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Investor sentiment in the European stock market

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ABSTRACT

In this paper, I study whether investor sentiment has a negative effect on stock returns in the European markets in the period 2017 to 2022. I used data from stocks in the Euronext index and I construct four proxies and the investor sentiment index Europe (ISIE) to capture investor sentiment. The effect is measured with a multivariable panel regression model, where the proxies and ISIE are examined against the stock returns of the Euronext index. I find results that indicate a positive relationship of investor sentiment with stock returns. This indicates that investors in European markets need to consider the effect of investor sentiment in their predictions. The model which looks at weekly stock returns proved to be the most significant.

Keywords: Stock returns, Investor sentiment, Asset pricing, European markets.

JEL codes: G40; G12; G15.

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CHAPTER 1 Introduction

In the field of finance and investments, studying the behavior of investors is one of the most essential issues for a better understanding of financial markets. One aspect of the numerous sorts of behaviors that investors show is overall sentiment. Investor sentiment is broadly defined as the aggregated beliefs, mood, and attitudes of investors towards the financial markets. This collective of beliefs can affect prices and their movements in different sectors. In addition, investor sentiment can among other things be influenced by the tone of the media. Tetlock (2007) finds a significant pattern between unusual high or low pessimism of the media and stock trading volumes. Furthermore, investor sentiment is influenced by various factors such as news events, economic indicators, and market trends Baker and Wurgler (2006). These external factors play a role in shaping the sentiment of investors which in turn affect different financial markets. One of those financial markets where investor sentiment can play a significant role is the stock market. The effect of investor sentiment on stock performance is a highly discussed topic in the field of finance. It is essential for investors, fund managers, and financial analysts looking to make informed investment decisions.

Recent empirical research on the effect of investor sentiment on stock performance has found a significant effect of investor sentiment on excess returns, with small stocks being more vulnerable for investor sentiment than large stocks, Yang and Zhou (2015). Similar, Bollen et.al. (2011) demonstrates that the public mood, measured on the social media platform Twitter, can predict stock returns for the Dow Jones Industrial Average. Furthermore, Schemling (2009) investigates the effect of investor sentiment on a global scale with different countries outside of the US. This study found a negative relation between consumer confidence, a proxy for investor sentiment, and the aggregate stock market returns on average across countries. A high sentiment led to a lower future return in the stock markets, while low sentiment led to a higher return in those markets. According to Yang and Zhou (2015), investor sentiment has shown to be a significant predictor for stock returns with the three factor-model of Fama and French (1993). This underlines the importance of investor sentiment in the context of asset pricing models and predictors. Investor sentiment could contribute to such models for a better understanding of asset pricing and stock returns.

Previous literature has used different proxies to measure investor sentiment for different financial markets. Investor sentiment is difficult to measure correctly for different countries. Schemling (2009) uses consumer confidence as a proxy for investor sentiment. Furthermore, Lemmon and Portniaguina (2006) use an index for consumer sentiment, which is the result of a survey about the future financial expectations of people. These two methods lack a more financial approach for measuring investor sentiment. Therefore, this paper uses the investor sentiment index (ISI) with four proxies to measure investor sentiment based on Yang and Zhou (2015): relative strength index (RSI), psychological line index (PSY), trading volume (VOL) and adjusted turnover rate (ATR). This comprehensive method of measuring investor sentiment has only been applied to the Shanghai market, which differs financially and in size from those in Europe and will therefore be used in this paper. Previous empirical research was more exclusively focused on financial markets in the US and China with limited research on European markets. These markets could show different results than those found in the US and China, due to political, cultural, and foremost fundamental financial differences. Hence, this paper is studying investor sentiment in Europe. Schemling (2009) researches the European market. However, this paper is limited by data from only 14 separate European countries and a dataset for those countries from 1985 till 2005. In recent years, big political and financial events have occurred which could have affected investor sentiment. For example, the fear element of the impact of Covid 19 on consumer behavior and the Russian invasion of Ukraine in 2022. This could show different results on the relationship between investor sentiment and stock returns in a more recent period. Therefore, this paper will look at data from the past five years with a more sophisticated dataset. Hence, the hypotheses of this paper: How does investor sentiment effect the stock returns in the European financial markets in the period 2017-2022?

The data used in this paper contains information on stock opening and closing prices, trading volume, shares outstanding and stock returns. This paper looks at stock data for the period 2017-2022 in European markets. The information on the stocks of each firm will be obtained from Compustat Global and the stock returns are based on the Euronext Index. The latter captures large and mid-cap representation across several markets in Europe and contains 165 constituents. Compustat Global contains annual and quarterly data, since 1986 and 2003 respectively, from more than 80 countries outside of the US and Canada. In addition, I use the Yahoo Finance database to obtain stock prices and volume from the Euronext index. This acquired data on the stocks in Europe will be used to determine the proxies for investor sentiment: RSI, PSY, VOL and ATR. RSI is a market indicator which shows if the market is oversold or overbought. It can be measured with the relative closing prices of the stocks. PSY looks for trend change by dividing the number of days the closing price of a stock at time t is higher than the closing price of a stock at time t – 1. VOL is the trading volume of a stock. The ATR is measured by multiplying the positive or negative return relative to the VOL divided by the shares outstanding. Each proxy will be measured with the data from Compustat for the period 2017-2022. In addition, I create an index variable of the combined investor sentiment proxies named investor sentiment index Europe (ISIE). To determine the effect of investor sentiment on stock performance, this paper makes use of market-level panel regression analysis following ordinary least squares regression (OLS) with log stock returns as dependent variable. Furthermore, the four proxies of investor sentiment will be added to the three-factor model of Fama and French (1993) together with a momentum return factor to measure the predictability of investor sentiment on stock returns in

European markets. The factors of Fama and French and the momentum return factor will be measured with the data from the Kenneth R. French database in the period 2017-2022. This database contains all the established factors of Fama and French for both the US market and international markets.

My expectation is that investor sentiment is a significant predictor for stock returns in European markets in 2017 to 2022. I hypothesize that investor sentiment, based on the four proxies RSI, PSY, VOL and ATR, has a negative and significant effect on stock returns and enhances the traditional three-factor model along with momentum for stock performance. Previous papers have shown that this effect is significant in US and Asian markets; this paper could show a different result in Europe in the period 2017 to 2022. Furthermore, the results could contribute to the present models on asset pricing and stock predictability and optimalization of investments in European portfolios. However, I expect that the underlying proxy for investor sentiment could be constructed in many ways and certainly leave room for future research to determine the most correct measurement for each market.

