0,16	-0,70	4,99	4,69	1,01	-2,83	-11,37
4	0,36	0,37	0,06	-0,11	-0,72	5,10	6,01	1,01	-1,83	-11,38
BIG	0,66	0,29	0,11	-0,47	-0,56	11,89	5,58	2,22	-8,42	-8,81

Figure 29 - Regression results Fama French five factor model, 25 Size INV portfolios.

INV ->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,05	0,14	0,13	0,11	-0,22	-0,79	2,30	2,05	1,74	-2,66
2	-0,07	0,10	0,18	0,06	-0,06	-0,99	1,56	2,57	1,04	-1,00
3	0,07	0,02	0,13	0,10	-0,04	0,87	0,26	1,63	1,43	-0,50
4	-0,01	0,00	0,12	0,15	0,07	-0,15	-0,03	1,54	1,93	0,89
BIG	-0,08	0,04	-0,03	0,03	0,00	-1,11	0,53	-0,50	0,48	-0,01
			b					t(b)		
Small	0,95	0,87	0,88	0,91	0,98	65,63	67,68	65,60	68,66	55,73
2	1,06	0,98	0,93	1,02	1,06	71,42	73,34	63,10	77,88	79,40
3	1,08	1,02	0,99	1,01	1,09	62,55	60,78	57,83	66,20	64,49
4	1,06	1,05	0,97	1,04	1,09	55,79	61,71	57,33	61,80	62,95
BIG	1,00	0,97	1,03	1,00	0,98	65,72	68,71	73,37	65,30	56,52
			s					t(s)		
Small	1,04	0,82	0,87	0,91	1,13	31,60	28,29	28,86	30,63	28,39
2	0,92	0,85	0,82	0,90	1,01	27,64	28,01	24,70	30,39	33,40
3	0,72	0,69	0,58	0,62	0,79	18,28	18,16	15,02	17,86	20,73
4	0,40	0,40	0,36	0,31	0,41	9,40	10,46	9,29	8,23	10,43
BIG	-0,13	-0,20	-0,19	-0,26	-0,15	-3,84	-6,13	-5,96	-7,50	-3,89
			h					t(h)		
Small	-0,06	0,08	0,17	0,06	-0,25	-1,63	2,41	4,80	1,76	-5,51
2	0,10	0,13	0,15	0,15	-0,19	2,44	3,77	3,74	4,42	-5,45
3	0,09	0,19	0,22	0,06	-0,10	2,06	4,33	4,89	1,41	-2,31
4	0,12	0,08	0,12	0,10	-0,12	2,39	1,80	2,60	2,26	-2,74
BIG	-0,08	0,02	-0,04	0,00	0,09	-2,08	0,43	-1,07	0,02	2,01
			r					t(r)		
Small	-0,26	-0,01	0,06	-0,10	-0,48	-5,24	-0,18	1,41	-2,31	-8,14
2	-0,01	0,14	0,06	0,17	-0,31	-0,24	3,09	1,31	3,79	-7,01
3	-0,01	0,10	0,19	0,03	-0,18	-0,23	1,78	3,24	0,64	-3,25
4	0,09	0,05	0,14	0,12	-0,20	1,37	0,82	2,45	2,03	-3,46
BIG	-0,09	0,06	-0,03	0,02	0,20	-1,68	1,32	-0,69	0,30	3,40
			c					t(c)		
Small	0,33	0,24	0,01	-0,02	-0,45	6,12	5,20	0,18	-0,49	-7,00
2	0,38	0,28	0,08	-0,16	-0,45	7,10	5,75	1,54	-3,32	-9,13
3	0,32	0,29	0,06	-0,16	-0,71	4,97	4,66	1,00	-2,81	-11,43
4	0,35	0,37	0,06	-0,11	-0,72	5,08	6,00	1,01	-1,83	-11,36
BIG	0,66	0,29	0,12	-0,47	-0,56	11,87	5,60	2,24	-8,47	-8,78
			i					t(i)		
Small	-0,06	0,05	-0,03	0,08	0,10	-1,21	1,24	-0,64	1,94	1,83
2	-0,05	0,07	-0,01	-0,02	0,06	-1,13	1,68	-0,25	-0,48	1,33
3	-0,05	-0,08	-0,02	0,03	-0,08	-0,93	-1,52	-0,37	0,72	-1,55
4	-0,06	0,01	-0,01	-0,01	0,00	-1,01	0,19	-0,25	-0,13	0,05
BIG	0,01	0,04	0,03	-0,07	0,03	0,13	0,91	0,75	-1,50	0,50

Figure 30 - Regression results Fama French five factor model + SENT, 25 Size INV portfolios.

7.2.4 Three sort portfolios

32 Size - B/M - INV portfolios

The GRS statistics in section 7.2.1 only showed a very slight increase in the models' ability to explain the excess returns of the 32 Size-B/M-INV portfolios when adding SENT as an additional factor. The increase could only be observed in the GRS statistics, as the p-value, average R^2, and average absolute alpha did not change when examined to with two decimals. The regression results are presented in Figure 31 and 32.

The Fama-French five-factor models encounter issues with explaining the excess returns of small stocks with high investments, unless they are in the most extreme value quartile. They exhibit intercepts in the interval of -0.21% to -0.24% (t = -2.53 to -3.06), indicating that these types of stocks tend to have lower returns than the model expects. These stocks are not the only issues for the model, as multiple portfolios of small stocks have intercepts with t-statistics above 2. However, the issue with high intercepts, and relative high t-statistics is not as pronounced in the big stock's portfolios, as only three portfolios exceed this threshold. These three intercepts are all positive, ranging from 0.22% to 0.27%. It is therefore evident that there are multiple issues preventing the 32 Size-B/M-INV portfolios from fully capturing the excess returns and ensuring it is rejecting the null hypothesis in the GRS test.

These issues represent the areas where the investor sentiment factor has the potential to improve the Fama-French five-factor model by capturing more of the excess returns and resulting in a lower intercept. However, the intercepts of the Fama-French five-factor model including the investor sentiment factor SENT are almost identical to those of the Fama-French five-factor model. There are some slight changes, but these are within the range of ± 1 basis point. Therefore, there are no signs that the model including the investor sentiment factor is better at explaining the excess returns of the 32 Size-B/M-INV portfolios. Additionally, the limited impact of the SENT factor on the expected returns is evident when examining the betas. The betas of SENT are very low, and only in three portfolios out of the total 32 portfolios is the t-statistics of the betas more than two.

Given the low and insignificant betas of SENT, examining patterns of its impact on expected returns offers little value. Therefore, the regression results on the 32 Size-Book-to-Market-Investment portfolios only reinforce previous findings, suggesting that the investor sentiment factor is redundant and fails to enhance the explanatory power of the Fama-French five-factor model.

	Small								BIG							
BM ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
	a				t(a)				a				t(a)			
Low INV	-0,11	0,06	0,13	-0,01	-0,98	0,55	1,40	-0,10	0,02	-0,18	0,09	-0,11	0,21	-1,51	0,82	-0,84
2	0,09	0,00	0,16	0,19	1,20	-0,01	2,38	2,01	0,09	0,27	0,11	0,05	0,76	2,84	0,97	0,37
3	0,10	0,11	-0,02	0,26	1,55	1,85	-0,32	2,80	0,24	0,12	-0,06	-0,10	2,11	1,07	-0,56	-0,80
High INV	-0,22	-0,21	-0,24	0,03	-3,06	-2,71	-2,53	0,19	0,22	0,00	-0,10	0,11	2,18	0,03	-0,79	0,66
	b				t(b)				b				t(b)			
Low INV	1,00	1,07	1,00	1,05	42,07	48,38	52,08	36,79	0,95	1,04	1,03	1,06	37,76	41,61	45,80	40,31
2	0,98	1,00	0,98	0,97	65,48	75,13	70,05	49,80	0,87	1,01	1,03	1,07	34,32	50,26	42,20	41,56
3	1,02	0,97	0,96	0,92	73,69	75,52	66,66	46,28	0,97	1,03	1,00	1,02	39,81	43,50	46,89	39,77
High INV	1,08	1,02	0,99	0,97	70,53	61,76	48,97	33,59	0,97	1,03	1,04	0,99	45,85	42,30	39,17	28,73
	s				t(s)				s				t(s)			
Low INV	0,93	0,86	0,93	1,13	17,19	17,27	21,35	17,57	-0,21	0,12	-0,08	0,08	-3,73	2,13	-1,60	1,27
2	0,79	0,82	0,80	0,84	23,29	27,14	25,40	19,09	-0,17	-0,16	-0,16	0,16	-3,01	-3,42	-2,90	2,71
3	0,87	0,84	0,83	0,80	27,75	28,79	25,55	17,97	-0,20	-0,24	-0,01	-0,03	-3,57	-4,53	-0,29	-0,53
High INV	1,02	0,98	0,85	1,00	29,44	26,20	18,53	15,26	-0,13	-0,04	-0,05	-0,25	-2,71	-0,72	-0,84	-3,22
	h				t(h)				h				t(h)			
Low INV	-0,39	-0,20	0,15	0,42	-6,21	-3,46	2,94	5,63	-0,67	-0,16	-0,04	0,51	-10,3	-2,51	-0,61	7,37
2	-0,28	0,09	0,23	0,37	-7,12	2,61	6,40	7,14	-0,51	-0,28	0,13	0,75	-7,73	-5,24	2,06	11,16
3	-0,18	0,12	0,41	0,52	-4,91	3,62	10,75	10,07	-0,65	-0,40	0,32	0,97	-10,1	-6,38	5,73	14,43
High INV	-0,49	0,04	0,39	0,53	-12,2	0,83	7,31	6,95	-0,17	-0,16	0,26	0,79	-3,03	-2,54	3,71	8,74
	r				t(r)				r				t(r)			
Low INV	-0,37	-0,18	-0,09	-0,10	-4,59	-2,39	-1,41	-1,04	0,16	0,25	-0,29	-0,31	1,89	3,04	-3,88	-3,47
2	-0,15	0,17	0,10	-0,01	-2,89	3,87	2,13	-0,21	-0,08	0,12	0,03	-0,26	-0,99	1,70	0,31	-3,03
3	0,04	0,17	0,29	-0,06	0,87	3,81	5,94	-0,94	-0,17	-0,08	0,17	0,06	-2,02	-0,95	2,33	0,72
High INV	-0,44	-0,17	0,07	-0,17	-8,61	-2,98	1,00	-1,71	0,23	0,02	0,16	-0,35	3,18	0,19	1,79	-2,99
	c				t(c)				c				t(c)			
Low INV	0,19	0,47	0,28	0,52	2,15	5,87	4,01	5,02	0,89	0,60	0,53	0,33	9,74	6,55	6,43	3,45
2	0,12	0,32	0,31	0,41	2,16	6,61	6,03	5,76	0,25	0,35	0,32	-0,27	2,75	4,71	3,54	-2,87
3	-0,22	0,03	0,05	0,04	-4,27	0,55	0,93	0,54	-0,03	0,44	-0,32	-0,58	-0,34	5,07	-4,14	-6,20
High INV	-0,57	-0,43	-0,38	-0,33	-10,1	-7,08	-5,11	-3,07	-0,87	-0,42	-0,19	-1,05	-11,2	-4,76	-1,91	-8,33

Figure 31 - Regression results Fama French five factor model, 32 Size - B/M - INV portfolios.

	Small								BIG							
BM ->	LOW	2,00	3,00	High	LOW	2,00	3,00	High	LOW	2,00	3,00	High	LOW	2,00	3,00	High
	a				t(a)				a				t(a)			
Low INV	-0,12	0,06	0,13	-0,02	-1,06	0,58	1,40	-0,13	0,02	-0,18	0,09	-0,11	0,17	-1,48	0,89	-0,89
2	0,09	0,00	0,16	0,18	1,20	0,01	2,35	1,97	0,10	0,27	0,12	0,05	0,83	2,87	0,99	0,40
3	0,10	0,12	-0,02	0,26	1,49	1,89	-0,28	2,77	0,24	0,12	-0,06	-0,11	2,07	1,10	-0,60	-0,91
High INV	-0,22	-0,21	-0,23	0,03	-3,05	-2,65	-2,44	0,19	0,21	0,01	-0,10	0,11	2,13	0,11	-0,80	0,65
	b				t(b)				b				t(b)			
Low INV	1,01	1,07	1,00	1,05	42,29	48,29	51,96	36,74	0,95	1,04	1,03	1,07	37,75	41,52	45,83	40,38
2	0,98	1,00	0,98	0,97	65,32	74,97	69,94	49,77	0,87	1,01	1,03	1,07	34,33	50,18	42,11	41,47
3	1,02	0,97	0,96	0,92	73,77	75,46	66,56	46,22	0,97	1,03	1,00	1,02	39,79	43,43	46,93	40,16
High INV	1,08	1,02	0,99	0,97	70,37	61,78	49,47	33,51	0,97	1,03	1,04	0,99	45,94	42,43	39,09	28,68
	s				t(s)				s				t(s)			
Low INV	0,92	0,86	0,93	1,13	17,20	17,27	21,30	17,52	-0,21	0,12	-0,08	0,07	-3,75	2,14	-1,56	1,23
2	0,79	0,82	0,80	0,84	23,24	27,11	25,34	19,04	-0,17	-0,15	-0,16	0,16	-2,97	-3,39	-2,88	2,72
3	0,87	0,84	0,83	0,80	27,73	28,81	25,55	17,92	-0,20	-0,24	-0,02	-0,03	-3,60	-4,50	-0,33	-0,61
High INV	1,02	0,98	0,85	1,00	29,37	26,27	18,85	15,23	-0,13	-0,04	-0,05	-0,25	-2,75	-0,66	-0,85	-3,23
	h				t(h)				h				t(h)			
Low INV	-0,38	-0,20	0,15	0,42	-6,04	-3,52	2,92	5,65	-0,67	-0,17	-0,04	0,52	-10,1	-2,55	-0,75	7,47
2	-0,28	0,09	0,24	0,37	-7,09	2,55	6,42	7,18	-0,52	-0,28	0,13	0,75	-7,86	-5,29	2,00	11,05
3	-0,17	0,12	0,40	0,53	-4,78	3,52	10,63	10,08	-0,65	-0,40	0,33	0,98	-10,0	-6,43	5,82	14,71
High INV	-0,49	0,03	0,38	0,53	-12,1	0,71	7,12	6,90	-0,16	-0,17	0,26	0,79	-2,90	-2,72	3,71	8,72
	r				t(r)				r				t(r)			
Low INV	-0,37	-0,18	-0,09	-0,10	-4,59	-2,40	-1,41	-1,04	0,16	0,25	-0,29	-0,31	1,90	3,03	-3,90	-3,46
2	-0,15	0,17	0,10	-0,01	-2,88	3,86	2,13	-0,20	-0,09	0,11	0,02	-0,26	-1,01	1,69	0,30	-3,03
3	0,04	0,17	0,29	-0,06	0,88	3,80	5,93	-0,93	-0,17	-0,08	0,17	0,06	-2,01	-0,95	2,34	0,75
High INV	-0,44	-0,17	0,07	-0,17	-8,59	-2,99	0,98	-1,71	0,23	0,01	0,16	-0,35	3,19	0,17	1,79	-2,99
	c				t(c)				c				t(c)			
Low INV	0,18	0,48	0,28	0,52	2,12	5,89	4,00	5,00	0,89	0,60	0,53	0,33	9,71	6,55	6,48	3,42
2	0,12	0,32	0,31	0,41	2,16	6,61	6,01	5,74	0,26	0,35	0,32	-0,27	2,79	4,73	3,55	-2,85
3	-0,22	0,03	0,05	0,04	-4,30	0,57	0,95	0,53	-0,03	0,44	-0,33	-0,59	-0,36	5,09	-4,17	-6,31
High INV	-0,57	-0,43	-0,37	-0,33	-10,1	-7,06	-5,10	-3,06	-0,87	-0,42	-0,19	-1,05	-11,3	-4,74	-1,92	-8,32
	i				t(i)				i				t(i)			
Low INV	-0,14	0,06	0,00	-0,05	-1,85	0,80	0,00	-0,57	-0,07	0,05	0,11	-0,11	-0,86	0,59	1,51	-1,33
2	0,01	0,02	-0,02	-0,05	0,14	0,50	-0,55	-0,78	0,12	0,06	0,04	0,05	1,55	0,89	0,53	0,59
3	-0,06	0,04	0,04	-0,04	-1,26	1,05	0,81	-0,64	-0,06	0,07	-0,08	-0,19	-0,81	0,91	-1,17	-2,40
High INV	0,00	0,07	0,18	0,01	-0,07	1,37	2,88	0,10	-0,09	0,15	-0,03	-0,04	-1,37	2,00	-0,30	-0,33

Figure 32 - Regression results Fama French five factor model + SENT, 32 Size - B/M - INV portfolios.

32 Size - B/M - OP portfolios

Table 33 and Table 34 show the regression results for the Fama-French five-factor model and the Fama-French five-factor model including SENT. The GRS results from Section 7.2.1 suggested that the intercepts and the general performance of these models are almost identical, and none of them is able to fully explain the excess returns of the Size-B/M-OP portfolios.

The intercepts for the Fama-French five-factor regression reveal large problems. The model encounters particular difficulties with small growth stocks with very low operating profitability (located in the left corner of the intercept matrix). These are producing negative intercept up to -0,72% per month (t-3,82). Additionally, the model struggles with small value stocks exhibiting medium to high operating profitability, resulting in positive intercepts of up to 0.39% (t = 4.3). While the issues are most pronounced with small stocks, there are also multiple problems regarding the portfolios of large stocks. These portfolios tend to have high positive intercepts, except for the portfolio with high operating profit and investing at the second lowest quartile level, which produce a negative intercept of -0.33% (t = -2.74). Overall, the Fama French five factor appear to have a tougher time explaining the Size - B/M - OP portfolios compared to the other sets of portfolios discussed in previous sections.

The regression results of the Fama-French five-factor model with the investor sentiment factor align with the findings in the GRS section 7.2.1 and the results of the regressions in the previous sections. The intercepts are either similar or decrease only very slightly when the additional factor is included in the model. It's therefore evident that the investor sentiment factor does not address any of the issues the Fama-French five-factor model encounters in explaining the excess returns of the 32 Size-B/M-OP portfolios.

The betas of the investor sentiment factor SENT is furthermore in most cases very low. There are however a few portfolios where it seems to impact the expected returns to some degree. The small value stocks with high operating profitability -0,31 (t = -2,26) and also the small value stocks with low operating profitability -0,2 (t=-1,6) have negative exposure to SENT. The same negative exposure can be seen when examining big value stocks, although not to the same extent. Despite a few instances where it demonstrates some explanatory power, it only marginally improves the explanation of excess returns by reducing the intercept with 2 basis points. Therefore, the results of the regression on these 32 Size-B/M-OP portfolios only reinforce the previous sections findings suggesting that the investor sentiment factor is redundant.

	Small								BIG							
BM ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
	a				t(a)				a				t(a)			
Low OP	-0,61	-0,72	-0,27	-0,21	-3,75	-3,82	-1,74	-1,10	0,31	0,04	0,28	0,07	1,04	0,20	2,24	0,68
2	-0,34	-0,13	-0,01	0,08	-2,52	-1,44	-0,16	0,97	0,18	0,35	-0,01	0,02	0,95	3,27	-0,15	0,18
3	-0,01	0,09	0,04	0,39	-0,12	1,59	0,74	4,30	0,05	0,01	-0,18	-0,16	0,39	0,12	-1,58	-1,11
High OP	0,10	0,06	0,23	0,32	2,02	0,95	2,83	1,51	0,11	-0,33	-0,04	-0,10	1,44	-2,74	-0,24	-0,34
	b				t(b)				b				t(b)			
Low OP	1,03	1,08	0,93	1,03	30,13	27,21	28,66	25,95	1,03	1,10	1,04	0,99	16,72	27,29	39,59	48,69
2	0,97	0,97	0,96	0,94	33,80	51,00	51,91	56,64	1,01	0,97	1,03	1,03	25,38	43,03	53,65	44,20
3	1,04	0,98	0,98	0,98	58,54	78,39	83,79	51,02	0,99	1,00	1,02	1,08	39,42	51,77	42,88	34,81
High OP	1,04	1,02	1,03	1,00	100,2	82,97	61,04	22,55	0,93	1,04	0,97	1,11	59,48	41,08	26,45	17,72
	s				t(s)				s				t(s)			
Low OP	1,27	1,28	1,12	1,19	16,49	14,24	15,20	13,35	0,00	0,08	-0,07	-0,04	0,00	0,86	-1,17	-0,82
2	0,74	0,82	0,73	0,83	11,39	18,99	17,49	22,18	-0,15	-0,22	-0,05	-0,02	-1,64	-4,26	-1,23	-0,34
3	0,89	0,83	0,85	0,86	22,16	29,35	32,20	19,73	-0,03	-0,15	-0,08	-0,07	-0,55	-3,49	-1,41	-0,94
High OP	0,89	0,85	0,91	1,14	38,01	30,52	23,88	11,33	-0,26	0,02	-0,28	0,33	-7,40	0,42	-3,41	2,37
	h				t(h)				h				t(h)			
Low OP	-0,85	-0,34	0,26	0,20	-9,52	-3,27	2,99	1,89	-0,98	-0,56	-0,13	0,62	-6,04	-5,31	-1,94	11,69
2	-0,55	-0,16	0,12	0,50	-7,29	-3,21	2,43	11,57	-0,56	-0,45	0,21	0,94	-5,38	-7,63	4,07	15,23
3	-0,45	0,00	0,36	0,47	-9,76	-0,07	11,64	9,23	-0,53	-0,16	0,29	0,71	-8,08	-3,11	4,62	8,66
High OP	-0,20	0,29	0,53	0,49	-7,24	8,90	11,89	4,19	-0,41	0,20	0,58	0,44	-9,95	3,00	6,08	2,69
	r				t(r)				r				t(r)			
Low OP	-1,27	-0,66	-0,40	-0,80	-11,1	-4,92	-3,64	-6,01	-0,91	-0,88	-0,65	-0,76	-4,34	-6,47	-7,29	-11,2
2	-0,83	-0,33	-0,05	-0,04	-8,57	-5,19	-0,76	-0,72	-0,02	-0,29	0,01	-0,03	-0,18	-3,86	0,10	-0,43
3	-0,31	0,05	0,25	0,13	-5,26	1,27	6,38	2,04	0,03	0,14	0,33	0,24	0,31	2,21	4,15	2,30
High OP	0,10	0,36	0,36	0,05	2,90	8,61	6,29	0,34	0,27	0,79	0,54	0,28	5,10	9,32	4,42	1,34
	c				t(c)				c				t(c)			
Low OP	-0,44	-0,39	-0,23	0,26	-3,50	-2,66	-1,95	1,79	-0,29	0,45	0,23	-0,44	-1,28	3,02	2,38	-5,96
2	-0,43	0,09	0,18	0,17	-4,08	1,34	2,65	2,72	0,14	0,30	0,01	-0,25	0,99	3,61	0,20	-2,93
3	-0,12	0,19	0,14	0,21	-1,82	4,26	3,25	2,94	-0,14	0,27	0,18	-0,13	-1,55	3,82	2,05	-1,13
High OP	-0,14	0,04	0,06	0,33	-3,77	0,91	0,92	2,01	0,05	0,03	-0,23	0,15	0,84	0,30	-1,69	0,65

Figure 33- Regression results Fama French five factor model, 32 Size - B/M - OP portfolios.

	Small								BIG							
BM ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
	a				t(a)				a				t(a)			
Low OP	-0,61	-0,73	-0,27	-0,22	-3,80	-3,85	-1,77	-1,17	0,29	0,04	0,28	0,06	1,00	0,22	2,27	0,66
2	-0,34	-0,13	-0,01	0,08	-2,53	-1,40	-0,06	1,01	0,17	0,35	-0,02	0,01	0,92	3,28	-0,22	0,07
3	-0,01	0,10	0,04	0,39	-0,14	1,68	0,77	4,25	0,05	0,02	-0,17	-0,17	0,44	0,20	-1,53	-1,13
High OP	0,10	0,06	0,23	0,30	2,00	0,96	2,81	1,43	0,10	-0,33	-0,05	-0,11	1,38	-2,72	-0,29	-0,36
	b				t(b)				b				t(b)			
Low OP	1,03	1,08	0,93	1,03	30,17	27,22	28,64	26,06	1,04	1,10	1,04	0,99	16,74	27,22	39,52	48,61
2	0,97	0,97	0,95	0,94	33,74	50,94	52,28	56,57	1,01	0,97	1,03	1,04	25,36	42,94	53,83	44,70
3	1,04	0,98	0,98	0,98	58,47	78,68	83,65	51,05	0,98	1,00	1,02	1,09	39,40	51,92	42,89	34,75
High OP	1,04	1,02	1,03	1,01	100,0	82,79	60,93	22,77	0,93	1,04	0,97	1,11	59,55	40,98	26,51	17,71
	s				t(s)				s				t(s)			
Low OP	1,26	1,28	1,11	1,19	16,46	14,20	15,16	13,33	0,00	0,08	-0,07	-0,04	-0,03	0,87	-1,14	-0,83
2	0,74	0,82	0,73	0,83	11,36	19,01	17,72	22,20	-0,15	-0,22	-0,06	-0,02	-1,66	-4,23	-1,28	-0,42
3	0,89	0,83	0,85	0,86	22,10	29,54	32,18	19,69	-0,03	-0,15	-0,07	-0,07	-0,51	-3,45	-1,37	-0,95
High OP	0,89	0,85	0,91	1,13	37,92	30,47	23,82	11,33	-0,26	0,02	-0,29	0,33	-7,45	0,43	-3,46	2,34
	h				t(h)				h				t(h)			
Low OP	-0,84	-0,33	0,26	0,21	-9,38	-3,18	3,05	2,03	-0,97	-0,57	-0,14	0,62	-5,93	-5,32	-2,01	11,66
2	-0,55	-0,17	0,11	0,50	-7,21	-3,29	2,22	11,43	-0,56	-0,45	0,21	0,95	-5,29	-7,64	4,21	15,55
3	-0,45	-0,01	0,35	0,47	-9,66	-0,25	11,51	9,30	-0,54	-0,17	0,28	0,71	-8,18	-3,28	4,48	8,65
High OP	-0,20	0,29	0,53	0,51	-7,17	8,82	11,87	4,41	-0,41	0,20	0,60	0,45	-9,81	2,95	6,19	2,73
	r				t(r)				r				t(r)			
Low OP	-1,27	-0,66	-0,40	-0,80	-11,0	-4,91	-3,63	-6,01	-0,90	-0,88	-0,65	-0,76	-4,33	-6,46	-7,30	-11,2
2	-0,83	-0,33	-0,05	-0,04	-8,55	-5,20	-0,79	-0,73	-0,02	-0,29	0,01	-0,03	-0,17	-3,86	0,11	-0,41
3	-0,31	0,05	0,25	0,13	-5,25	1,26	6,37	2,05	0,02	0,14	0,33	0,24	0,30	2,21	4,15	2,30
High OP	0,10	0,36	0,36	0,05	2,89	8,59	6,28	0,36	0,27	0,79	0,55	0,28	5,12	9,30	4,44	1,35
	c				t(c)				c				t(c)			
Low OP	-0,44	-0,39	-0,23	0,25	-3,53	-2,69	-1,96	1,76	-0,30	0,45	0,23	-0,44	-1,31	3,03	2,39	-5,96
2	-0,43	0,10	0,18	0,17	-4,08	1,37	2,73	2,74	0,14	0,30	0,01	-0,26	0,97	3,61	0,17	-3,01
3	-0,12	0,20	0,14	0,21	-1,83	4,32	3,26	2,91	-0,14	0,27	0,18	-0,13	-1,53	3,88	2,09	-1,14
High OP	-0,14	0,04	0,06	0,32	-3,77	0,92	0,90	1,97	0,05	0,03	-0,23	0,15	0,81	0,31	-1,72	0,63
	i				t(i)				i				t(i)			
Low OP	-0,13	-0,12	-0,08	-0,20	-1,18	-0,94	-0,75	-1,60	-0,18	0,05	0,07	-0,03	-0,92	0,42	0,86	-0,46
2	-0,03	0,06	0,14	0,05	-0,38	1,04	2,50	0,97	-0,08	0,04	-0,10	-0,19	-0,66	0,53	-1,61	-2,56
3	-0,04	0,08	0,03	-0,07	-0,63	1,96	0,73	-1,11	0,10	0,12	0,11	-0,04	1,31	1,90	1,42	-0,41
High OP	-0,01	0,02	-0,02	-0,31	-0,30	0,39	-0,45	-2,26	-0,06	0,03	-0,15	-0,12	-1,27	0,38	-1,33	-0,61

Figure 34 - Regression results Fama French five factor model + SENT, 32 Size - B/M - OP portfolios.

32 Size - B/M - OP portfolios

Table 35 and 36 present the regression results for the Fama French five-factor model and the Fama French five-factor model with the investor sentiment factor SENT, respectively. Although the GRS-statistics indicated a slight improvement in the models' ability to explain excess returns with the addition of the SENT factor, the other remained unchanged when measured to two decimal places.

The 32 Size - B/M - OP portfolios was highlighted in Eugen F. Fama and Kenneth R. French test and publication of their five-factor model, as the stocks of small firms that invest a lot despite low profitability, was a large challenge for the model. These stocks displayed large negative intercepts, leading Fama and French to suggest that these unexplained excess returns could be due to behavioral stories (Fama & French, 2015). Consequently, demonstrating improvement in this weak spot of the Fama French five-factor model could strengthen the case for the investor sentiment factor, which has so far shown limited effectiveness.

The intercepts of the Fama French five-factor model in Table 35 reveals a serious issue with stocks of small firms that invest heavily despite low profitability, consistent with the findings of Fama and French (2015). This issue can be observed the left bottom corner of the intercept matrix, with an intercept of -0.84% (t=-4.87), the largest observed across the different sets of portfolios. Generally, it appears that for small firms that invest heavily, are a problem for the Fama French five-factor model. In contrast, none of these issues are observed for big stocks. The five-factor model seems to perform well at explaining the excess returns of big stocks in this portfolio set. For instance, compared to small stocks where the lethal combination of low operating profitability and high investment resulted in an intercept of -0.84% (t=-4.87), the intercept for big stocks with this combination is only 0.08% (t=0.48)

The five-factor model, including the investor sentiment factor SENT, does not appear to address the issues with the high intercepts observed in the Fama French five-factor model. Similar to previous test results on portfolios, the changes are minimal, with the intercept decreasing by 2 basis points in some cases and increasing by the same amount in others. Therefore, the inclusion of SENT does not seem to help the model explaining the excess returns of portfolios. The betas of the SENT factor is also very low, indicating that the factor has minimal impact on the model's results. This can be seen in the minimal changes to intercept, GRS-statistics, and other metrics. The largest SENT beta is observed in the stocks of firms that does not invest much and have low profitability, with a beta of -0.25 (t=-2.49).