CHAPTER 2 Theoretical Framework

2.1 Investor sentiment

In academic literature, sentiment is often placed with one's beliefs and or feelings (positive or negative) towards a certain topic. Sentiment is seen as an immanent result of human emotion or desires and can be briefly defined as a settled opinion reflective of one's feelings, Pang and Lee (2008). In context for investors, this definition can be broadened to the investor's feelings, beliefs, or attitude towards the financial markets. According to Baker and Wurgler (2007), investor sentiment is a circumstance where the investors follow a belief that is not justified by the facts that are presented to them. This concerns beliefs about investments risks and future cash flows.
Investor sentiment can be seen as part of an individual's bias or irrationality. According to behavorial economics theory, investors are often flawed in their financial decisions due to several biases. These biases, such as overconfidence and optimism, are something investors should look out for when making investment decisions, Kahneman and Riepe (1998).

Zweig (1973) introduces the idea of investor expectations affecting the financial markets. This paper constructs the Theory on Investor Expectations using closed-end fund premiums. Lee et al. (1991) follows this idea by introducing investor sentiment as a factor to explain an anomaly in closed-end funds. They find that the observed closed-end funds typically sell at discounts with no plausible explanation in traditional theory. When accounting for investment sentiment in the market they find a significant effect causing a lower net asset value (NAV).

In addition, early papers have shown that investor sentiment influences volume and pricing of initial public offerings (IPOs). Lowry (2003) examines volume of IPOs that seem to fluctuate substantially over time. This research finds trough variations in the level of optimism of investors a significant effect on fluctuations in volume. Derrien (2005) expands to this finding by examining demand from individual investors for IPOs. The more appreciative sentiment by individual investors at time of the offering, the more influence on IPO prices and long-term performance.

2.2 Stock pricing and returns

In financial literature, pricing stocks and estimating returns is fundamental for investors looking for arbitrage in stock options and optimize their portfolios. There is a large body of theoretical framework covering the concepts of asset valuation. According to traditional asset pricing theory, the fundamentals cash flows and discount rates determine the different results in stock returns, Fama & French (1993). They examine a three-factor model to explain excess stock returns with the use of the size factor (SMB), book-to-market factor (HML), and the overall market factor (RMRF). They find significant influence of these factors to the variation in stock returns. Fama & French (2015) expand this older model by adding two more factors which have a suggested affiliation with stock returns: the profitability and investment factor. They failed, however, to explain the variation of low returns on small stocks. Carhart (1979) adds a momentum factor (WML) to the three-factor model which shows to be significant predictor for stock returns and an enhanced version of the previous three-factor model.

One of the first inquiries on asset pricing and stock price behavior is the CAPM model, Sharpe (1964) and Linter (1965). The CAPM model consists of the risk-free rate and the market risk premium which is adjusted by the beta coefficient. These factors are based on systematic and unsystematic risk and covariance of the expected returns of an asset. The authors created a simplified version of stock price behavior based on homogenous investor expectations, assumed they are equivalent with the market itself.
One of the early papers on stock price movements and expected returns contains the idea of the efficient market hypotheses (EMH), closely associated with Fama (1970). The EMH, or Random Walk Theory, states that all current stock prices reflect all the available information of the firm. This implicates that excess returns above market are unreachable for investors. The Arbitrage Pricing Theory (APT) contributes to the explanation of stock price movements differing from the previous risk based CAPM model, Ross (1976). The APT includes multiple factors to explain stock returns in terms of arbitrage pricing instead of only the systematic risk of the previous CAPM model.

Later studies on stock price behavior focused on the psychological side of investors attempting to explain anomalies in prices and returns forecasts. Schiller (2003) incorporated the idea of psychological factors that could shape the decisions of investors in asset pricing and explain the anomalies found in expected stock returns. In his paper, he contradicts the idea of the efficient capital market where all genuine information is reflected by changes in prices. Instead, he proposes a more psychological and social view offered by the developing field of behavioral finance.

2.3 Investor sentiment and expected stock returns

In behavioral finance, several papers study the relationship with investor sentiment on stock performance. Investor sentiment is frequently closely associated with investor attention and consumer confidence. In accordance with most financial research, this relationship has mostly been studied for stock markets in the US. One of the first papers that builds a model around this relationship describes the anomaly of underreaction to news such as earnings announcements and overreaction of stock prices to a series of good or bad news, Barberis et al. (1998). They establish a relationship between investor sentiment, which seems to be the reason for under and overreaction of the studied market, and stock returns. However, they do not provide any direct evidence trough statistical evidence themselves, other than stating findings from previous empirical research. Baker en Wurgler (2006) provide direct significant evidence for the effect of investor sentiment on the cross-section of stock returns. In this paper, six different proxies were used to capture investor sentiment: the NYSE share turnover, the average closed end-fund discount, the number and average first day returns on IPO's, the equity share in new issues, and the dividend premium. They show that when sentiment is relatively low, stock returns across different types of stocks tend to be high. When sentiment is high the vice versa takes place. The empirical results including the proxies used for investor sentiment were based on data from the US stock markets between 1962 trough 2001. In addition, that stocks that are difficult to arbitrage or value are mostly affected by investor sentiment, Baker and Wurgler (2007). Huang et al. (2014) study the relationship between investor sentiment and stock performance with an amended version of the previous six proxies established by Baker and Wurgler (2006). They find a significant relationship on an aggregate stock market level and better predictability than most macroeconomic variables. This significant predictability of investor sentiment on stock returns seems to be a result of beliefs by investors on future cash flows, not discount rates. In Da et al. (2011), the search volume index (SVI) establishes investor attention- or sentiment- based on frequency in Google searches. They find an increase in stock prices in 2 weeks after the occurrence of a high SVI. Furthermore, IPO stocks tend to have a long run underperformance along with a large first-day return due to increase in investor attention. Brown and Cliff (2005) find significant impact of investor sentiment on stock returns in the next 1-3 years. Their methodology contains data from a survey on investor expectations on the market -based on 'bearish' or 'bullish' newsletters- which is used as a proxy for investor sentiment. They show that future returns are negatively related to investor sentiment over a span of multiple years. Lemmon and Portniaguina (2006) analyze stock returns using surveys on consumer confidence to measure the investor sentiment of the market. They find significant forecasting abilities of investor sentiment on returns of small-stocks and in particular stocks which are held by individuals.