The results of adding the investor sentiment factor SENT to the Fama French five-factor model have proven to be very underwhelming, not only in this portfolio set but also across all the portfolio sets examined. This provides clear evidence that the investor sentiment factor, as constructed in this research, appears to be redundant when applied to these portfolios.

	Small								BIG							
OP ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
	a				t(a)				a				t(a)			
Low INV	-0,18	0,00	0,16	0,11	-1,20	0,00	1,75	1,08	-0,02	0,09	-0,13	-0,04	-0,15	0,81	-1,17	-0,40
2	-0,38	0,20	0,11	0,16	-1,65	2,71	2,05	2,53	0,22	0,18	0,03	-0,02	1,72	1,71	0,31	-0,21
3	-0,28	-0,01	0,17	0,17	-1,43	-0,09	3,72	3,42	0,20	0,06	-0,05	0,09	1,52	0,52	-0,40	0,82
High INV	-0,84	-0,42	-0,16	0,04	-4,87	-4,52	-2,19	0,58	0,08	0,10	-0,09	0,03	0,49	0,78	-0,75	0,24
	b				t(b)				b				t(b)			
Low INV	1,01	1,02	1,01	1,04	32,13	55,90	51,41	48,98	1,05	1,05	1,01	0,97	44,91	45,85	42,65	44,73
2	1,08	0,92	1,00	1,00	22,28	59,81	85,17	76,01	1,09	1,02	1,00	0,89	40,15	46,43	42,61	41,71
3	0,94	0,90	0,95	1,03	22,47	52,37	101,0	99,04	0,97	1,01	1,03	1,03	34,00	42,53	41,63	45,27
High INV	1,07	1,03	1,05	1,06	29,44	52,19	68,62	66,53	1,10	0,97	1,05	0,97	33,06	34,37	40,47	40,88
	s				t(s)				s				t(s)			
Low INV	1,16	0,89	0,90	0,84	16,38	21,64	20,27	17,44	0,04	-0,10	-0,02	-0,07	0,80	-1,95	-0,40	-1,49
2	1,20	0,71	0,84	0,79	10,98	20,57	31,78	26,71	-0,05	-0,17	-0,13	-0,06	-0,76	-3,41	-2,37	-1,18
3	0,97	0,71	0,83	0,91	10,22	18,13	39,40	38,75	-0,14	-0,13	-0,11	-0,20	-2,18	-2,38	-1,89	-3,94
High INV	1,33	0,91	0,97	1,03	16,27	20,52	27,98	28,74	-0,06	-0,07	0,04	-0,20	-0,74	-1,13	0,76	-3,76
	h				t(h)				h				t(h)			
Low INV	-0,52	0,10	0,05	0,24	-6,27	2,15	1,03	4,38	0,11	0,00	-0,08	-0,28	1,83	-0,08	-1,27	-4,87
2	-0,06	0,08	0,14	0,17	-0,45	1,98	4,66	5,03	0,05	0,12	0,05	0,03	0,73	2,04	0,83	0,45
3	0,20	0,24	0,19	0,10	1,84	5,23	7,80	3,78	0,33	0,09	-0,14	-0,32	4,47	1,40	-2,08	-5,40
High INV	-0,53	-0,03	-0,02	-0,10	-5,52	-0,54	-0,44	-2,46	-0,18	0,21	0,16	0,07	-2,08	2,82	2,41	1,13
	r				t(r)				r				t(r)			
Low INV	-1,06	-0,23	0,05	0,29	-10,0	-3,75	0,69	4,11	-0,76	-0,27	0,26	0,48	-9,70	-3,48	3,28	6,56
2	-0,44	-0,14	0,08	0,29	-2,73	-2,75	2,08	6,44	-0,96	-0,17	0,27	0,50	-10,5	-2,26	3,43	7,02
3	-0,62	-0,15	0,17	0,31	-4,40	-2,66	5,40	8,97	-0,73	-0,10	-0,01	0,31	-7,58	-1,24	-0,10	3,99
High INV	-0,96	-0,38	-0,13	0,01	-7,83	-5,77	-2,54	0,25	-0,90	0,10	0,36	0,46	-8,07	1,01	4,12	5,70
	c				t(c)				c				t(c)			
Low INV	0,27	0,46	0,41	0,17	2,37	6,81	5,73	2,18	0,45	0,64	0,61	0,62	5,21	7,65	7,00	7,83
2	0,18	0,39	0,34	0,20	1,01	6,93	7,90	4,18	0,01	0,06	0,44	0,09	0,07	0,73	5,09	1,15
3	-0,70	-0,04	0,01	-0,10	-4,56	-0,58	0,38	-2,60	-0,56	-0,13	0,01	0,20	-5,36	-1,51	0,07	2,36
High INV	-0,60	-0,52	-0,42	-0,48	-4,51	-7,19	-7,44	-8,21	-0,53	-0,69	-0,65	-0,76	-4,34	-6,68	-6,81	-8,77

Figure 35 - Regression results Fama French five factor model, 32 Size - INV - OP portfolios.

	Small								BIG							
OP ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
		a				t(a)				a				t(a)		
Low INV	-0,20	0,01	0,16	0,11	-1,32	0,09	1,70	1,06	-0,01	0,08	-0,13	-0,04	-0,13	0,75	-1,12	-0,36
2	-0,39	0,20	0,11	0,16	-1,70	2,73	2,05	2,48	0,23	0,17	0,04	-0,02	1,77	1,67	0,41	-0,17
3	-0,29	0,00	0,17	0,17	-1,45	-0,02	3,72	3,37	0,20	0,05	-0,04	0,08	1,45	0,49	-0,38	0,78
High INV	-0,84	-0,42	-0,15	0,05	-4,88	-4,47	-2,11	0,63	0,08	0,10	-0,08	0,02	0,48	0,75	-0,67	0,20
		b				t(b)				b				t(b)		
Low INV	1,01	1,02	1,01	1,04	32,49	56,13	51,49	48,90	1,05	1,05	1,01	0,97	44,81	45,93	42,62	44,68
2	1,08	0,92	1,00	1,00	22,31	59,69	84,97	76,03	1,09	1,02	1,00	0,89	40,11	46,42	42,80	41,66
3	0,95	0,90	0,95	1,03	22,46	52,48	100,8	99,03	0,97	1,01	1,03	1,03	34,12	42,49	41,53	45,28
High INV	1,07	1,03	1,05	1,06	29,40	52,12	69,04	66,46	1,10	0,97	1,04	0,97	32,98	34,33	40,56	40,86
		s				t(s)				s				t(s)		
Low INV	1,16	0,90	0,89	0,84	16,44	21,83	20,24	17,40	0,04	-0,10	-0,02	-0,07	0,82	-2,00	-0,36	-1,46
2	1,20	0,71	0,84	0,79	10,95	20,56	31,71	26,67	-0,04	-0,17	-0,12	-0,06	-0,72	-3,43	-2,31	-1,15
3	0,97	0,71	0,83	0,91	10,18	18,25	39,33	38,70	-0,14	-0,13	-0,11	-0,20	-2,23	-2,40	-1,87	-3,97
High INV	1,33	0,91	0,97	1,03	16,23	20,53	28,26	28,76	-0,06	-0,07	0,05	-0,20	-0,74	-1,15	0,82	-3,78
		h				t(h)				h				t(h)		
Low INV	-0,50	0,09	0,06	0,25	-6,08	1,96	1,15	4,39	0,11	0,00	-0,09	-0,28	1,77	0,04	-1,37	-4,94
2	-0,04	0,08	0,14	0,18	-0,35	1,92	4,62	5,11	0,04	0,12	0,04	0,02	0,63	2,11	0,63	0,36
3	0,21	0,23	0,19	0,11	1,90	5,07	7,73	3,86	0,34	0,09	-0,14	-0,32	4,60	1,46	-2,10	-5,29
High INV	-0,52	-0,03	-0,03	-0,11	-5,44	-0,62	-0,65	-2,54	-0,18	0,21	0,15	0,08	-2,05	2,86	2,25	1,20
		r				t(r)				r				t(r)		
Low INV	-1,06	-0,23	0,05	0,29	-10,1	-3,79	0,70	4,11	-0,76	-0,27	0,26	0,48	-9,69	-3,47	3,27	6,55
2	-0,44	-0,14	0,08	0,29	-2,72	-2,76	2,07	6,45	-0,96	-0,17	0,27	0,50	-10,5	-2,25	3,43	7,02
3	-0,62	-0,16	0,17	0,31	-4,39	-2,69	5,39	8,98	-0,72	-0,10	-0,01	0,31	-7,58	-1,23	-0,10	4,00
High INV	-0,96	-0,38	-0,13	0,01	-7,82	-5,77	-2,58	0,24	-0,90	0,10	0,36	0,46	-8,06	1,02	4,12	5,70
		c				t(c)				c				t(c)		
Low INV	0,27	0,46	0,41	0,17	2,34	6,90	5,71	2,16	0,45	0,64	0,61	0,63	5,21	7,62	7,03	7,85
2	0,17	0,39	0,34	0,20	0,99	6,94	7,89	4,15	0,01	0,06	0,44	0,09	0,09	0,71	5,18	1,18
3	-0,71	-0,03	0,01	-0,10	-4,57	-0,54	0,39	-2,62	-0,56	-0,13	0,01	0,19	-5,40	-1,52	0,08	2,33
High INV	-0,60	-0,52	-0,41	-0,48	-4,51	-7,17	-7,44	-8,19	-0,53	-0,69	-0,64	-0,77	-4,34	-6,69	-6,79	-8,78
		i				t(i)				i				t(i)		
Low INV	-0,25	0,12	-0,08	-0,03	-2,49	2,11	-1,33	-0,43	0,04	-0,10	0,09	0,07	0,58	-1,34	1,18	1,00
2	-0,16	0,03	0,01	-0,05	-1,07	0,61	0,15	-1,09	0,09	-0,07	0,16	0,07	1,09	-0,96	2,21	1,04
3	-0,09	0,10	0,01	-0,03	-0,70	1,77	0,28	-1,03	-0,14	-0,05	0,03	-0,07	-1,54	-0,72	0,36	-0,97
High INV	-0,05	0,06	0,11	0,05	-0,47	0,92	2,33	1,03	-0,01	-0,05	0,15	-0,06	-0,14	-0,61	1,85	-0,83

Figure 36 - Regression results Fama French five factor model + SENT, 32 Size - INV - OP portfolios.

7.2.4 Conclusion Portfolio testing

The test of the three asset pricing models' ability to explain the excess returns of the six sets of portfolios, showed that none of the models suggested was fully able to explain the excess returns of portfolios. This result is not different from the results of past research and therefore was it expected that the GRS test rejected the null hypothesis stating that the excess returns are indistinguishable from zero. These results were then further investigated using the regression results from the Fama French five factor model and the Fama French five factor model with SENT as an additional factor, as this performed slightly better in the GRS score than its orthogonalized version PSENT.

The regression results clearly identified the portfolio consisting of small firms, which, despite having low profitability, invest heavily, as problematic for the Fama-French five-factor model. This portfolio exhibited the highest absolute intercept of -0.84. This portfolio is the same one that Fama and French highlighted in their paper presenting the five-factor model, demonstrating that these stocks pose challenges not only in the US market but also in the European market. Another significant issue was identified in the 32 Size - B/M - OP portfolios, where the small growth stocks with low operating profitability exhibited intercepts of -0.61 and -0.73. Generally, were the largest challenges for the Fama-French five-factor model found in the portfolios of small stocks.

The issues with the Fama-French five-factor model were areas where the investor sentiment factors, SENT or PSENT, could potentially improve the model. However, the models that included these sentiment factors performed almost identically to the Fama-French model. The GRS statistics changed slightly, but the other measures in Figure 24 showed no variation to two decimal places, except in the Size-INV portfolio set, where the p-value decreased upon adding the SENT and PSENT factors. Furthermore, an examination of the regression results reveals that the intercepts barely changed, and the SENT betas were low and, in most cases, also insignificant. This leads to the conclusion that, in a portfolio context, the investor sentiment factors constructed in this paper are redundant and do not enhance the Fama-French five-factor model's ability to explain excess returns. Therefore, further research on portfolios excess returns will not be pursued, while the potential of the investor sentiment factors to improve the explanatory power of the Fama-French five-factor model on individual stocks will be more thoroughly examined.

8. Dynamic conditional beta

The results presented in Section 7.2.4 indicate that incorporating investor sentiment factors enhance the explanatory power of the Fama-French five factor model for individual stocks' excess returns, measured by R^2 and adj R^2. This analysis was an in-sample test with fixed betas, estimated using the entire dataset and assuming non time-varying betas. However, assuming that betas remain constant over a 24-year period may represent an oversimplification of reality, potentially undermining the model's explanatory power (Engle, 2016; Ferreira, Gil-Bazo, & Orbe, 2011). This issue is particularly relevant due to the stock selection method, which chose the 19 largest non-financial stocks in Europe by market value at the end of the data period. These stocks may have exhibited significantly different characteristics at the beginning of the period and could have undergone multiple changes throughout. Therefore, is a more dynamic model used to evaluate whether this method could be better at explaining the excess returns than a fixed model and afterward which of the dynamic models that best captures the excess returns.

The dynamic betas are constructed using rolling period of five years, with 60 monthly observations of excess returns and corresponding factors. Each observation within the rolling window is equally weighted to estimate the betas. This is a simpler method than the more complex method like nonparametric approach, that do not assume any predefined form of relationship between variables but estimate the relationship directly from the data allowing the model to adapt and being flexible. So, where the simpler rolling method is using a simple uniform kernel for the estimation as all the observations in the window have the same weights, is the nonparametric approach letting the kernel capture nonlinear relations, where the weights can vary and the model can weigh nearby observations more heavily (Ferreira, Gil-Bazo, & Orbe, 2011). However, is the simpler rolling approach used in this research paper. For each month, the data window rolls forward by one month, incorporating a new month's data while excluding the oldest. This process continues, with betas recalculated and recorded each month, until they have been estimated for all periods following the initial 60-month data window. This method ensures that the betas are dynamic, changing with each period, and that there is no forward-looking bias, as they are derived solely from historical information.

8.1 Dynamic conditional betas vs Fixed betas

In the analysis of the results of dynamic conditional beta approach will the average betas and alphas be calculated and compared to previously estimated fixed alphas and betas. The primary focus will be on comparing the absolute average alphas, as a decrease in the absolute average alpha indicates that the dynamic betas improve the model's ability to explain the excess returns of individual stocks. Additionally, the average betas of the sentiment factors, specifically SENT and PSENT, will be of interest to determine if these factors have a greater impact on expected returns when allowed to change over time. These average betas will provide initial insights into how the dynamic betas have changed the models. Furthermore, the dynamic betas of a few selected stocks will also be plotted to dive deeper into the impact of time-varying betas. Furthermore, will the dynamic betas be compared to their fixed counterparts be measured using R^2 and adj R^2 with the main focus of determining whether the dynamic betas are generally better suited to explaining the excess returns of individual stocks compared to the fixed betas.

8.1.1 Average dynamic conditional betas

Figure 37 presents the average dynamic alphas and betas for the three models on each stock individually, calculated from the 228 estimated alphas and betas, as 59 observations are lost due to the rolling method. The average dynamic alphas and betas for the individual stocks will in this section be called dynamic alphas and betas, to avoid misunderstanding, when discussing the averages across models.

The average absolute betas of the factors Mkt-RF, SMB, and CMA are nearly unchanged, though there is a slight decrease in Mkt-RF and CMA. Meanwhile, the factors HML and RMW have experienced significant decreases in their average absolute betas. However, as these changes are not the focus of this thesis, they will not be further investigated. Instead, the focus will be on the average dynamic betas of the investor sentiment factors SENT and PSENT. There is no change in the average absolute beta of SENT compared to its fixed value in Section 7.1.2. However, PSENT has experienced an increase in beta from 0.41 to 0.50, a rise of 21.95% compared to its fixed beta. This indicates that the shift from fixed to dynamic betas has had the most significant impact on PSENT.

Another noteworthy change is that while the average betas of the investor sentiment factor PSENT have increased and remained stable for SENT, the maximum values of these dynamic betas have significantly decreased compared to the maximum values of the fixed betas. For instance, VWS-DK had fixed betas of 1.3 for SENT and 1.69 for PSENT. In contrast, the dynamic betas are only 0.65 for SENT and 0.86 for PSENT. This might be due to the nature of the dynamic betas, that due to their constructions now can fluctuate, having highly positive values in some periods and highly negative in other periods. These fluctuations can offset each other, resulting in less extreme dynamic beta values compared to their fixed counterparts.

The average alpha for the individual models reported in Figure 37 is calculated by averaging the absolute values of the alphas across all 19 stocks. The use of absolute values ensures that a model's strong performance, indicated by a low average alpha, is not the result of stocks with extreme negative intercepts and stocks with extreme positive intercepts cancelling each other out. The absolute average alpha across all three models has decreased significantly compared to the absolute average alpha of the models with fixed betas, dropping from 0.7 to 0.53, a decrease of 24.29%. This suggests that the dynamic betas are more effective at capturing and explaining the excess returns. The model that performed the best and improved the most, measured by the average absolute alpha, is the Fama-French five factor model without any investor sentiment factor, which decreased from 0.68 to 0.47 (30.88%).

Stock	Begin Date	End Date	Observation	a	b	s	h	r	c	i	p
							Average Coefficients				
ASML-NL	31-12-2004	30-11-2023	228	0,98	0,83	-0,81	-0,13	-0,45	-0,19		
ASML-NL	31-12-2004	30-11-2023	228	0,95	0,80	-0,79	-0,16	-0,50	-0,16	0,26	
ASML-NL	31-12-2004	30-11-2023	228	0,87	0,78	-0,78	-0,19	-0,50	-0,15		0,70
ASSA.B-SE	31-12-2004	30-11-2023	228	0,22	0,59	-0,43	-0,06	0,22	0,05		
ASSA.B-SE	31-12-2004	30-11-2023	228	0,07	0,57	-0,42	-0,07	0,14	0,03	0,21	
ASSA.B-SE	31-12-2004	30-11-2023	228	0,53	0,56	-0,45	-0,11	0,17	0,07		0,26
ATCO.A-SE	31-12-2004	30-11-2023	228	0,85	0,69	-0,27	0,15	-0,16	-0,57		
ATCO.A-SE	31-12-2004	30-11-2023	228	0,94	0,67	-0,27	0,15	-0,19	-0,55	0,17	
ATCO.A-SE	31-12-2004	30-11-2023	228	1,27	0,67	-0,29	0,12	-0,20	-0,55		0,09
COLO.B-DK	31-12-2004	30-11-2023	228	0,56	0,26	-0,13	0,01	0,31	0,02		
COLO.B-DK	31-12-2004	30-11-2023	228	0,49	0,24	-0,10	-0,02	0,27	-0,02	0,28	
COLO.B-DK	31-12-2004	30-11-2023	228	0,50	0,20	-0,14	-0,03	0,23	0,01		0,84
DNB-NO	31-12-2004	30-11-2023	228	0,16	0,75	0,00	0,74	-0,44	-0,99		
DNB-NO	31-12-2004	30-11-2023	228	0,00	0,75	0,00	0,74	-0,45	-0,99	0,00	
DNB-NO	31-12-2004	30-11-2023	228	-0,04	0,74	0,02	0,74	-0,43	-0,99		0,23
DSV-DK	31-12-2004	30-11-2023	228	0,56	0,91	0,56	0,30	0,57	-0,65		
DSV-DK	31-12-2004	30-11-2023	228	0,70	0,89	0,57	0,27	0,55	-0,66	0,42	
DSV-DK	31-12-2004	30-11-2023	228	0,72	0,88	0,56	0,27	0,53	-0,64		0,36
ERIC.B-OME	31-12-2004	30-11-2023	228	-0,14	0,59	-0,26	-1,04	-1,58	0,13		
ERIC.B-OME	31-12-2004	30-11-2023	228	-0,41	0,59	-0,23	-1,04	-1,52	0,15	0,34	
ERIC.B-OME	31-12-2004	30-11-2023	228	-0,83	0,57	-0,24	-1,04	-1,55	0,18		0,73
HEXA.B-SE	31-12-2004	30-11-2023	228	0,66	1,05	0,72	0,11	0,87	-0,66		
HEXA.B-SE	31-12-2004	30-11-2023	228	0,76	1,02	0,73	0,06	0,81	-0,66	0,37	
HEXA.B-SE	31-12-2004	30-11-2023	228	0,76	0,99	0,69	0,05	0,80	-0,63		0,89
HM.B-OME	31-12-2004	30-11-2023	228	0,12	0,52	-0,40	-0,07	0,17	-0,06		
HM.B-OME	31-12-2004	30-11-2023	228	0,46	0,52	-0,44	-0,09	0,09	-0,09	-0,27	
HM.B-OME	31-12-2004	30-11-2023	228	0,10	0,50	-0,40	-0,10	0,15	-0,05		0,28
MAERSK.B-DK	31-12-2004	30-11-2023	228	-0,17	0,76	0,64	0,25	-0,02	-0,21		
MAERSK.B-DK	31-12-2004	30-11-2023	228	0,30	0,77	0,60	0,24	0,00	-0,17	-0,44	
MAERSK.B-DK	31-12-2004	30-11-2023	228	0,13	0,77	0,60	0,23	-0,01	-0,20		-0,13
MC-FR	31-12-2004	30-11-2023	228	0,58	0,80	-0,51	-0,04	-0,06	-0,53		
MC-FR	31-12-2004	30-11-2023	228	0,60	0,80	-0,50	-0,03	-0,07	-0,54	0,19	
MC-FR	31-12-2004	30-11-2023	228	0,85	0,78	-0,53	-0,07	-0,11	-0,53		0,28
NESN-CH	31-12-2004	30-11-2023	228	0,29	0,34	-0,36	-0,56	0,02	0,28		
NESN-CH	31-12-2004	30-11-2023	228	0,35	0,32	-0,35	-0,59	-0,01	0,29	0,36	
NESN-CH	31-12-2004	30-11-2023	228	0,54	0,30	-0,39	-0,60	-0,05	0,28		0,59
NOVO.B-DK	31-12-2004	30-11-2023	228	1,14	0,34	-0,38	-0,49	0,16	0,03		
NOVO.B-DK	31-12-2004	30-11-2023	228	1,17	0,32	-0,36	-0,53	0,12	0,01	0,55	
NOVO.B-DK	31-12-2004	30-11-2023	228	0,93	0,29	-0,40	-0,53	0,12	0,06		0,94
OR-FR	31-12-2004	30-11-2023	228	0,27	0,57	-0,82	-0,32	0,08	0,26		
OR-FR	31-12-2004	30-11-2023	228	0,36	0,56	-0,81	-0,34	0,06	0,29	0,16	
OR-FR	31-12-2004	30-11-2023	228	0,57	0,53	-0,86	-0,38	0,01	0,28		0,57
RMS-PAR	31-12-2004	30-11-2023	228	1,15	0,48	-0,67	-0,28	-0,20	-1,01		
RMS-PAR	31-12-2004	30-11-2023	228	1,35	0,47	-0,66	-0,28	-0,20	-1,04	0,27	
RMS-PAR	31-12-2004	30-11-2023	228	1,09	0,47	-0,66	-0,29	-0,22	-1,02		0,27
SAND-SE	31-12-2004	30-11-2023	228	-0,03	0,88	0,23	0,23	0,74	-0,19		
SAND-SE	31-12-2004	30-11-2023	228	-0,14	0,86	0,24	0,22	0,74	-0,13	0,33	
SAND-SE	31-12-2004	30-11-2023	228	0,06	0,84	0,21	0,20	0,71	-0,14		0,59
SAP-DE	31-12-2004	30-11-2023	228	0,69	0,74	-0,65	-0,47	-0,93	-0,72		
SAP-DE	31-12-2004	30-11-2023	228	0,69	0,74	-0,63	-0,49	-0,94	-0,77	0,21	
SAP-DE	31-12-2004	30-11-2023	228	0,34	0,72	-0,61	-0,48	-0,94	-0,72		0,54
VOLV.B-SE	31-12-2004	30-11-2023	228	-0,08	0,99	0,38	0,36	0,16	-0,22		
VOLV.B-SE	31-12-2004	30-11-2023	228	-0,10	0,98	0,38	0,36	0,15	-0,20	0,15	
VOLV.B-SE	31-12-2004	30-11-2023	228	0,02	0,97	0,37	0,34	0,14	-0,19		0,31
VWS-DK	31-12-2004	30-11-2023	228	0,30	0,97	1,37	0,00	-0,28	-0,54		
VWS-DK	31-12-2004	30-11-2023	228	1,09	0,92	1,33	-0,07	-0,46	-0,61	0,65	
VWS-DK	31-12-2004	30-11-2023	228	0,45	0,91	1,34	-0,07	-0,35	-0,56		0,86
Mean			228	0,47	0,67	-0,10	-0,09	-0,07	-0,30	0,22	0,48
Median			228	0,50	0,74	-0,27	-0,07	0,00	-0,19	0,26	0,54
Absolute mean				0,53	0,67	0,50	0,30	0,38	0,38	0,30	0,50
				(Absolute)							
Mean FFFFM			228	0,47	0,69	-0,09	-0,07	-0,04	-0,30	0,00	0,00
Mean SENT			228	0,57	0,67	-0,09	-0,09	-0,07	-0,31	0,22	0,00
Mean PSENT			228	0,56	0,66	-0,10	-0,10	-0,08	-0,29	0,00	0,48

Figure 37 - Average dynamic conditional betas for the three asset pricing models.

Figure 38 of VWS-DK dynamic betas clearly illustrates the fluctuations in the betas, as the betas changes significantly over time. The beta of PSENT, for example, has fluctuated between -10 and 5. A notable large negative spike in the beta of PSENT occurred around 2017 and 2018, during a period of high investor sentiment measured by PSENT. Intriguingly, this suggests that the high level of investor sentiment during that period had a negative effect on the expected return. This result is somewhat counterintuitive, as the fixed beta indicated that VWS-DK stock was very positively prone to investor sentiment, and therefore positively affected by an increase in investor sentiment. However, an examination of the stock price of VWS-DK shows that the dynamic beta of PSENT to some degree follow some of the patterns of the stock price, but with a more extreme decrease in 2017-2018.

Figure 38 - Plot of the VWS-DK dynamic betas, stock price as well as the PSENT factor.

Figure 39 plotting the betas of the MAERSK.B-DK is clearly illustrating the time-varying betas. The fixed betas for PSENT and SENT for the MAERSK.B-DK stock were quite low, with values of 0.02 and 0.1, respectively. This has changed with the use of dynamic beta, as the average dynamic betas for the MAERSK.B-DK stock are now -0.44 for SENT and -0.13 for PSENT, respectively. The shift to significantly higher-level absolute level suggests that they are more effective at utilizing investor sentiment information to explain the excess returns of MAERSK.B-DK. This may be attributed to the fixed structure being too rigid, whereas investor sentiment has had a varying impact on MAERSK.B-DK stock.

Figure 39 - Plot of the MAERSK.B-DK dynamic betas, stock price as well as the PSENT factor.

8.1.2 T-statistics and p-values

To test whether the average betas is significantly different from zero is the t-statistics and p-values calculated and reported in figure 40. The result in Table 40 shows significantly higher t-values and thereby also to a larger degree, betas that are significantly different from zero compared to the results from the fixed betas in Section 7.1.2. The higher t-values of the betas are clear when comparing the average t-statistics in Table 44 with the average t-statistics from Section 7.1.2.

One example is the t-statistics for the beta of MKT-RF, that have increased from 7.74 to 44.18. However, this increase is not particularly important because this factor was already significant from 0 for all stocks with fixed betas. A more interesting thing is that t-statistics and p-values of the investor sentiment indexes, PSENT average dynamic beta is significant for all stocks expect for DNB-NO and SENT average dynamic beta is significant for all stocks expect for MAERSK.B-DK and ACTO.A-SE. This indicates the investor sentiment factors with time-varying beta of the has a higher chance of being significantly different from zero compared to with fixed betas. This time-varying effect of the investor sentiment PSENT was also clearly illustrated in Figures 38 and 39, which show how the impact of the investor sentiment factor on expected returns changes over time.

The increase in t-statistics is also the case for the alphas, which also have the dynamic characteristics. This even though the average absolute alphas decreased as discussed in section 8.1.1. The number of significant alphas at a 0.05 significance level increased from six for all models using fixed betas to 15 with the Fama-French five-factor model, 14 with the inclusion of SENT, and 16 with PSENT. Part of this increase in number significant alphas might be due to the different time period, as the rolling methods means losing 59 observations of betas. However, the increase is so large that it more likely is due to the alpha with its now dynamic estimations can vary and the individual stocks can have periods of abnormal returns followed by periods of no abnormal returns. This relation is clearly illustrated in the plots of MAERSK.B-DK and VWS-DK in figure 38 and 39. Both stocks have periods of positive alphas, negative alphas.