Research outside of the US stock markets seem to show familiar results on the significance of this relationship. Schemling (2009) studies 18 countries outside of the US with an estimation of consumer confidence as a proxy for investor sentiment. They find a significant predictive power of investor sentiment for stocks with a relative short to medium horizon (one to six months). The relationship of investor sentiment with expected tock returns is negative: high sentiment leads to low returns and vice versa. This relation seems to work for small, growth and value stocks. They address the substance of cultural and institutional factors which could shape the amount of impact sentiment has stock returns. Baker et al. (2012) takes indices from six stock markets: US, Japan, Germany, France, UK and Canada. They construct different proxies for investor sentiment for each country based on 'the volatility premium', volume of IPO's and their first-day initial returns. This results in a finding that investor sentiment seems to predict the time series of cross-section international stock market returns as well as international market by country-level returns. They create a global sentiment index which appears to influence and predict market-level returns on an economically significant level. The local sentiment, for each studied country, has an even greater effect on stock returns. Leaving the US out of the total sentiment led to the same results.

My paper is from a method perspective probably closest to the research on investor sentiment affecting the Shanghai Stock Exchange (SSE) by Yang and Zhou (2015). They study investor sentiment using four different proxies that consist of different financials. They find a significant relation for investor sentiment and investor trading behavior on excess stock returns. In addition, the affects seem to be greater for growth portfolios than value portfolios. They note that returns of small stocks are explained by investor trading behavior and sentiment in their model, which contradicts the findings and substantiations of Fama & French (1993, 2012, 2015). Their findings in the SSE seem to correspondingly reflect those of earlier studies in the US, Canada, and Europe.

In accordance with the earlier empirical results, my expectation is that there is a significant relationship between investor sentiment and stock returns. This relation should be negative: a high sentiment leads to lower stock returns and vice versa. While previous literature is more focused on US markets and sentiment could depend on cultural and institutional factors, I expect this effect to be significant for markets in Europe, which reflects the results of Schemling (2009). Therefore, my hypothesis is the following:
H1: *Investor sentiment has a significant negative impact on stock returns in European markets in the period 2017-2022.*

CHAPTER 3 Data

In this paper I will be studying two different components: Investor sentiment and stock returns. Prior work has shown that there is no flawless way to fully capture investor sentiment in a single variable. I will be looking at a more financial approach to this obstacle by using different proxies based on fundamentals of stock prices. These proxies form the investor sentiment index Europe (ISIE) as studied by Yang and Zhou (2015). They suggest four proxies: the adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI), and the trading volume (VOL). The stock returns to reflect the market portfolio will be measured based on the Euronext Index (Euro's), which captures the financials of 165 companies in Europe. These companies are listed on several stock exchanges throughout Europe and reflect all sorts of markets. Countries which are included are: the Netherlands (AEX), Belgium (BEL 20), France (CAC 40), Ireland (ISEQ 20), Italy (FTSE MIB), Portugal (PSI 20), and Norway (OBX 25). These financials are gathered from the Compustat Global database together with data from Yahoo Finance on historical stock prices. The returns from the Euronext Index are daily and computed from the period January 2017- December 2022.
In addition, the proxies for investor sentiment are complemented with factors from the Fama & French (1993) paper. These are the RMRF (market excess returns) factor, the SMB (small-minus-big returns) factor, and the HML (high-minus-low returns) factor. I add an extra control variable which reflects momentum to the model (MOM). The data for these factors is acquired from the Data Library by Kenneth R. French, which mainly focuses on research within the US on computed portfolios with these factors. However, it does contain data on the European FF (Fama and French) three factors and momentum (MOM) in the period July 1990- April 2023. This is based on daily, monthly, or annual returns from European markets. Since the gathered returns of the Euronext index are of a daily measure to fully capture the price movements in recent period, these factors together with the proxies for investor sentiment follow the same level of measure. The number of observations for each variable is 1413, which consists of the number of days in between January 2017- December 2022, not including weekends and shortages due to missing values in the available dataset.

The adjusted turnover rate (ATR): the adjusted turnover rate is based on the investor sentiment index in Yang and Zhang (2014). In prior literature, the turnover rate to be a possible predictor for stock returns. Datar et al. (1998) uses the turnover rate as a proxy for liquidity in the market which in turn can influence stock prices and returns. They find a strong relation of turnover rate with stock performance. Baker and Stein (2004) and Ho & Hung (2009) use a high share turnover as a proxy for market liquidity. They find a strong relationship between the liquidity and stock returns. The liquidity of the market can be an indicator for sentiment. An exceptional liquid market is one where there are many irrational investors who tend to be relatively positive. This can be seen as a reflection of a 'bullish' market. An illiquid market is in turn an indicator that irrational investors are relatively negative, which indicates a 'bearish' market. Therefore, the turnover rate can be used to reflect investor sentiment. The adjusted turnover rate which I will use as a proxy for investor sentiment is defined as follows:

$$ATR_{it} = \frac{Ret_{it}}{|Ret_{it}|} \times \frac{VOL_{it}}{Shares\ outstanding_t}.$$

where Ret_{it} is the logarithmic of return of stocks from the Euronext index at time t, and VOL is the trading volume of the stocks at time t. The turnover rate is a fraction of the trading volume of the stocks at time t divided by the shares outstanding at time t. If the return of stock is positive, the adjusted turnover rate should be positive which reflects a bullish market where irrational investors tend to be positive. If the return of stock is negative, the adjusted turnover rate should reflect a bearish market. The ATR is, together with the other three proxies, constructed from daily data from the Euronext index, reflecting 165 companies. The number of observations, as seen in the summarized statistics in Table 3.1, is 1413 and reflects the daily observations which is the same for each variable.

The psychological line index (PSY): the psychological line index reflects the number of days I which the stock prices rise over the total trading period. Ryu et al. (2016) uses the PSY as a proxy for investor sentiment and find a significant relationship with stock returns. The PSY reflects who is in control in the market, the buyers, or the sellers. An average PSY of above 50% indicates a higher buyer power than sell power and vice versa. This indicates if the market is overbought or oversold, which reflects investor sentiment. The psychological line index can be defined as follows:

$$PSY_{it} = \frac{CloseHigh_n}{T_n} \times 100.$$

where $CloseHigh_n$ reflects the number of days in which the closing price of a stock at time n is higher than the closing price at time n-1, and T_n is the trading period. I will measure the PSY using a trading period of each 14 days in the period 2017-2022.