Stock	Begin Date	End Date	Observation	t-stat(a)	t-stat(b)	t-stat(s)	t-stat(h)	t-stat(r)	t-stat(c)	t-stat(i)	t-stat(p)
MAERSK.B-DK	31-12-2004	30-11-2023	228	-3,67***	31,63***	10,16***	6,58***	-0,35	-3,21***		
MAERSK.B-DK	31-12-2004	30-11-2023	228	3,88***	30,49***	8,92***	6,83***	0,02	-2,34**		-6,66***
MAERSK.B-DK	31-12-2004	30-11-2023	228	1,52	28,69***	9,67***	6,3***	-0,29	-2,96***	-1,84*	
ASML-NL	31-12-2004	30-11-2023	228	13,57***	34,99***	-41,8***	-1,94*	-3,56***	-4,08***		
ASML-NL	31-12-2004	30-11-2023	228	11,87***	38,79***	-39,61***	-2,38**	-3,74***	-3,26***		3,19***
ASML-NL	31-12-2004	30-11-2023	228	9,49***	39,61***	-37,95***	-2,71***	-3,64***	-2,96***	6,79***	
ASSA.B-SE	31-12-2004	30-11-2023	228	3,11***	85,31***	-11,32***	-1,21	2,53**	1,29		
ASSA.B-SE	31-12-2004	30-11-2023	228	0,8	86,31***	-10,93***	-1,62	1,55	0,78		2,92***
ASSA.B-SE	31-12-2004	30-11-2023	228	7,29***	77,67***	-11,69***	-2,46**	1,86*	1,78*	3,57***	
ATCO.A-SE	31-12-2004	30-11-2023	228	22,74***	47,59***	-5,96***	2,8***	-2,39**	-13,15***		
ATCO.A-SE	31-12-2004	30-11-2023	228	16,86***	42,2***	-5,98***	2,63***	-2,71***	-12,4***		3,38***
ATCO.A-SE	31-12-2004	30-11-2023	228	19,35***	38,87***	-6,4***	2,08**	-2,74***	-12,34***	1,25	
COLO.B-DK	31-12-2004	30-11-2023	228	9,1***	13,88***	-2,91***	0,09	5,07***	0,61		
COLO.B-DK	31-12-2004	30-11-2023	228	6,34***	13,41***	-2,39**	-0,21	4,26***	-0,39		7,92***
COLO.B-DK	31-12-2004	30-11-2023	228	4,34***	10,67***	-3,75***	-0,42	3,91***	0,35	13,15***	
DNB-NO	31-12-2004	30-11-2023	228	2,57**	47,85***	-0,06	13,42***	-5,73***	-17,63***		
DNB-NO	31-12-2004	30-11-2023	228	0	49,38***	0,02	13,25***	-5,97***	-17,66***		0,12
DNB-NO	31-12-2004	30-11-2023	228	-0,58	48,11***	0,42	13,4***	-5,7***	-17,51***	6,02***	
DSV-DK	31-12-2004	30-11-2023	228	11,59***	43,48***	27,45***	3,42***	10,11***	-14,31***		
DSV-DK	31-12-2004	30-11-2023	228	15,38***	46,41***	27,63***	3,15***	9,51***	-14,74***		9,03***
DSV-DK	31-12-2004	30-11-2023	228	12,59***	48,8***	26,6***	3,1***	9,13***	-14,35***	6,38***	
HM.B-OME	31-12-2004	30-11-2023	228	1,86*	27,8***	-7,69***	-1,12	3,03***	-1,47		
HM.B-OME	31-12-2004	30-11-2023	228	5,12***	27,15***	-7,6***	-1,4	1,35	-1,9*		-3,49***
HM.B-OME	31-12-2004	30-11-2023	228	0,98	26,36***	-7,58***	-1,58	2,45**	-1,36	4,12***	
RMS-PAR	31-12-2004	30-11-2023	228	20,26***	46,39***	-19,32***	-5,24***	-2,54**	-14,67***		
RMS-PAR	31-12-2004	30-11-2023	228	16,38***	43,6***	-18,99***	-5,04***	-2,54**	-14,32***		5,35***
RMS-PAR	31-12-2004	30-11-2023	228	12,31***	40,73***	-19,12***	-5,15***	-2,74***	-14,19***	4,27***	
HEXA.B-SE	31-12-2004	30-11-2023	228	14,22***	97,26***	14,51***	2,34**	10,34***	-10,05***		
HEXA.B-SE	31-12-2004	30-11-2023	228	13,86***	94,71***	14,79***	1,31	9,53***	-10,13***		7,7***
HEXA.B-SE	31-12-2004	30-11-2023	228	8,48***	95,96***	15,04***	1,03	9,88***	-9,49***	13,99***	
OR-FR	31-12-2004	30-11-2023	228	4,97***	67,1***	-39,27***	-8,12***	1,92*	11,41***		
OR-FR	31-12-2004	30-11-2023	228	5,68***	71,1***	-38,16***	-8,51***	1,47	12,94***		4,96***
OR-FR	31-12-2004	30-11-2023	228	7,94***	60,97***	-47,01***	-10***	0,24	12,04***	14,57***	
MC-FR	31-12-2004	30-11-2023	228	11,26***	67,68***	-15,11***	-0,66	-1,32	-12,5***		
MC-FR	31-12-2004	30-11-2023	228	11,73***	72,01***	-15,08***	-0,61	-1,38	-12,19***		6,33***
MC-FR	31-12-2004	30-11-2023	228	12,19***	67,64***	-15,76***	-1,28	-2,3**	-12,13***	6,15***	
NESN-CH	31-12-2004	30-11-2023	228	12,57***	39,57***	-15,62***	-26,45***	0,98	9,72***		
NESN-CH	31-12-2004	30-11-2023	228	15,09***	34,59***	-14,75***	-30,93***	-0,37	10***		15,43***
NESN-CH	31-12-2004	30-11-2023	228	10,82***	29,24***	-17,09***	-32,54***	-2,5**	9,83***	22,11***	
NOVO.B-DK	31-12-2004	30-11-2023	228	21,86***	17,33***	-14,06***	-11,19***	2,66***	0,73		
NOVO.B-DK	31-12-2004	30-11-2023	228	14,39***	15,57***	-13,41***	-12,6***	2,11**	0,24		17,09***
NOVO.B-DK	31-12-2004	30-11-2023	228	6,45***	13,79***	-15,8***	-13,03***	2,09**	1,38	12,64***	
SAND-SE	31-12-2004	30-11-2023	228	-0,66	44***	4,17***	5,45***	15,12***	-3,43***		
SAND-SE	31-12-2004	30-11-2023	228	-1,97**	39,87***	4,47***	4,95***	13,28***	-2,27**		6,55***
SAND-SE	31-12-2004	30-11-2023	228	0,82	39,07***	4,1***	4,29***	13,34***	-2,41**	10,62***	
SAP-DE	31-12-2004	30-11-2023	228	10,31***	29,43***	-19,87***	-9,99***	-13,97***	-14,37***		
SAP-DE	31-12-2004	30-11-2023	228	7,57***	30,16***	-19,96***	-9,31***	-14,05***	-14,99***		3,67***
SAP-DE	31-12-2004	30-11-2023	228	3,18***	30,07***	-19,44***	-9,01***	-13,53***	-14,25***	7,82***	
ERIC.B-OME	31-12-2004	30-11-2023	228	-1,55	26,41***	-3,95***	-11,18***	-10,23***	1,81*		
ERIC.B-OME	31-12-2004	30-11-2023	228	-3,06***	26,51***	-3,54***	-10,72***	-9,52***	2,16**		4,1***
ERIC.B-OME	31-12-2004	30-11-2023	228	-4,35***	24,7***	-3,63***	-11***	-9,75***	2,55**	5,38***	
VWS-DK	31-12-2004	30-11-2023	228	2,49**	37,11***	22,33***	0,03	-2,89***	-6,27***		
VWS-DK	31-12-2004	30-11-2023	228	6,35***	38,08***	20,6***	-0,68	-4,84***	-6,36***		4,16***
VWS-DK	31-12-2004	30-11-2023	228	2,16**	34,14***	21,87***	-0,66	-3,8***	-6,12***	4,9***	
VOLV.B-SE	31-12-2004	30-11-2023	228	-1,45	57,61***	8,13***	5,83***	2,69***	-4,05***		
VOLV.B-SE	31-12-2004	30-11-2023	228	-1,43	50,21***	8,14***	5,76***	2,31**	-3,72***		3,16***
VOLV.B-SE	31-12-2004	30-11-2023	228	0,33	50,42***	7,98***	5,54***	2,25**	-3,46***	6,52***	
Mean			228	7,29	44,18	-5,89	-2,41	0,17	-4,73	7,81	4,99
Absolute mean			228	7,94	44,18	14,90	6,40	4,91	7,53	8,01	6,06
Median			228	6,45	39,61	-5,98	-0,68	0,02	-3,43	6,38	4,16
Mean FFFFM			228	8,17	45,39	-5,80	-1,95	0,60	-4,93		
Mean SENT			228	7,62	44,77	-5,57	-2,43	0,01	-4,77		
Mean PSENT			228	6,07	42,40	-6,29	-2,85	-0,10	-4,50		

*Figure 40 - Average dynamic betas T-statistics 19 largest non-financial stocks EURO STOXX 600. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.*

8.1.3 Performance measure by R^2 and $adj\ R^2$

The performance of the three models with dynamic betas relative to those with fixed betas, measured by R^2 and adj R^2, is presented in Figure 41. Initially focusing on the Fama-French five factor model without any investor sentiment factors, there is a notable improvement in the model's ability to explain excess returns. This improvement is demonstrated by an increase from an average R^2 of 0.3 with fixed betas to an average R^2 of 0.39 with dynamic betas, reflecting a 30% increase. The most significant increase in R^2 was observed for Coloplast, which R^2 increased by 250%, from 0.07 to 0.24. Conversely, only two of the 19 stocks showed a decrease in explanatory power. The largest decline was for ERIC.B-OME, which experienced a 69% decrease in R^2 from 0.35 with fixed betas to 0.11 with dynamic betas.

These results, as measured by the R^2, is consistent with those of the adj R^2 for the Fama-French five factor model. In fact, the increase in performance is even more pronounced when measured by adj R^2. The average adj R^2 increased from 0.29 using fixed betas to 0.38 with dynamic betas, representing a 31% improvement compared to the 30% increase observed with R^2. Furthermore, the highest increase is observed in the excess returns of Coloplast, where the adj R^2 increased from 0.05 to 0.22, translating to an increase of 333%. The dynamic betas are therefore both measured by the average absolute alphas in the past section and by the R^2 and adj R^2 improving the Fama French five factor model ability to explain the excess returns of the individual stocks.

The models that incorporate one of the investor sentiment factors, SENT or PSENT, appear to have improved even more than the Fama-French Five Factor Model without sentiment factors. This improvement, contrasts with the performance measured by the average absolute alpha. The R^2 increase 35% and 34% for respectively SENT and PSENT, when utilizing dynamic betas instead of the fixed betas. Both models arching an average R^2 of 0.41, compared to 0.3 and 0.31 with fixed betas. This suggests that similar to the results of the Fama-French five factor model, that utilizing dynamic betas, estimated using a rolling window of five years, is improving the model’s ability to explain the excess returns. Additionally, the results from the dynamic betas are consistent with those from the fixed betas, as the inclusion of the investor sentiment factor increases the R^2.

The adjusted R^2 values are consistent with the results of the R^2, demonstrating once again that including the investor sentiment factor increases the explanatory power of the model. Moreover, there is a notable enhancement in explanatory power when utilizing dynamic betas instead of fixed betas, with an average increase in adj R^2 ranging from 0.31% to 0.37%. These results, combined with those measured by average absolute alpha, clearly indicate that dynamic betas outperform their fixed counterparts in explaining the excess returns of these 19 individual stocks.

Stock	R^2	R^2 S	R^2 P	Adj R^2	Adj R^2 S	Adj R^2 P
ASML-NL	0,37	0,36	0,36	0,35	0,35	0,34
Fixed beta	0,39	0,39	0,39	0,38	0,38	0,38
% increase	*-6%*	*-8%*	*-8%*	*-8%*	*-9%*	*-10%*
ASSA.B-SE	0,36	0,39	0,38	0,34	0,37	0,37
Fixed beta	0,27	0,27	0,28	0,26	0,26	0,26
% increase	*32%*	*43%*	*38%*	*33%*	*45%*	*40%*
ATCO.A-SE	0,41	0,43	0,43	0,40	0,42	0,42
Fixed beta	0,32	0,32	0,32	0,30	0,30	0,30
% increase	*31%*	*37%*	*36%*	*32%*	*38%*	*38%*
COLO.B-DK	0,24	0,28	0,27	0,22	0,26	0,25
Fixed beta	0,07	0,07	0,07	0,05	0,05	0,06
% increase	*250%*	*300%*	*266%*	*330%*	*422%*	*362%*
DNB-NO	0,61	0,63	0,63	0,60	0,62	0,62
Fixed beta	0,49	0,49	0,49	0,48	0,48	0,48
% increase	*25%*	*29%*	*27%*	*26%*	*30%*	*28%*
DSV-DK	0,51	0,53	0,53	0,50	0,52	0,52
Fixed beta	0,37	0,38	0,38	0,36	0,37	0,37
% increase	*40%*	*41%*	*40%*	*41%*	*42%*	*41%*
ERIC.B-OME	0,11	0,13	0,14	0,09	0,10	0,12
Fixed beta	0,35	0,35	0,35	0,34	0,34	0,34
% increase	*-69%*	*-64%*	*-59%*	*-73%*	*-69%*	*-65%*
HEXA.B-SE	0,49	0,50	0,51	0,47	0,49	0,49
Fixed beta	0,36	0,36	0,36	0,34	0,35	0,35
% increase	*37%*	*40%*	*39%*	*38%*	*42%*	*41%*
HM.B-OME	0,34	0,36	0,35	0,33	0,34	0,34
Fixed beta	0,16	0,16	0,16	0,14	0,14	0,14
% increase	*119%*	*124%*	*121%*	*132%*	*140%*	*136%*
MAERSK.B-DK	0,38	0,41	0,41	0,37	0,39	0,39
Fixed beta	0,28	0,28	0,28	0,26	0,26	0,26
% increase	*38%*	*48%*	*47%*	*39%*	*50%*	*50%*
MC-FR	0,55	0,56	0,56	0,54	0,55	0,54
Fixed beta	0,45	0,46	0,46	0,44	0,44	0,44
% increase	*21%*	*23%*	*22%*	*21%*	*24%*	*22%*
NESN-CH	0,30	0,34	0,35	0,29	0,33	0,33
Fixed beta	0,17	0,20	0,20	0,15	0,18	0,18
% increase	*80%*	*77%*	*75%*	*88%*	*84%*	*82%*
NOVO.B-DK	0,25	0,28	0,27	0,23	0,26	0,25
Fixed beta	0,08	0,08	0,09	0,06	0,06	0,07
% increase	*222%*	*239%*	*213%*	*280%*	*313%*	*273%*
OR-FR	0,48	0,50	0,51	0,46	0,48	0,49
Fixed beta	0,35	0,35	0,36	0,33	0,33	0,34
% increase	*38%*	*43%*	*41%*	*39%*	*45%*	*43%*
RMS-PAR	0,34	0,36	0,36	0,33	0,34	0,34
Fixed beta	0,21	0,21	0,21	0,20	0,20	0,20
% increase	*60%*	*68%*	*68%*	*64%*	*73%*	*74%*
SAND-SE	0,46	0,47	0,48	0,45	0,46	0,46
Fixed beta	0,37	0,37	0,37	0,36	0,36	0,36
% increase	*25%*	*28%*	*29%*	*25%*	*29%*	*30%*
SAP-DE	0,42	0,42	0,43	0,40	0,40	0,41
Fixed beta	0,41	0,41	0,41	0,40	0,40	0,40
% increase	*2%*	*2%*	*3%*	*1%*	*1%*	*2%*
VOLV.B-SE	0,48	0,50	0,50	0,47	0,49	0,49
Fixed beta	0,41	0,41	0,41	0,40	0,39	0,40
% increase	*19%*	*23%*	*23%*	*19%*	*24%*	*23%*
VWS-DK	0,30	0,34	0,33	0,28	0,33	0,31
Fixed beta	0,21	0,22	0,23	0,19	0,20	0,22
% increase	*45%*	*55%*	*42%*	*48%*	*59%*	*44%*
Mean Dynamic	0,39	0,41	0,41	0,38	0,40	0,39
Mean Fixed	0,30	0,30	0,31	0,29	0,29	0,29
Mean % increase	53%	60%	56%	62%	73%	66%
% Increase of means	30%	35%	34%	31%	37%	35%

Figure 41 - Performance comparison between the models with fixed betas and their dynamic counterparts.

8.2 Comparison of dynamic models.

The performance of the Fama French five factor model utilizing dynamic betas is to be compared to the revised Fama French five factor model with an investor sentiment factor, also using dynamic betas. The performance metrics used for comparing the models are R^2, adj R and the average absolute alphas.

The R^2 and adj R^2 averages in Figure 42 show an increase when an investor sentiment factor is added to the Fama-French five factor model. Measured by R^2 are the average increase 6.7% with the inclusion of SENT and 6.9% with PSENT. Similarly, the results for adjusted R^2 show increases of 6.3% and 6,7%, respectively. Furthermore, the R^2 values are identical to two decimal places between the models incorporating the investor sentiment factors, SENT and PSENT. The average adj R^2 is 0.01 higher when using SENT as the investor sentiment factor compared to PSENT, suggesting that in this sample, SENT with dynamic conditional betas increases the explanatory power of the Fama-French model more than PSENT. The increases of both average R^2 and adjusted R^2 in the models including either SENT or PSENT indicate that a Fama-French five factor model utilizing dynamic betas, combined with an investor sentiment factor, is better for explaining the excess returns of individual stocks. However, is the average absolute alpha of the Fama French five model 0,47 which is lower than the 0,57 with SENT and 0,56 with PSENT. This indicates that the Fama French five factor has less unexplained excess return compared to the models including the investor sentiment.

Stock	R^2	R^2 S	R^2 P	% incr S	% incr P	Adj R^2	Adj R^2 S	Adj R^2 P	% incr S	% incr P
ERIC.B-OME	0,11	0,13	0,14	*15,6%*	*29,8%*	0,09	0,10	0,12	*15,0%*	*32,8%*
SAP-DE	0,42	0,42	0,43	*0,6%*	*2,1%*	0,40	0,40	0,41	*0,0%*	*1,5%*
COLO.B-DK	0,24	0,28	0,27	*16,1%*	*14,6%*	0,22	0,26	0,25	*16,2%*	*14,6%*
MAERSK.B-DK	0,38	0,41	0,41	*7,2%*	*6,7%*	0,37	0,39	0,39	*6,9%*	*6,4%*
VWS-DK	0,30	0,34	0,33	*14,9%*	*10,8%*	0,28	0,33	0,31	*15,1%*	*10,6%*
RMS-PAR	0,34	0,36	0,36	*5,0%*	*5,1%*	0,33	0,34	0,34	*4,4%*	*4,5%*
DSV-DK	0,51	0,53	0,53	*3,9%*	*3,7%*	0,50	0,52	0,52	*3,6%*	*3,4%*
OR-FR	0,48	0,50	0,51	*4,6%*	*6,5%*	0,46	0,48	0,49	*4,3%*	*6,3%*
ASML-NL	0,37	0,36	0,36	*-1,1%*	*-1,7%*	0,35	0,35	0,34	*-2,0%*	*-2,7%*
SAND-SE	0,46	0,47	0,48	*3,2%*	*4,2%*	0,45	0,46	0,46	*2,8%*	*3,9%*
NESN-CH	0,30	0,34	0,35	*13,7%*	*14,0%*	0,29	0,33	*0,33*	*13,7%*	*14,1%*
HM.B-OME	0,34	0,36	0,35	*4,2%*	*3,1%*	0,33	0,34	0,34	*3,5%*	*2,4%*
HEXA.B-SE	0,49	0,50	0,51	*3,8%*	*4,0%*	0,47	0,49	0,49	*3,5%*	*3,8%*
ASSA.B-SE	0,36	0,39	0,38	*8,8%*	*6,8%*	0,34	0,37	0,37	*8,5%*	*6,4%*
DNB-NO	0,61	0,63	0,63	*2,9%*	*2,4%*	0,60	0,62	0,62	*2,7%*	*2,2%*
MC-FR	0,55	0,56	0,56	*2,2%*	*0,9%*	0,54	0,55	0,54	*1,9%*	*0,6%*
VOLV.B-SE	0,48	0,50	0,50	*3,6%*	*3,6%*	0,47	0,49	0,49	*3,3%*	*3,2%*
ATCO.A-SE	0,41	0,43	0,43	*4,4%*	*4,7%*	0,40	0,42	0,42	*4,0%*	*4,3%*
NOVO.B-DK	0,25	0,28	0,27	*12,9%*	*9,7%*	0,23	0,26	0,25	*12,7%*	*9,2%*
Mean	0,39	0,41	0,41	*6,7%*	*6,9%*	0,38	0,40	0,39	*6,3%*	*6,7%*
Median	0,38	0,41	0,41	*4,4%*	*4,7%*	0,37	0,39	0,39	*4,0%*	*4,3%*
Max	0,61	0,63	0,63	*16,1%*	*29,8%*	0,60	0,62	0,62	*16,2%*	*32,8%*
Min	0,11	0,13	0,14	*-1,1%*	*-1,7%*	0,09	0,10	0,12	*-2,0%*	*-2,7%*

Figure 42 - Comparing the results of the three models all utilizing dynamic betas using R^2 and $adj\ R^2$.

The results of the models using dynamic betas are therefore mixed regarding whether that investor sentiment increases the Fama French five factor models explanatory power over the excess returns of individual stocks. Furthermore, is the result between the two investor sentiment factors very similar both measured by the average R^2, adj R^2 and average absolute alpha. This therefore suggests that the simpler measurement SENT could be used with the same or better result than the less intuitive PSENT. This result has its advantages as SENT, easier and faster to construct.

8.3 Conclusion dynamic betas

The time-varying betas demonstrated superior performance compared to their fixed counterparts. The average absolute alphas decreased significantly, while both R^2 and adj R^2 increased substantially. The performance of the three models with dynamic betas was comparable to that of the fixed models, as the inclusion of a sentiment factor enhanced the explanatory power of the Fama-French five-factor model measured by R^2 and adj R^2. This suggests that investor sentiment does affect individual stock returns, with some stocks being more prone to this factor than others. However, was the increase in average alpha when using the model with an investor sentiment factor, indicating that the Fama French five factor model without an investor sentiment factor had less unexplained excess return.

9. Main Findings

This thesis has investigated whether incorporating an investor sentiment factor into the Fama-French five-factor model could enhance its explanatory power of European stocks' excess returns. To explore this, four versions of an investor sentiment factor (raw, orthogonalized, and their lagged counterparts) were constructed. The analysis focused on the non-lagged versions, SENT and PSENT, due to their near-perfect correlation with their lagged forms. Both of these versions demonstrated strong correlations with the EURO STOXX 600 market and also showed correlations with the US investor sentiment created by Baker & Wurgler (2006), aligning with the results of past research. The investor sentiment factors were almost uncorrelated with the five factors from the Fama-French model, suggesting that they introduce new information to the model.

The time-series testing of the revised Fama-French five-factor model, which includes an investor sentiment factor, was applied to 19 individual non-financial stocks. This analysis revealed an increase in explanatory power, measured by R^2 and adjusted R^2, mainly attributable to a few stocks with very large percentage increases. There was also a slight increase in the absolute average alpha, but no change in the number of significant alphas at a 0.05 significance level. Thus, the results of the time-series testing on individual stocks were mixed: while the R^2 and adjusted R^2 indicated increased explanatory power, the average absolute alpha suggested a larger unexplained excess return, and the number of significant alphas showed no change.

The results of the portfolio time-series testing of the revised Fama French five factor model including an investor sentiment factor were clearer. The GRS test indicated that none of the three proposed asset pricing models could fully explain the excess returns of the portfolios. The outcomes of the three asset pricing models were almost identical, as the p-values, average R^2, and the average absolute alpha were similar to two decimal places, except for the Size-INV portfolio, where the p-value decreased for the revised models. As SENT performed slightly better according to the GRS-statistic than PSENT, it was used for a more detailed analysis, focusing on the intercepts of each portfolio as well as SENT's betas. The main finding from this analysis was that the revised model including SENT did not significantly change the explanatory power of the Fama-French five-factor model, as the model including SENT encountered the same issues as the Fama-French five factor model. Generally, the largest challenges were found in portfolios of small stocks, consistent with the patterns reported by Fama and French when proposing a five-factor model. Therefore, the deeper analysis of the portfolio testing aligned with the GRS results, showing no signs of an increase in explanatory power for the excess returns of the portfolios.

As the time-series results for individual stocks were less conclusive compared to the portfolio results, further testing was applied. Dynamic betas were introduced to analyze the excess returns of individual stocks. This part focused on whether time-varying betas could more accurately explain excess returns and determine if this method could yield more decisive results. The time-varying betas demonstrated a significant increase in both R^2 and adjusted R^2 across all models, as well as a significant decrease in average absolute alpha compared to the fixed models. The dynamic beta approach therefore showed better ability to explain the excess returns of the individual stocks. The results of the revised Fama-French five-factor model with dynamic betas, when compared to the model without the investor sentiment factor, remained somewhat consistent with those of the fixed betas. The inclusion of an investor sentiment factor increased the R^2 and adjusted R^2, even more so than with fixed betas. The average absolute alphas also increased with the addition of the investor sentiment factor, and again, more than with the fixed betas.

Thus, the outcomes of adding an investor sentiment factor to the Fama-French five-factor model are still mixed when applied to individual European stocks. The increasing absolute alphas suggest larger unexplained excess returns, while the R^2 and adjusted R^2 indicate improved explanatory power of the model including investor sentiment.

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11. Appendix

The codes used for constructing the investor sentiment factors and generating the statistics throughout this report will be provided in separate files. Additionally, the data sets for stock prices, the European five factors, and the investor sentiment proxies will also be included. The overview in 11.1 explains the content of the different files attached to the report. The appendix attached in this paper withstands of the graphs of the macroeconomic factors used for the orthogonalization of investor sentiment proxies as well as the portfolio regression results of the asset pricing model with PSENT.

11.1 Content of attached files

1. SENT.ipynb

   Python code used for the construction of SENT.
2. SENT_L.ipynb

   Python code used for the construction of SENT_L and comparison of SENT and SENT_L.
3. PSENT.ipynb

   Python code used for the construction of PSENT and comparison with SENT, EURO STOXX 600 and Baker and Wurgler's investor sentiment index.
4. PSENT_L.ipynb

   Python code used for the construction of PSENT_L and comparison with PSENT.
5. Stock test.ipynb

   Python code used for the test on the 19 non-financial European stocks, including the tests from Section 7.1, 8 and 9.
6. Portfolio test.ipynb

   Python code used for portfolio test from section 7.2 except the GRS test section 7.2.1.
7. GRS test.R

   R-studio code used for the GRS test in section 7.2.1.
8. Data PCA.xlsx

   The investor sentiment proxy data including CCI, ESI, VSTOXX, Gold price, German 3-year treasury yield, German 10-year treasury yield and the spread.
9. Stock.xlsx

   The price data for the 19 European non-financial stocks.

10. Europe_5_Factors.xlsx

The European five factor data from the Kennth R. French data library including the risk-free rate.

11.2 Plots of macroeconomic factors

The three macroeconomic factors used for the orthogonalization process for the construction of the investment sentiment factor PSENT is plotted below.

Graphs of Unemployment rate in Europe

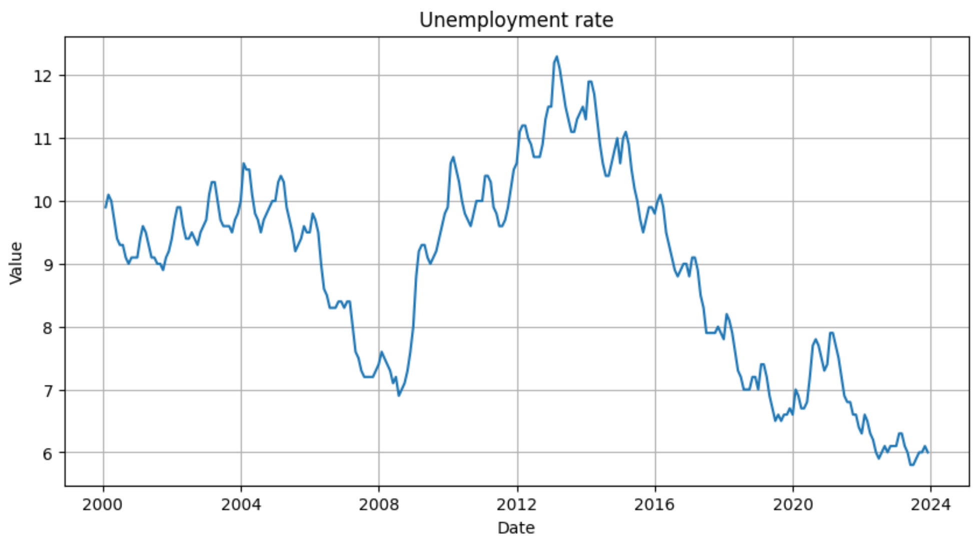

Figure 43 - Plot showing the Unemployment rate in Europe, source se section 5.1.

Graph of Industrial production Index

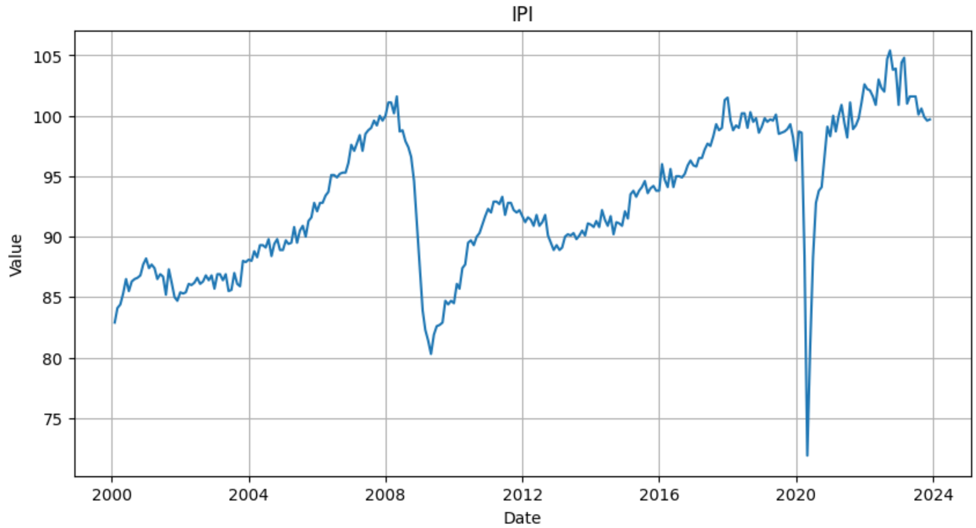

Figure 44 - Plot showing the Industrial production index, source se section 5.1.