The relative strength index (RSI): the relative strength index is an indicator which shows if the market is overbought or oversold. It is based on momentum and follows price movements in the market. If the RSI is above 70 it indicates an overbought market and an oversold market for a level of below 30. The relative strength index can be defined as follows:

$$RSI_t = \frac{RS_t}{(1 + RS_t)} \times 100;$$

$$RS_t = \frac{\sum_{t=1}^{14} \max\,(P_t - P_{t-1}, 0)}{\sum_{t=1}^{14} \max\,(P_{t-1} - P_t, 0)}.$$

where RS_t reflects the ratio between the positive average gain and average loss at time t over the last 14 days. P_t is the closing price of a stock at time t, and P_{t-1} is the closing price of a stock at time t - 1. *The trading volume (VOL)*: the trading volume of a stock can reflect sentiment of investors. Liu (2015) studies the effect of market liquidity on stock returns and uses proxies for trading volume. A higher sentiment in the market would lead to an increase in trading volume by uninformed investors. Siganos et al. (2014) show a relationship between trading volume and sentiment, where an increase in trading volume could lead to negative sentiment by investors. Therefore, I will be using trading volume as a proxy for investor sentiment. Together with the other three proxies, the trading volume will form the investor sentiment index (ISI) as proposed by Yang and Zhou (2015).

Table 3.1 provides the summery statistics of the four proxies used for this analysis. Each variable is continuous, and the total number of observations is 1413 for each variable. Notable is the low mean of the adjusted turnover rate (ATR) of 0.003 with a relatively high standard deviation of 0.043. The mean of trading volume (VOL) is 2.062e+08 and shows a considerable difference in lowest and largest trading volume, which could indicate some outliers. The means of the psychological line index (PSY) and relative strength index (RSI) are relatively close to each other with 54.974 and 54.895 respectively. They both represent if the market is overbought or oversold, so one can expect some similarities in the variable statistics. The RSI shows a considerable difference in lowest and biggest value which are 4.588 and 96.521 respectively. This could indicate some outliers for this variable or could show the volatility of the market given the measured time frame of 14 days.

Table 3.1 Summary statistics of the investor sentiment proxies ATR, PSY, RSI, and VOL.

	Obs.	Mean	Std. Dev.	Min.	Max.
ATR	1413	.003	.043	-.153	.187
PSY	1413	54.974	13.016	21.429	85.714
RSI	1413	54.895	17.254	4.588	96.521
VOL	1413	2.062e+08	79470116	2077300	9.405e+08

Note: This table represents the summery statistic of the four proxies for sentiment adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI) and trading volume (VOL) on the Euronext index in the period 2 January 2017 to 30 December 2022. The number of observations for each variable is the number of days, 1413, measured in this period.

Furthermore, I will use the three factors RMRF, SMB and HML together with an extra control variable momentum (MOM) to measure the ability of the investor sentiment proxies to predict stock returns from the three-factor model of Fama & French (1993). In prior literature, they have been widely used in the field of asset pricing to predict stock returns and capture price movements. These factors will be used in the market-level panel regression analysis following ordinary least squares regression (OLS) with stock returns of the Euronext index. These factors are all put together through the data library of Kenneth R. French.

The market excess returns factor (RMRF): the market excess returns factor captures a premium which the market return has over the risk-free rate. This is usually described as excess returns by the market portfolio and is computed by subtracting the market rate of return with the risk-free rate of return. The number of observations for this factor and the other three factors correspond to the proxies for investor sentiment with a total of 1413 observations.

The Small Minus Big return factor (SMB): the small-minus-big return factor captures the difference in small-cap stocks over the large-cap stocks in returns. Small-cap stocks tend to outperform large-cap stocks, affecting portfolio performance. This factor captures the difference between weighted average returns of portfolios based on small stocks and portfolios of big stocks.

The High Minus Low return factor (HML): the high minus low return factor captures the value premium. Firms with value stocks, that is a high book-to-market ratio, tend to outperform firms with growth stocks. The difference in weighted-average returns between portfolios based on firms with value stocks and firms with growth stocks in captured in this factor.

The Momentum return factor (MOM): the momentum return factor captures the tendency of stocks to perform well after a period of high returns and vice versa. This factor from the Kenneth R. French database is based on the momentum factor proposed by Carhart (1997): winners minus losers returns (WML). WML reflects the difference in weighted-average returns between winner portfolios and loser portfolios.

Log returns LnRET: the logarithmic returns are based on The Euronext Index. To measure the power of predictability of the investor sentiment proxies, the log returns are constructed based on a t + 1 period. This means that the daily model measures the effect of investor sentiment on stock returns one day after a negative or positive observed sentiment.

The investor sentiment index Europe (ISIE): the investor sentiment index Europe is constructed using principal component analysis (PCA) shown in Table 5.4 of the appendix. It is based on the four proxies Adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI) and trading volume (VOL). The ISIE reflects the investor sentiment index (ISI) by Yang and Zhou (2015).

Table 3.2 provides the summary statistics of the three factors RMRF, SMB and HML together with the momentum factor (MOM). In addition, this table contains the log returns of the Euronext index. The key statistics are the means and standard deviations for the factor and log returns. The market excess return factor (RMRF) has a mean of 0.028 with a relatively high standard deviation of 1.12, which describes a volatile market. This factor shows a relatively large range between the minimum and maximum value, which are -6.34 and 8.46 respectively. These statistics could indicate large daily movements in market excess returns. The means of SMB and HML are -0.006 and -0.004 together with relatively high standard deviations of 0.405 and 0.639 respectively. The momentum return factor (MOM) has a mean of 0.04 with a relatively high standard deviation of 0.801, which is another indicator for a volatile market for this sample. The investor sentiment index Europe (ISIE) has a mean close to zero, with a relatively high standard deviation of 1. The average logarithmic stock return is fairly low with 0.0003, thus 0.03% on daily basis. The standard deviation of the log returns is relatively high with 0.011. The number of observations is 1413 for each variable which matches the observations for the investor sentiment proxies.