Graph of Harmonized index of consumer prices

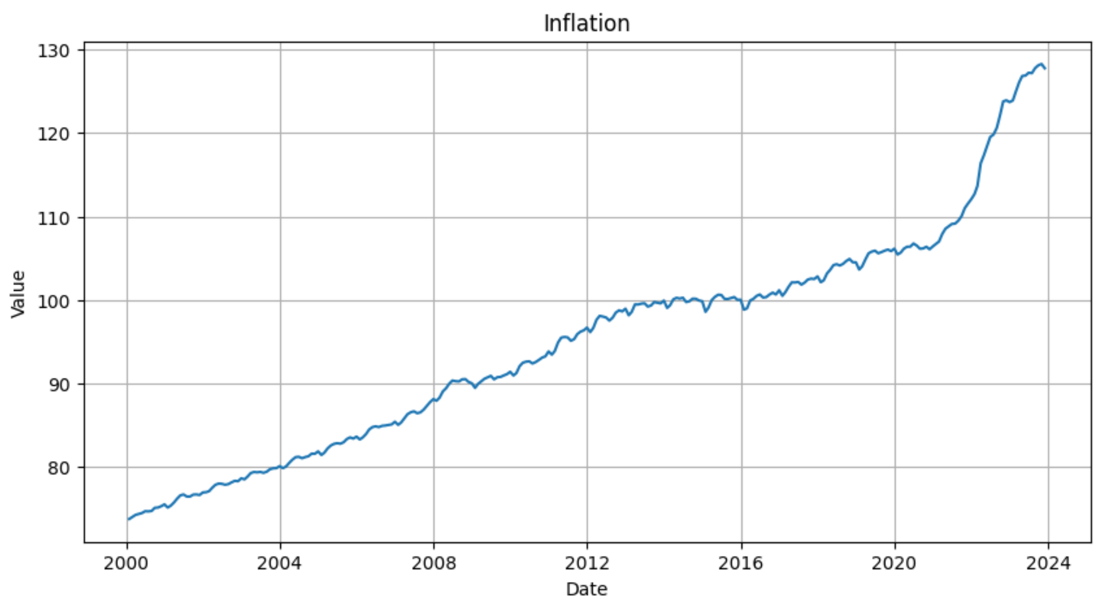

Figure 45 - Plot showing the Harmonized index of consumer prices, source se section 5.1.

11.3 Portfolio regression PSENT

Due to the delimitations outlined in section 7.2.2, the regressions of the asset pricing model including P-SENT on portfolio excess returns were not included in the report. Although the results are nearly identical to those of the model including SENT, they are therefore reported below but not discussed.

Size - B/M

B/M ->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,37	-0,08	0,03	0,02	0,15	-3,69	-0,99	0,39	0,25	2,53
2	-0,06	0,14	-0,01	-0,03	0,08	-0,66	1,84	-0,15	-0,44	1,37
3	0,21	0,07	-0,05	-0,02	0,06	2,21	0,95	-0,66	-0,24	0,73
4	0,29	0,21	0,00	-0,01	-0,12	3,37	2,31	-0,04	-0,08	-1,26
BIG	0,17	0,04	-0,01	0,01	-0,05	2,19	0,54	-0,17	0,10	-0,59
			b					t(b)		
Small	0,96	0,95	0,93	0,93	0,88	44,85	54,55	59,41	71,56	69,77
2	1,06	1,03	1,01	0,99	0,99	59,40	65,20	77,10	76,92	78,12
3	1,07	1,07	1,04	1,03	1,02	52,77	64,73	59,67	62,06	60,28
4	1,04	1,04	1,02	1,05	1,05	56,11	53,32	62,67	58,97	53,26
BIG	0,93	0,99	1,04	1,00	1,04	55,63	71,95	69,85	56,11	54,13
			s					t(s)		
Small	1,10	1,02	0,95	0,94	0,93	22,93	25,96	26,95	32,21	32,78
2	1,03	0,87	0,95	0,86	0,86	25,69	24,59	32,42	29,51	30,25
3	0,69	0,71	0,67	0,65	0,64	15,19	19,18	17,18	17,36	16,82
4	0,31	0,36	0,34	0,43	0,40	7,57	8,30	9,29	10,86	9,10
BIG	-0,31	-0,24	-0,16	-0,20	-0,20	-8,38	-7,61	-4,80	-5,06	-4,63
			h					t(h)		
Small	-0,48	-0,25	-0,13	0,04	0,29	-8,51	-5,53	-3,26	1,20	8,63
2	-0,54	-0,26	0,00	0,29	0,43	-11,52	-6,38	-0,13	8,65	13,00
3	-0,51	-0,21	0,17	0,28	0,51	-9,61	-4,95	3,80	6,48	11,50
4	-0,50	-0,23	0,07	0,29	0,69	-10,24	-4,42	1,62	6,28	13,31
BIG	-0,60	-0,29	-0,07	0,32	0,84	-13,76	-7,95	-1,92	6,98	16,64
			r					t(r)		
Small	-0,58	-0,36	-0,30	-0,06	-0,05	-8,19	-6,12	-5,74	-1,34	-1,08
2	-0,33	-0,16	0,01	0,18	0,07	-5,47	-3,08	0,16	4,23	1,58
3	-0,34	0,04	0,25	0,23	0,01	-4,96	0,69	4,25	4,10	0,16
4	-0,18	0,02	0,19	0,12	0,05	-2,95	0,36	3,50	2,04	0,82
BIG	0,03	0,27	-0,06	-0,03	-0,48	0,48	5,85	-1,15	-0,42	-7,41
			c					t(c)		
Small	-0,27	-0,21	-0,13	0,10	0,15	-3,52	-3,28	-2,29	2,13	3,23
2	-0,27	-0,14	0,09	0,06	0,20	-4,16	-2,38	1,85	1,37	4,32
3	-0,51	0,02	0,04	0,08	0,10	-6,91	0,29	0,69	1,28	1,57
4	-0,26	0,13	0,14	0,09	-0,11	-3,88	1,86	2,43	1,32	-1,47
BIG	0,01	0,32	0,20	-0,03	-0,49	0,22	6,44	3,67	-0,51	-6,97
			p					t(p)		
Small	0,02	0,02	0,08	0,07	0,06	0,25	0,30	1,59	1,79	1,44
2	-0,13	0,00	0,06	0,09	0,02	-2,43	0,01	1,47	2,30	0,59
3	0,04	-0,02	-0,04	-0,01	-0,03	0,60	-0,46	-0,83	-0,13	-0,58
4	0,03	0,07	0,08	0,03	0,09	0,51	1,11	1,59	0,51	1,55
BIG	-0,04	0,02	0,06	0,01	-0,18	-0,70	0,44	1,30	0,18	-3,11

Figure 46 - Regression results Fama French five factor model + PSENT, 25 Size B/M portfolios.

Size - OP

OP ->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,27	0,14	0,16	0,36	0,10	-3,77	2,14	2,48	5,68	1,32
2	-0,12	0,03	0,02	0,12	0,22	-1,78	0,42	0,23	1,65	2,87
3	-0,04	0,13	0,10	0,00	0,17	-0,54	1,91	1,30	0,05	2,03
4	0,02	0,03	0,00	0,23	0,12	0,19	0,40	0,00	2,79	1,51
BIG	0,05	0,16	0,10	-0,22	0,01	0,54	2,36	1,22	-3,45	0,13
			b					t(b)		
Small	0,93	0,88	0,93	0,96	0,94	60,36	64,81	68,13	71,42	56,41
2	1,00	0,97	1,03	1,04	1,06	69,82	76,33	73,26	69,66	65,44
3	1,04	1,04	1,00	1,06	1,08	61,40	69,65	63,81	61,67	60,83
4	1,06	0,97	1,07	1,04	1,05	49,31	53,10	63,02	59,47	60,99
BIG	1,04	1,01	1,02	1,01	0,93	49,10	68,90	61,91	76,57	71,62
			s					t(s)		
Small	1,05	0,89	0,97	0,94	1,00	30,40	28,97	31,57	31,17	26,89
2	0,91	0,87	0,94	0,91	0,99	28,32	30,43	29,55	27,33	27,22
3	0,68	0,63	0,73	0,68	0,73	17,76	18,81	20,82	17,54	18,31
4	0,39	0,34	0,39	0,39	0,36	7,99	8,32	10,14	10,06	9,43
BIG	-0,23	-0,22	-0,27	-0,13	-0,27	-4,89	-6,72	-7,17	-4,23	-9,16
			h					t(h)		
Small	-0,17	0,07	0,10	0,03	0,02	-4,13	1,92	2,76	0,99	0,37
2	-0,03	0,10	0,09	0,07	0,03	-0,87	3,11	2,34	1,84	0,62
3	-0,04	0,12	0,12	0,07	0,16	-0,95	3,01	2,94	1,56	3,42
4	-0,06	0,24	0,18	0,00	-0,10	-1,03	5,11	3,98	-0,03	-2,17
BIG	0,16	0,16	-0,20	0,06	-0,15	2,92	4,25	-4,60	1,86	-4,39
			r					t(r)		
Small	-0,53	-0,09	0,07	0,07	0,06	-10,26	-1,92	1,53	1,50	1,03
2	-0,41	-0,03	0,16	0,27	0,23	-8,48	-0,76	3,30	5,41	4,16
3	-0,48	0,03	0,26	0,27	0,37	-8,40	0,60	4,88	4,71	6,22
4	-0,55	0,02	0,28	0,20	0,19	-7,61	0,26	4,88	3,43	3,29
BIG	-1,09	-0,36	-0,13	0,42	0,51	-15,39	-7,40	-2,33	9,48	11,81
			c					t(c)		
Small	-0,10	0,10	0,04	0,03	-0,03	-1,81	2,04	0,88	0,68	-0,42
2	-0,14	0,10	0,18	0,05	-0,07	-2,67	2,20	3,56	0,90	-1,15
3	-0,08	0,09	-0,04	-0,01	-0,23	-1,25	1,61	-0,67	-0,19	-3,61
4	0,09	-0,04	0,01	0,00	-0,04	1,12	-0,65	0,15	0,07	-0,65
BIG	-0,33	0,00	0,21	-0,10	0,06	-4,31	-0,03	3,55	-2,12	1,35
			p					t(p)		
Small	0,01	0,06	0,06	0,08	0,11	0,23	1,45	1,37	1,90	2,11
2	0,02	0,02	0,01	0,00	-0,03	0,47	0,62	0,20	-0,03	-0,69
3	-0,06	0,00	0,11	0,00	-0,11	-1,11	-0,02	2,24	-0,02	-2,01
4	0,04	0,06	0,09	0,03	0,05	0,56	1,11	1,66	0,53	0,99
BIG	0,00	-0,06	0,06	0,11	-0,09	-0,03	-1,31	1,23	2,80	-2,32

Figure 47 - Regression results Fama French five factor model + PSENT, 25 Size - OP portfolios.

Size - Inv

INV->	LOW	2,00	3,00	4,00	High	LOW	2,00	3,00	4,00	High
			a					t(a)		
Small	-0,05	0,14	0,13	0,11	-0,22	-0,74	2,33	2,07	1,71	-2,68
2	-0,07	0,10	0,18	0,06	-0,07	-1,02	1,55	2,63	1,01	-1,03
3	0,07	0,02	0,14	0,11	-0,04	0,89	0,24	1,69	1,46	-0,48
4	-0,01	0,00	0,13	0,16	0,08	-0,11	-0,01	1,59	1,97	0,93
BIG	-0,08	0,04	-0,04	0,04	0,00	-1,12	0,52	-0,55	0,50	0,02
			b					t(b)		
Small	0,95	0,87	0,88	0,90	0,98	65,05	67,37	65,20	67,95	55,16
2	1,06	0,98	0,93	1,02	1,06	71,50	72,77	62,75	77,74	78,74
3	1,08	1,02	0,99	1,01	1,09	62,12	60,82	57,47	65,87	64,09
4	1,06	1,05	0,97	1,04	1,09	55,35	61,34	56,98	61,43	62,59
BIG	1,00	0,97	1,03	1,00	0,97	65,35	68,25	72,99	64,86	56,23
			s					t(s)		
Small	1,04	0,82	0,87	0,91	1,12	31,54	28,26	28,86	30,40	28,17
2	0,93	0,84	0,82	0,90	1,00	27,86	27,87	24,71	30,51	33,24
3	0,72	0,69	0,58	0,61	0,79	18,30	18,35	15,01	17,83	20,78
4	0,40	0,40	0,35	0,31	0,41	9,41	10,44	9,27	8,21	10,41
BIG	-0,13	-0,20	-0,19	-0,26	-0,15	-3,84	-6,18	-5,96	-7,39	-3,97
			h					t(h)		
Small	-0,07	0,08	0,17	0,06	-0,25	-1,74	2,34	4,76	1,79	-5,44
2	0,10	0,13	0,14	0,15	-0,19	2,54	3,75	3,62	4,51	-5,38
3	0,09	0,19	0,21	0,05	-0,10	2,00	4,42	4,76	1,34	-2,32
4	0,12	0,08	0,11	0,10	-0,13	2,29	1,75	2,48	2,17	-2,82
BIG	-0,08	0,02	-0,04	0,00	0,09	-2,08	0,43	-0,95	-0,02	1,92
			r					t(r)		
Small	-0,26	-0,01	0,06	-0,11	-0,48	-5,23	-0,29	1,41	-2,37	-8,15
2	-0,01	0,13	0,06	0,17	-0,32	-0,13	2,99	1,23	3,86	-7,01
3	-0,01	0,11	0,18	0,03	-0,18	-0,21	1,90	3,17	0,55	-3,17
4	0,09	0,04	0,14	0,11	-0,20	1,35	0,78	2,38	1,98	-3,51
BIG	-0,09	0,06	-0,03	0,02	0,19	-1,68	1,27	-0,65	0,35	3,31
			c					t(c)		
Small	0,33	0,25	0,01	-0,02	-0,45	6,13	5,27	0,18	-0,47	-6,96
2	0,38	0,28	0,09	-0,16	-0,45	7,06	5,77	1,60	-3,37	-9,10
3	0,32	0,28	0,07	-0,15	-0,71	4,96	4,61	1,05	-2,76	-11,42
4	0,36	0,38	0,07	-0,11	-0,72	5,09	6,02	1,06	-1,79	-11,33
BIG	0,66	0,29	0,11	-0,47	-0,55	11,86	5,60	2,20	-8,45	-8,75
			p					t(p)		
Small	0,00	0,07	-0,01	0,05	0,06	0,07	1,86	-0,26	1,33	1,14
2	-0,09	0,06	0,05	-0,05	0,03	-1,91	1,58	1,05	-1,22	0,67
3	-0,02	-0,11	0,05	0,07	-0,06	-0,32	-2,06	0,93	1,39	-1,18
4	0,00	0,03	0,05	0,04	0,05	-0,03	0,62	0,93	0,76	0,87
BIG	0,00	0,03	-0,02	-0,05	0,07	0,10	0,71	-0,46	-1,01	1,34

Figure 48 - Regression results Fama French five factor model + PSENT, 25 Size - Inv portfolios.