Table 3.2 Summary statistics for the three factors RMRF, SMB, HML, MOM, ISIE and log returns

	Obs.	Mean	Std. Dev.	Min.	Max.
RMRF	1413	.028	1.120	-6.34	8.46
SMB	1413	-.006	.405	-3.31	1.91
HML	1413	-.004	.639	-3	4.38
MOM	1413	.040	.801	-5.19	3.67
ISIE	1413	.000	1.000	-2.916	2.413
lnRET	1413	.0003	.011	-.084	.079

Note: This table shows the summary statistics for the three factors by Fama & French (1993) market excess return (RMRF), small minus big return (SMB), high minus low return (HML) and momentum (MOM) together with the log returns of the Euronext index (lnRET). The number of observations for each variable is 1413, which represents trading days in the period 2 January 2017 to 30 December 2022.

CHAPTER 4 Method

The following part shows the methods I used to compute and generate results for the relationship between investor sentiment and stock returns. The methodology follows Yang and Zhou (2015) for the previously stated hypothesis by running a market-level panel multivariable linear regression analysis following ordinary least squares regression (OLS) with the three factors from Fama & French (1993) and the momentum return factor (MOM). I use logarithmic stock returns and data for the investor sentiment proxies of the Euronext index instead of the excess returns in the Shangai Stock Exchange (SSE). I will compute two separate regressions. The first multivariable regression model consists of the dependent variable LnRET and the four proxy independent variables adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI) and trading volume (VOL). Therefore, the first market level panel linear regression model is defined as follows:

$$LnRET_{it+1} = \alpha_i + \beta_1 ATR_t + \beta_2 PSY_t + \beta_3 RSI_t + \beta_4 VOL_t + \boldsymbol{\beta_5 Control\ Variables} + \epsilon_{it}$$

where, $LnRET_{it+1}$ is the daily log stock return of the Euronext index at time t + 1, followed with the four proxies for investor sentiment ATR, PSY, RSI and VOL at time t. The α_i is the constant and ϵ_{it} is the standard error of the model. Here, the *control variables* capture the market excess return (RMRF), small minus big return factor (SMB), high minus low return factor (HML) and the momentum return factor (MOM) factor separately. These factors serve as control variables to measure the effectiveness of the proxies for investor sentiment in affecting stock returns. The α_i is the constant and ϵ_{it} is the standard error of the model. I compute four multivariable market level panel linear regressions with each proxy of investor sentiment separately, accompanied by the control variables. Then, I perform a second multivariable linear regression with an index variable based on Principal Component Analysis (PCA). This index variable is constructed with the four proxies for investor sentiment ATR, PSY, RSI and VOL shown in Table 5.4 of the appendix. This index variable represents the Investor Sentiment Index Europe (ISIE), and is accompanied by the control variables RMRF, SMB, HML, and MOM. PCA separates the common component of the four proxies since they all reflect sentiment. The first principal component explains the most variance in the data in comparison with the other components with 48,2%. This results in the highest eigenvalue, which means that the first principal component captures most of the common factor. Hence, the ISIE is measured with the coefficients of the first principal component (PC1). The ISIE is constructed as follows:

$$ISIE_t = 0.341ATR_1 + 0.631PSY_t + 0.639RSI_t - 0.279VOL_t$$

where, ISIE is the Investor Sentiment Index Europe in the period January 2017 to December 2022 at time t with the proxy variables ATR, PSY, RSI and VOL at time t. After the construction of ISIE, I perform a second multivariable regression based on daily, weekly, and monthly log returns, which is defined as follows:

$$LnRET_{it+1} = \alpha_i + \beta_1 ISIE_t + \boldsymbol{\beta_2 Control\,Variables} + \epsilon_{it}$$

where, $LnRET_{it+1}$ is the log returns of the Euronext index at time t + 1, $ISIE_t$ is the constructed index variable of the four investor sentiment proxies, and control variables are RMRF, SMB, HML and MOM. First, I sort the index data on closing prices by date from the Yahoo Finance database and combine them with the daily firm data of the firms in the Euronext index from Compustat Global. After merging the data based on the period January 2017- December 2022, the dataset contains daily closing prices, trading volumes and shares outstanding for each company in the Euronext Index for each time t in this period. Next, I created the three proxies for investor sentiment ATR, RSI and PSY with the formulas mentioned in the data section. The returns are created by taking the logarithmic of the difference in the closing price with the previous period. The trading volume (VOL) is computed by collapsing the data in STATA to create the total daily trading volume of the Euronext index based on all the listed firms in the index. Then I merged the data with the factors RMRF, SMB, HML and MOM from the Kenneth R. French database sorted by date. Before running the actual regression, I account for heteroskedasticity in the error terms of the model given the relatively high standard deviations towards the means of the variables ATR, RMRF, SMB, HML, MOM and LnRET. Therefore, I estimate multivariable regressions with robust standard errors in STATA. I check for unexplainable outliers in the data, linearity between the variables, multicollinearity between the variables and for normally distributed residuals. To account for multicollinearity, I create a correlation matrix and look for high correlation between the independent variables as presented in Table 5.3 of the appendix. In addition, I looked at the Variance Inflation Factor (VIF) to account for multicollinearity shown in Table 5.5 of the appendix. Table 5.3 and Table 5.5 show low correlation between the independent variables, which means that there is no multicollinearity. The values of VIF in Table 5.5 represent those of two multivariable panel regressions: one with the investor sentiment proxies (shown in column (1) and one with the ISIE in column (2) with the corresponding control variables for both models. The VIF values are between 1.05 and 2.2 showing low to zero correlations between independent variables. Furthermore, I perform a multivariable panel regression and separate the returns by day, week, and month. By running the regression for different frequencies, I can test the predictability of the investor proxies for the stock returns at a weekly and monthly horizon.

CHAPTER 5 Results & Discussion

This section covers the results and discussion of the findings on the effect of investor sentiment on stock returns. The regression models are based on a logarithmic dependent variable stock return, with continuous independent variables. The regression models presented in Table 5.1 and Table 5.2 is a multivariable regression using Ordinary Least Squares (OLS), which means that the results for each variable can be interpreted as follows: a change in the independent variable by one unit is associated with a exp (independent variable) change in the dependent variable. Thus, a one-unit change of the adjusted turnover rate *(ATR)* gives us a change in stock return of exp (-0.0099) ≈ 0.9901, which means a decrease in the stock return variable of 1-0.9901 ≈ 0.01 or 1%. The same interpretation is applicable for each independent variable in Table 5.1 and Table 5.2.

Results presented in the Table 5.1 are on average significant in explaining the dependent variable logarithmic stock returns. The first model, presented in column (1), is the effect of a single proxy variable adjusted turnover rate *(ATR)* on stock returns with the three factors from Fama & French (1993) as control variables. The R-squared of this model is 0.006, which means that 0.6% of the variance of the stock returns can be explained by the adjusted turnover rate with the control variables *RMRF*, *SMB*, *HML*, and *MOM*. The coefficient of the *ATR* is -0.0099, which means that a one-unit change of the adjusted turnover rate results in a exp (-0.0099) ≈ 1% negative change in stock returns of the Euronext index. The corresponding p-value is higher than 0.05, so this effect is not significant for this model. The second model adds the psychological line index *(PSY)* in column (2). The R-squared is 0.027, which means that the variance of stock returns is with 2,7% significantly explained by the psychological line index with the control variables *RMRF*, *SMB*, *HML*, *MOM*. The coefficient of *PSY* is 0.0001 which indicates a direct relationship with the stock returns with a one-unit change resulting in a stock return increase of exp (0.0001) ≈ 1.0001 ≈ 0.1%. The effect is considerably small and close to zero, however still positive and significant with a corresponding p-value lower than 0.01. Column (3) shows similar results for the relative strength index *(RSI)*, with a coefficient of 0.0001. The p-value is lower than 0.01, hence the effect is positive and significant. The R-squared of this model is 0.049. Therefore, the variance in stock returns is with 4.9% significantly explained by the psychological line index and the other control variables. The fourth column contains the *trading volume (VOL)*, with a R-squared of 0.006. Therefore, the variance of stock returns is explained by *VOL* with 0.6% which is corresponding with the first model. In line with the *ATR* and *RSI*, the trading volume coefficient is also close to zero (≈0.0000). However, this effect is insignificant due to a p-value which is higher than 0.1. The last column (5) of Table 5.1 shows the results of the combined proxies for investor sentiment. The R-squared is 0.052, which reflects an 5.2% explanation of the

Table 5.1 Multivariable regression analysis for the investor sentiment proxies on stock returns.

Variable	(1)	(2)	(3)	(4)	(5)
ATR	-0.0099				-0.0222*
	(0.0130)				(0.0132)
PSY		0.0001***			0.0000
		(2.31e-05)			(0.0000)
RSI			0.0001***		0.0001***
			(0.0000)		(0.0000)
VOL				-0.0000	0.0000
				(0.0000)	(0.0000)
RMRF	0.0001	-0.0003	-0.0006	-0.0002	0.0000
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
SMB	0.0007	0.0007	0.0005	0.0008	0.0000
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0013)
HML	0.0001	0.0000	-0.0002	-0.0002	-0.0002
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
MOM	-0.0009**	-0.0008*	-0.0008*	-0.0010**	-0.0007
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Constant	0.0003	-0.007***	-0.0074***	0.0015	-0.0086***
	(0.0003)	(0.0014)	(0.0014)	(0.0016)	(0.0021)
Observations	1,413	1,413	1,413	1,413	1,413
R-squared	0.006	0.027	0.049	0.006	0.052

Note: These are the multivariable regression results of the investor proxies adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI) and trading volume (VOL) on log stock returns of the Euronext index with market excess return (RMRF), small minus big return (SMB), high minus low return (HML) and momentum (MOM) as control variables. Column (1), (2), (3) and (4) show the effect of each proxy for investor sentiment on log stock returns with RMRF, SMB, HML and MOM as control variables. Column 5 shows the effect of all the proxies together on log stock returns with RMRF, SMB, HML and MOM as control variables. The number of observations is 1413 and represent trading days in the period January 2017 to December 2022. The robust standard errors are in parentheses; the significance level is ***p<0.01, **p<0.05, *p<0.1.

variance in stock returns by the four proxies *ATR*, *PSY*, *RSI*, and *VOL* with the control variables *RFRM*, *SMB*, *HML,* and *MOM*. The coefficient of *ATR* is -0.0222, which means a exp (-0.0222) ≈ 0.978 ≈ 2.2% negative change in stock returns with a one unit change in *ATR*. The coefficients of *PSY* and *VOL* are both close to zero and insignificant with a p-value higher than 0.1. However, the effect of *ATR* and *RSI* on stock returns is significant with a p-value lower than 0.1 and 0.01 respectively. Notable is the insignificant coefficients of the control variables *RMRF*, *SMB,* and *HML* for each model with a p-value higher than 0.1. This is in contradiction with the findings from Fama & French (1993). The high-minus-low return factor does not seem to effect stock returns in this model for this dataset of European markets. It is possible, in this study, that the effect of the value premium in European

Table 5.2 Multivariable regression analysis for the investor sentiment proxies on stock returns by day, week, and month.

Variables	(1)	(2)	(3)
ISIE	0.0024***	0.0009**	0.0006
	(0.0004)	(0.0004)	(0.0008)
RMRF	-0.0006	0.0014***	-0.0004
	(0.0005)	(0.0004)	(0.0004)
SMB	0.0005	0.0008	-0.0006
	(0.0014)	(0.0016)	(0.0013)
HML	-0.0002	-0.00046	0.0003
	(0.0007)	(0.0007)	(0.0007)
MOM	-0.0008*	-0.0002	-0.0003
	(0.0005)	(0.0005)	(0.0006)
Constant	0.0004	0.0006*	0.0002
	(0.0003)	(0.0004)	(0.0006)
Observations	1,413	287	69
R-squared	0.049	0.093	0.024

Note: These are the multivariable regression results of the investor proxies adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI) and trading volume (VOL). These proxies are combined into an index variable Investor Sentiment Index Europe (ISIE) on logarithmic stock returns of the Euronext index. The logarithmic stock returns reflect the period t + 1. The control variables for these models are the market excess return (RMRF), the small minus big return (SMB), the high minus low return (HML), and momentum (MOM) factor. Column (1) shows the results for daily observations; column (2) shows results for weekly observations; column (3) shows results for monthly observations. The number of observations for daily, weekly, and monthly is 1413, 281, and 62 respectively reflecting trading days, weeks, and months in the period January 2017 to December 2022. The robust standard errors are in parentheses, with the following significance for the coefficients: ***p<0.01, **p<0.05, *p<0.1.

markets is insignificant for daily stock returns or that the *MOM* factor picks up on some or most of the effect of stock returns. The same reasoning applies for the *RFRM* and *SMB* control variables. Fama and French (2012) find that the value premium decreases with size in European markets. The Euronext index contains mostly mid-cap to large-cap stocks. This could explain the low effect of the three factors, given that the small cap stocks outperform large cap stocks. The momentum control factor shows significance in the first four models which corresponds with Asness et al. (2013). They find a large significance of momentum returns in European markets. However, the *MOM* factor loses its significance in the fifth model.