Size - B/M - Inv

	Small								BIG							
BM ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
	a				t(a)				a				t(a)			
Low INV	-0,12	0,06	0,13	-0,02	-1,03	0,61	1,40	-0,14	0,02	-0,18	0,10	-0,11	0,20	-1,50	0,92	-0,92
2	0,09	0,00	0,16	0,18	1,22	-0,02	2,37	1,98	0,10	0,28	0,11	0,05	0,83	2,91	0,99	0,37
3	0,10	0,12	-0,02	0,27	1,54	1,92	-0,28	2,83	0,23	0,12	-0,06	-0,10	2,03	1,09	-0,58	-0,81
High INV	-0,22	-0,21	-0,23	0,03	-3,08	-2,67	-2,44	0,18	0,22	0,01	-0,10	0,10	2,14	0,12	-0,76	0,63
	b				t(b)				b				t(b)			
Low INV	1,01	1,06	1,00	1,05	41,94	48,01	51,66	36,63	0,95	1,04	1,02	1,07	37,49	41,26	45,61	40,46
2	0,98	1,00	0,98	0,97	64,94	74,59	69,51	49,47	0,86	1,01	1,03	1,07	34,04	49,93	41,83	41,23
3	1,02	0,97	0,96	0,91	73,12	75,12	66,15	45,88	0,98	1,03	1,00	1,02	40,12	43,12	46,61	39,51
High INV	1,08	1,02	0,99	0,97	70,10	61,26	49,26	33,33	0,97	1,02	1,04	0,99	45,66	42,10	38,81	28,61
	s				t(s)				s				t(s)			
Low INV	0,93	0,86	0,93	1,13	17,23	17,23	21,29	17,58	-0,21	0,12	-0,09	0,08	-3,71	2,12	-1,70	1,35
2	0,79	0,82	0,80	0,84	23,22	27,09	25,34	19,07	-0,18	-0,16	-0,16	0,16	-3,09	-3,49	-2,92	2,70
3	0,87	0,84	0,83	0,80	27,68	28,79	25,49	17,91	-0,19	-0,24	-0,01	-0,03	-3,51	-4,55	-0,27	-0,51
High INV	1,02	0,98	0,84	1,00	29,41	26,13	18,75	15,22	-0,13	-0,04	-0,05	-0,25	-2,67	-0,82	-0,87	-3,19
	h				t(h)				h				t(h)			
Low INV	-0,38	-0,21	0,15	0,43	-6,07	-3,59	2,91	5,68	-0,67	-0,17	-0,05	0,52	-10,2	-2,51	-0,85	7,56
2	-0,28	0,09	0,24	0,37	-7,13	2,62	6,37	7,13	-0,53	-0,29	0,13	0,75	-7,89	-5,40	2,00	11,08
3	-0,18	0,12	0,40	0,52	-4,87	3,45	10,59	9,93	-0,64	-0,40	0,32	0,97	-9,94	-6,40	5,75	14,37
High INV	-0,48	0,03	0,37	0,53	-12,0	0,75	7,06	6,91	-0,16	-0,18	0,25	0,80	-2,92	-2,78	3,61	8,77
	r				t(r)				r				t(r)			
Low INV	-0,36	-0,18	-0,09	-0,09	-4,51	-2,49	-1,41	-0,99	0,16	0,25	-0,30	-0,30	1,90	3,01	-4,06	-3,35
2	-0,15	0,17	0,10	-0,01	-2,91	3,88	2,13	-0,18	-0,09	0,11	0,02	-0,26	-1,11	1,59	0,27	-3,02
3	0,04	0,16	0,29	-0,07	0,87	3,70	5,86	-0,99	-0,15	-0,08	0,17	0,06	-1,88	-0,98	2,36	0,75
High INV	-0,44	-0,17	0,05	-0,17	-8,54	-3,02	0,78	-1,71	0,23	0,00	0,16	-0,34	3,23	0,03	1,73	-2,93
	c				t(c)				c				t(c)			
Low INV	0,18	0,48	0,28	0,52	2,10	5,95	4,00	4,97	0,89	0,60	0,54	0,33	9,71	6,54	6,58	3,37
2	0,12	0,32	0,31	0,41	2,18	6,58	6,01	5,73	0,26	0,35	0,32	-0,27	2,83	4,80	3,55	-2,86
3	-0,22	0,03	0,05	0,04	-4,25	0,63	0,98	0,58	-0,04	0,44	-0,33	-0,58	-0,45	5,09	-4,15	-6,21
High INV	-0,57	-0,43	-0,37	-0,33	-10,1	-7,03	-5,04	-3,06	-0,87	-0,42	-0,18	-1,06	-11,2	-4,69	-1,87	-8,35
	p				t(p)				p				t(p)			
Low INV	-0,08	0,10	0,01	-0,07	-1,08	1,43	0,12	-0,81	-0,01	0,01	0,16	-0,15	-0,19	0,18	2,29	-1,91
2	0,03	-0,01	-0,01	-0,02	0,55	-0,33	-0,13	-0,41	0,14	0,11	0,03	0,00	1,75	1,71	0,45	0,02
3	0,00	0,07	0,05	0,05	-0,02	1,69	1,04	0,80	-0,17	0,05	-0,04	-0,03	-2,30	0,62	-0,56	-0,39
High INV	-0,03	0,04	0,22	0,00	-0,62	0,76	3,54	-0,04	-0,06	0,17	0,06	-0,08	-0,90	2,26	0,77	-0,76

Figure 49 - Regression results Fama French five factor model + PSENT, 32 Size - B/M - Inv portfolios.

Size - B/M - OP

	Small								BIG							
BM ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
	a				t(a)				a				t(a)			
Low OP	-0,61	-0,72	-0,27	-0,21	-3,78	-3,81	-1,72	-1,13	0,30	0,05	0,29	0,06	1,01	0,24	2,36	0,66
2	-0,34	-0,13	-0,01	0,08	-2,52	-1,43	-0,08	1,02	0,17	0,35	-0,01	0,01	0,92	3,33	-0,16	0,10
3	-0,01	0,10	0,04	0,39	-0,13	1,69	0,79	4,29	0,06	0,02	-0,17	-0,17	0,48	0,19	-1,52	-1,16
High OP	0,10	0,06	0,23	0,30	2,02	0,98	2,83	1,44	0,10	-0,33	-0,06	-0,10	1,37	-2,74	-0,33	-0,35
	b				t(b)				b				t(b)			
Low OP	1,03	1,08	0,93	1,03	30,05	27,01	28,39	25,84	1,04	1,10	1,04	0,99	16,69	27,02	39,47	48,40
2	0,97	0,97	0,95	0,94	33,57	50,59	51,69	56,21	1,02	0,96	1,03	1,04	25,27	42,70	53,27	44,35
3	1,04	0,98	0,97	0,98	58,13	78,23	83,25	50,62	0,98	1,00	1,02	1,09	39,22	51,43	42,57	34,79
High OP	1,04	1,02	1,03	1,01	99,40	82,31	60,56	22,69	0,94	1,04	0,98	1,11	59,60	40,78	26,77	17,63
	s				t(s)				s				t(s)			
Low OP	1,27	1,28	1,11	1,19	16,51	14,21	15,15	13,35	0,00	0,08	-0,08	-0,04	0,03	0,82	-1,28	-0,80
2	0,74	0,82	0,72	0,83	11,37	18,94	17,50	22,14	-0,15	-0,22	-0,05	-0,01	-1,61	-4,32	-1,21	-0,27
3	0,89	0,83	0,85	0,86	22,12	29,45	32,17	19,68	-0,04	-0,16	-0,08	-0,06	-0,64	-3,57	-1,48	-0,88
High OP	0,89	0,85	0,91	1,14	37,91	30,44	23,82	11,43	-0,26	0,02	-0,27	0,34	-7,36	0,43	-3,34	2,37
	h				t(h)				h				t(h)			
Low OP	-0,84	-0,34	0,25	0,20	-9,37	-3,24	2,93	1,94	-0,97	-0,57	-0,15	0,63	-5,92	-5,37	-2,21	11,67
2	-0,55	-0,16	0,11	0,50	-7,21	-3,19	2,22	11,39	-0,56	-0,46	0,21	0,95	-5,27	-7,75	4,07	15,42
3	-0,45	-0,01	0,35	0,47	-9,66	-0,30	11,46	9,17	-0,55	-0,17	0,28	0,72	-8,34	-3,27	4,44	8,76
High OP	-0,20	0,29	0,53	0,51	-7,20	8,78	11,81	4,36	-0,40	0,20	0,61	0,45	-9,76	3,00	6,35	2,71
	r				t(r)				r				t(r)			
Low OP	-1,26	-0,66	-0,40	-0,79	-11,0	-4,89	-3,66	-5,94	-0,89	-0,89	-0,66	-0,76	-4,28	-6,51	-7,53	-11,1
2	-0,82	-0,33	-0,06	-0,05	-8,51	-5,18	-0,91	-0,81	-0,02	-0,30	0,01	-0,02	-0,13	-3,96	0,12	-0,30
3	-0,31	0,05	0,25	0,13	-5,22	1,12	6,29	2,04	0,01	0,14	0,32	0,25	0,15	2,10	4,05	2,39
High OP	0,10	0,36	0,36	0,07	2,88	8,54	6,26	0,46	0,28	0,80	0,56	0,29	5,24	9,29	4,61	1,36
	c				t(c)				c				t(c)			
Low OP	-0,44	-0,39	-0,23	0,25	-3,54	-2,66	-1,92	1,75	-0,30	0,45	0,24	-0,44	-1,32	3,06	2,52	-5,97
2	-0,43	0,09	0,19	0,17	-4,08	1,34	2,76	2,78	0,14	0,30	0,01	-0,26	0,95	3,68	0,19	-3,03
3	-0,12	0,20	0,14	0,21	-1,83	4,39	3,31	2,93	-0,13	0,28	0,19	-0,14	-1,46	3,90	2,13	-1,19
High OP	-0,14	0,04	0,06	0,31	-3,75	0,94	0,91	1,93	0,04	0,03	-0,24	0,14	0,75	0,29	-1,81	0,63
	p				t(p)				p				t(p)			
Low OP	-0,10	-0,02	0,05	-0,08	-0,95	-0,14	0,46	-0,66	-0,15	0,11	0,21	-0,03	-0,78	0,89	2,61	-0,55
2	-0,03	0,01	0,12	0,06	-0,29	0,09	2,13	1,26	-0,08	0,10	-0,02	-0,14	-0,67	1,46	-0,31	-1,92
3	-0,02	0,09	0,05	0,00	-0,34	2,25	1,33	-0,02	0,18	0,10	0,12	-0,13	2,31	1,66	1,62	-1,34
High OP	0,00	0,03	0,00	-0,24	0,14	0,70	-0,01	-1,76	-0,09	-0,02	-0,27	-0,07	-1,90	-0,20	-2,40	-0,35

Figure 50 - Regression results Fama French five factor model + PSENT, 32 Size - B/M - OP portfolios.

Size - Inv - OP

	Small								BIG							
OP ->	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**	**LOW**	**2,00**	**3,00**	**High**
		a				t(a)				a				t(a)		
Low INV	-0,18	0,00	0,16	0,11	-1,23	0,03	1,71	1,08	-0,01	0,08	-0,12	-0,04	-0,11	0,76	-1,11	-0,38
2	-0,39	0,20	0,11	0,16	-1,68	2,70	2,05	2,50	0,23	0,18	0,04	-0,02	1,76	1,68	0,40	-0,20
3	-0,27	0,00	0,17	0,17	-1,37	-0,02	3,79	3,41	0,20	0,06	-0,05	0,08	1,46	0,58	-0,40	0,75
High INV	-0,84	-0,42	-0,15	0,05	-4,89	-4,52	-2,13	0,61	0,08	0,10	-0,08	0,02	0,53	0,77	-0,65	0,19
		b				t(b)				b				t(b)		
Low INV	1,01	1,02	1,01	1,04	31,97	55,43	51,21	48,59	1,04	1,05	1,01	0,97	44,53	45,70	42,33	44,35
2	1,08	0,92	1,00	1,00	22,21	59,34	84,48	75,49	1,08	1,02	1,00	0,89	39,80	46,14	42,42	41,35
3	0,94	0,90	0,95	1,03	22,21	52,03	100,5	98,26	0,97	1,00	1,03	1,03	33,99	42,19	41,33	45,40
High INV	1,07	1,03	1,05	1,06	29,32	51,82	68,23	65,99	1,09	0,97	1,04	0,98	32,74	34,10	40,39	40,84
		s				t(s)				s				t(s)		
Low INV	1,17	0,89	0,90	0,84	16,37	21,58	20,29	17,40	0,04	-0,10	-0,02	-0,07	0,76	-1,91	-0,46	-1,51
2	1,20	0,71	0,84	0,80	11,00	20,52	31,69	26,67	-0,05	-0,17	-0,13	-0,06	-0,80	-3,38	-2,47	-1,19
3	0,97	0,70	0,83	0,91	10,18	18,11	39,43	38,65	-0,14	-0,13	-0,11	-0,20	-2,13	-2,44	-1,87	-3,88
High INV	1,34	0,91	0,96	1,03	16,28	20,48	27,98	28,67	-0,06	-0,07	0,04	-0,20	-0,77	-1,12	0,66	-3,71
		h				t(h)				h				t(h)		
Low INV	-0,51	0,10	0,06	0,24	-6,16	2,05	1,13	4,34	0,11	0,00	-0,09	-0,28	1,71	0,03	-1,43	-4,89
2	-0,05	0,08	0,14	0,18	-0,37	1,96	4,60	5,04	0,04	0,12	0,04	0,02	0,62	2,07	0,59	0,41
3	0,19	0,23	0,19	0,10	1,69	5,05	7,61	3,76	0,34	0,08	-0,13	-0,31	4,59	1,25	-2,04	-5,21
High INV	-0,52	-0,03	-0,02	-0,11	-5,41	-0,51	-0,61	-2,51	-0,19	0,21	0,14	0,08	-2,16	2,80	2,15	1,26
		r				t(r)				r				t(r)		
Low INV	-1,06	-0,23	0,05	0,29	-9,92	-3,79	0,76	4,09	-0,77	-0,26	0,25	0,48	-9,75	-3,40	3,18	6,51
2	-0,44	-0,14	0,08	0,29	-2,67	-2,75	2,05	6,44	-0,96	-0,16	0,26	0,50	-10,5	-2,22	3,29	6,97
3	-0,64	-0,16	0,17	0,31	-4,50	-2,78	5,29	8,94	-0,72	-0,11	-0,01	0,32	-7,48	-1,33	-0,08	4,13
High INV	-0,95	-0,38	-0,14	0,01	-7,76	-5,73	-2,65	0,20	-0,91	0,10	0,34	0,46	-8,12	1,01	3,97	5,78
		c				t(c)				c				t(c)		
Low INV	0,27	0,46	0,41	0,17	2,34	6,84	5,68	2,17	0,45	0,64	0,62	0,63	5,25	7,59	7,09	7,84
2	0,17	0,39	0,34	0,20	0,98	6,91	7,89	4,14	0,01	0,06	0,45	0,09	0,11	0,71	5,23	1,17
3	-0,69	-0,03	0,02	-0,10	-4,49	-0,50	0,46	-2,59	-0,57	-0,13	0,01	0,19	-5,42	-1,44	0,06	2,28
High INV	-0,60	-0,52	-0,41	-0,48	-4,53	-7,18	-7,37	-8,16	-0,52	-0,69	-0,63	-0,77	-4,29	-6,67	-6,75	-8,83
		p				t(p)				p				t(p)		
Low INV	-0,06	0,05	-0,06	0,00	-0,67	0,81	-1,02	0,05	0,08	-0,07	0,12	0,03	1,06	-1,06	1,58	0,49
2	-0,11	0,00	0,01	-0,02	-0,75	0,06	0,25	-0,44	0,08	-0,03	0,17	0,03	0,99	-0,50	2,30	0,39
3	0,19	0,09	0,05	0,00	1,49	1,68	1,66	-0,02	-0,12	0,10	-0,02	-0,13	-1,34	1,41	-0,26	-1,86
High INV	-0,08	-0,02	0,08	0,03	-0,71	-0,25	1,65	0,71	0,10	0,00	0,22	-0,10	0,95	-0,04	2,76	-1,34

Figure 51 - Regression results Fama French five factor model + PSENT, 32 Size - Inv - OP portfolios.