The results if the proxies for investor sentiment can predict stock returns for different frequencies is

presented in Table 5.2. Column (1) contains the results based on daily observations between January 2017 to December 2022, which corresponds to column (5) of Table 5.1. However, the common effect of the four investor sentiment proxies is now put together in the investor sentiment index Europe (*ISIE*). The *ISIE* shows a coefficient of 0.0024, which means that a one-unit change in investor sentiment results in a exp (0.0024) ≈ 1.0024 ≈ 2.4% change in daily stock returns. This effect is significant, with a corresponding p-value lower than 0.01. Furthermore, the momentum factor is significant with a p-value of lower than 0.1 and a corresponding coefficient of -0.0008. This implicates a exp (-0.0008) ≈ 0.08% negative change in stock return per unit change of momentum.
Column (2) shows the multivariable regression results using OLS with weekly observations, which equals 287 weeks. The R-squared of this model is 0.093, which implicates an explanation of 9,3% in the variance of stock returns by weekly observed data from the investor sentiment proxies along with the control variables *RMRF*, *SMB*, *HML*, and *MOM.* This is the highest predictive power out of the three models. The coefficient of ISIE is 0.0009 and significant with a corresponding p-value lower than 0.05. A one-unit change of *ISIE* in this model results in a exp (0.0009) ≈ 0.09% change in stock weekly returns. Notice that the *RMRF* control variable is significant with a p-value lower than 0.01. The market excess returns variable seems to only be significant when studying weekly observations in European markets. Column (3) shows the multivariable regression results with monthly observations. The R-squared is 0.024, which indicates a 2.4% explanation in variance of the monthly observed investor sentiment proxies with the control variables on stock returns. This statistic is a bit lower than the previous models suggesting a lower predictable power on monthly based stock returns. The number of observations is relatively low with 69 months which could affect the overall outcome of the model. In contradiction with the previous models, the effect of both the proxies and control variables seems to disappear when looking at a monthly frequency. The predictive power of investor sentiment on stock returns seems to drop considerably when looking at monthly returns. The *ISIE* variable shows significance for the daily and weekly observations.

The results overall present a significant, however partial low effect, of the combination of investor sentiment proxies *ATR*, *PSY*, *RSI*, and *Vol* in the variable *ISIE* on stock returns for both the daily and weekly based observation models. The stock returns do not seem to be sensitive to the *HML* and *SMB* factor for all three models, which could be a result of the observed mid-cap and large-cap stocks in the Europe index as suggested for the model which measures the proxy variables individually. The results partially agree with the stated hypothesis *H1* in the theoretical framework section: there is a significant effect of investor sentiment on stock returns in European markets during the period 2017-2022. However, this effect is not always negative as previously predicted: the effect of the psychological line index (*PSY*) and the relative strength index (*RSI*) is positive. Only the adjusted turnover rate (*ATR*) shows a negative relationship. In addition, the trading volume (*VOL*) seems to have no relationship at all regarding the stock returns of the Euronext index. The most relevant finding is that the investor sentiment index Europe (*ISIE*) is positive and significant for the daily and weekly based observations model. This suggest that the relationship between investor sentiment and European stock returns is positive. Hence, I find only partial support for Hypothesis 1. Furthermore, the effect of the control variables disappears in the monthly model. It is possible, in this particular model, that there is an unsignificant effect of the three factors *RFRM*, *SMB*, and *HML* due to the low number of observations (69) and the relatively large size of the observed firms in the Euronext index. The latter reflects the finding in Fama and French (2012) that the value premium decreases with size.

My findings are partially in line with those of earlier studies examining the relationship with investor sentiment on stock returns. Most importantly, my findings are in line with the research from Yhang & Zhou (2015). This follows my expectations, given the similarities in method and proxies for investor sentiment. They find a significant effect of the four proxies combined with the control variables on stock returns in the Shanghai index (SSE), which applies to the daily observations model. The monthly observation model does show insignificant results for the predictability of the investor sentiment proxies on stock returns, which corresponds with my findings. In addition, they find that when the market sentiment increases, the stock returns increase. This is fully in line with my results, given the positive relationship with the investor sentiment index Europe (*ISIE*) on stock returns. However, the adjusted turnover rate (*ATR*) shows a negative effect on stock returns. Combined, these results suggest that the proxies for investor sentiment *ATR*, *PSY*, and *RSI* suffice to consider when creating a stock portfolio for both the Shanghai market as the European markets. My findings differ from the those by Baker and Wurgler (2006, 2007) and Brown and Cliff (2005). Contrary to my results, they find a significant negative relationship between investor sentiment and stock returns: when market sentiment is high, stock returns should decrease and vice versa. However, relationship itself is still significant. This could show that the relationship with investor sentiment differs in European markets than those in the US. The studied time frame could give some explanation due to potential cultural and institutional differences that could affect sentiment in markets, as stated by Schemling (2009). They studied several European countries and found a negative relationship of investor sentiment with stock returns. This contradicts my findings. However, they study the effect on country-level, which differs from my market level analysis. The Euronext index consists mostly of companies which are listed in the relatively larger indices in Europe: AEX, BEL 20, CAC 40, ISEQ 20, FTSE MIB, PSI 20, and OBX 25. This could give an explanation to the different results since sentiment can differ between financial markets and countries individually. My results correspond with Baker et al. (2012). They find that investor sentiment affects stock returns based on different proxies for investor sentiment. Their finding is applicable to both international market-level returns as market by country-level returns. In particular, they study indices in the markets of UK, France and Germany. My overall finding that there is a relationship between investor sentiment and stock returns is in line with Lemmon and Portniaguina (2006) and Da et al. (2011). The result that the trading volume (*VOL*) does not affect stock returns in all my models is in contradiction with Yang and Zhou (2015) and Tetlock (2007). The findings in these papers would suggest that sentiment affects trading volume and therefore should affect stock returns. A possible explanation for this difference is the combination of the four investor sentiment proxies into one index variable, Investor Sentiment Index (*ISI*). The individual effect of the proxies could disappear into the mutual one, reducing the impact itself of trading volume on stock returns in correspondence with the computed *ISIE* variable.

My findings on when looking at different frequencies (day, week, and month) contribute to those of earlier studies. Da et al. (2011) finds an increase in stock prices in 2 weeks after the occurrence of a high sentiment. Brown and Cliff (2005) find significant impact of investor sentiment on stock returns in the next 1-3 years. Schemling (2009) find a significant predictive power of investor sentiment for stocks with a relative short to medium horizon (one to six months). My results show that especially weekly stock returns are better predicted by investor sentiment, than those of monthly returns. The monthly based returns show a relatively low R-squared of 2.4% which would be insufficient to fully change a portfolio strategy.

CHAPTER 6 Conclusion

In this paper I have looked at the relationship between Investor sentiment and stock returns. Prior literature has established a relationship between these two variables, which was either negative or positive. The focus of recent research was primarily on the financial markets in the US or on international country-level data. However, there was insufficient work on the magnitude of this effect in European markets in a recent period with the necessary proxies for investor sentiment. The available research on European countries showed a prominently negative impact of investor sentiment on stock returns. Therefore, I studied the following question in this paper: "Does investor sentiment have a significant negative impact on stock returns in European markets in the period 2017-2022?"

To give an answer to this research question, I formed four proxies for investor sentiment. The four proxies were as follows: the adjusted turnover rate (ATR), the psychological line index (PSY), the relative strength index (RSI), and the trading volume (VOL). To give a representation of the European markets I took stock returns from the Euronext index and formed the four proxies based on 165 companies listed in this index. I calculated the proxies based on the combined dataset and added the control variables market excess returns (RFRM), small-minus-big returns (SMB), high-minus-low returns (HML) and momentum returns (MOM). Then, I used a multivariable market-level regression analysis and discussed the results. Four regressions were constructed: for each proxy separately and one combined. This was based on 1413 observations, which represents trading days in the period January 2017 to December 2022. I constructed an index variable using principal component analysis to compute the investor sentiment index Europe (ISIE). Two other regressions were formed to measure the predictability of investor sentiment on weekly and monthly stock returns. The applied regressions showed mixed results. The overall effect of investor sentiment showed to be positive, rather than negative, based on the proxy RSI and on the index variable ISIE. VOL showed no relationship at all. The model based on monthly stock returns resulted to be of no significant value to the impact of investor sentiment on stock returns. The model on weekly stock returns showed a relative high power in explaining the variance of stock returns, with significant positive coefficients of ISIE and RMRF.

The conclusion of this study is therefore that, opposing previous literature, the impact of investor sentiment on stock returns is positive in European markets. This effect is according to the models in this paper the most visible for weekly stock returns. Combined with prior work on this topic, the relationship between investor sentiment and stock returns is significant, however the direction of this effect seems to differentiate between markets. The implication for investors who are looking to make informed optimal investment decisions is that when choosing possible stocks or portfolios in European markets, they should consider the impact of investor sentiment for their returns. In addition, the results could contribute to the present models on asset pricing and stock predictability, given the established relationship between investor sentiment and stock returns.

This paper had several limitations which could have influenced the results. I acknowledge that there are multiple ways to conduct the proxies for investor sentiment which could alter the results. Previous academic literature has constructed many different underlying proxies with no real conformity on the most significant one. Hence, there are certainly possibilities for future research to determine the best way to capture investor sentiment in models to predict stock returns. Another potential limitation is the use of four control variables to measure the relationship. In the literature of asset pricing, there could be other possible control variables which influence stock returns. These can catch other influences on stock returns to create a more 'complete' model. In future research, these control variables could be added to or replace the ones in this paper. In addition, future research can study the effect of investor sentiment in other financial markets and look for potential differences to fully grasp the impact of this factor.

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APPENDIX A Statistics

Table 5.3 Matrix of correlations of the independent variables and log returns

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ATR	1.000								
(2) PSY	0.259	1.000							
(3) RSI	0.220	0.717	1.000						
(4) VOL	-0.046	-0.145	-0.238	1.000					
(5) RMRF	0.669	0.132	0.200	-0.099	1.000				
(6) SMB	-0.385	0.003	-0.013	-0.026	-0.336	1.000			
(7) HML	0.069	-0.009	0.038	-0.056	0.061	-0.208	1.000		
(8) MOM	-0.182	-0.061	-0.097	-0.113	-0.276	0.142	-0.357	1.000	
(9) lnRET	-.0251	0.151	0.209	-0.030	-0.000	-0.025	0.012	-0.060	1.000

Note: this table represents the correlations between each independent variable and the dependent variable log stock returns to check for multicollinearity. It contains the proxies for investor sentiment: adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI), and trading volume (VOL) with the control variables market excess return (RMRF), small minus big return (SMB), and high minus low return (HML).

Table 5.4 Principal component analysis for the proxies ATR, PSY, RSI and VOL

Variable	PC1	PC2	PC3	PC4
ATR	0.341	0.562	-0.752	0.040
PSY	0.631	0.102	0.326	-0.697
RSI	0.639	-0.043	0.294	0.710
VOL	-0.279	0.820	0.491	0.097
Eigenvalue	1.929	0.963	0.832	0.276
Variance explained (%)	48.2	24.1	20.8	6.9
Cumulative variance explained (%)	48.2	72.3	93.1	100
Observations	1413			

Note: this table shows the principal component analysis of the proxy variables adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI), and trading volume (VOL). This is based on 1413 observations in the period January 2017 to December 2022. The variance explained and cumulative variance explained are both in percentages. The principal components capture the variance in the data. Since there are 4 proxy variables, there are 4 principal components. The amount of variance carried by each principal component is shown in the eigenvalue, which results in the variance explained.

Table 5.5 Variance inflation factor (VIF) for the measured variables

Variable	(1)	(2)
ATR	2.05	
PSY	2.17	
RSI	2.20	
VOL	1.11	
ISIE		1.05
RMRF	2.01	1.26
SMB	1.26	1.18
HML	1.21	1.19
MOM	1.29	1.24
Mean VIF	1.66	1.184

Note: this table contains the variance inflation factor (VIF) of the variables adjusted turnover rate (ATR), psychological line index (PSY), relative strength index (RSI), trading volume (VOL), investor sentiment index Europe (ISIE), and control variables market excess return (RMRF), small-minus-big returns (SMB), high-minus-low returns (HML), and the momentum factor (MOM). These are constructed on two multivariable panel regressions on log returns lnRET: one with the proxies for investor sentiment in column (1) and one with the index variable ISIE in column (2) with the corresponding control variables for both models. VIF = 1 means variables are not correlated; VIF > 1 and < 5 means a moderate correlation between variables; VIF > 5 means high correlation between the variables.