ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ
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Διπλωματική Εργασία

INVESTMENT STRATEGIES AND MARKET ANOMALIES. THE PAST AND THE FUTURE.

Παναγιώτης Αθανάσιος Τσελίκης

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Παράρτημα Β: Βεβαίωση Εκπόνησης Διπλωματικής Εργασίας

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(περιλαμβάνεται ως ξεχωριστή (δεύτερη) σελίδα στο σώμα της διπλωματικής εργασίας)

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«Investment Strategies and Market Anomalies. The Past and the Future.».

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Υπογραφή Μεταπτυχιακού Φοιτητή/ τριας

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INVESTMENT STRATEGIES AND MARKET ANOMALIES. THE PAST AND THE FUTURE.

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Keywords: Market Anomalies, Investment Strategy, Fama - French 5 Factor Model, Efficient Market Hypothesis, Abnormal returns

Abstract

In the present thesis, a variety of Market Anomalies demonstrated and investigated. This research focuses on stock returns of European Equities Markets. Especially, the paper analyzes a group of four market anomalies and applies the proposed, by literature, methodology in order to define the existence and the powerful of these anomalies. Finally, a set of conclusions and implications, which are useful for the development of investment strategies and further research, are excluded.

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Chapter 1: Introduction

One of the most discussed topics in Finance is the efficient management or allocation of the resources, which are available for investing. Mainly this efficiency is achievable through the allocation of available resources in different assets, such as equities, bonds, financial derivatives or even in real assets, such as houses, land, etc. Market participants, also known as investors, consume a great amount of their time in order to gather information, which are significant for the formulation of their decisions. Investors based on these decisions create a plan aiming to achieve their investment goals or, as referred in literature, to develop their investment strategy.

Into a hypothetical deterministic universe, where the future is accurately predictable, the formulation of an investment strategy would be a mechanistic process which is followed by a fully predictable result. Into our stochastic universe, which characterized by uncertainty, the decision-making process and the investment strategy development by investors is a far more difficult procedure.

Market participants trying to reduce the uncertainty and to take rational decision exploiting a set of tools, one of which is statistics. In general, statistical analysis could provide predictive models, which describe a phenomenon, using historical data as input. In other words, investors try to predict the future fluctuations of the price or value of an asset.

Except for statistics, investors have at their disposal a theoretical background, which provides to them a direction for their value-seeking process. In literature, we could find a plenty of this knowledge.

Especially, in this paper we focus on the market anomalies phenomena and how we are able to identify and exploit them. On a methodology point of view, in order to achieve this goal, we combine both the theoretical background of market anomalies phenomena and the statistical tools.

Research is motivated by a desire to increase knowledge and understanding about Market Anomalies. This can be driven by a variety of factors, such as a scientific curiosity, the need to solve a practical problem, or the desire to improve the human condition. Additionally, research can also be motivated by financial incentives, such as grants or funding, or by the prospect of career advancement. Ultimately, the motivation behind research is to discover new information, test hypotheses, and contribute to the advancement of knowledge and understanding in a particular field.

Research on market anomalies could provide insights into market inefficiencies and potential opportunities for investment. Anomalies could be occurred when securities or markets deviate from their expected behavior based on historical trends or fundamental factors. By identifying and understanding these anomalies, investors and traders may be able to capitalize on them to achieve higher returns or to develop more effective investment strategies. Additionally, research on market anomalies could help to improve our understanding of how markets function and could inform the development of more sophisticated financial models.

The main objective of research in market anomalies is to identify patterns or deviations in financial market data that deviate from typical market behavior or expectations. These anomalies could be related to stock prices, trading volume, or other financial metrics. The goal of this research is to understand the underlying causes of these anomalies, and potentially use this knowledge to make well- informed investment decisions. Additionally, research in market anomalies could also help us improve the overall understanding of financial markets and the behavior of market participants.

Several indicative recent developments in the field of market anomalies are described briefly below.

<u>Machine learning techniques</u>: Researchers are using machine learning techniques such as neural networks and genetic algorithms to identify and exploit market anomalies.

Machine learning techniques have become increasingly popular in the field of market anomalies. These techniques can be used to identify and exploit market inefficiencies. Some examples of how machine learning techniques are being used in this field include:

a. Anomaly detection: Machine learning algorithms can be trained to identify unusual patterns in market data that may indicate a market anomaly. This can be done using techniques such as neural networks, decision trees, and clustering algorithms.
b. Algorithmic trading: Machine learning algorithms can be used to develop trading strategies that exploit market anomalies. This is feasible using techniques such as reinforcement learning, genetic algorithms, and support vector machines.
c. Risk management: Machine learning algorithms could be used to predict and manage risk in market anomalies. This can be done using techniques such as Bayesian networks, Gaussian processes, and ensemble methods.

d. Sentiment Analysis: Machine learning algorithms can be used to analyze news and social media data to identify market sentiment and predict market trends.
e. Predictive modeling: Machine learning algorithms can be used to predict future market prices, returns, and other financial metrics, which can be used to identify and exploit market anomalies.

These are some of the main ways that machine learning techniques are being used to identify and exploit market anomalies. However, it is important to note that these techniques could be quite complex and require significant expertise and computational resources to implement effectively.

High-frequency trading: The use of high-frequency trading algorithms has led to the discovery of new market anomalies and the ability to exploit them at faster speeds.

High-frequency trading (HFT) is a type of algorithmic trading that uses advanced computer algorithms to execute trades at extremely high speeds. HFT has been used to exploit market anomalies, such as latency arbitrage, where traders take advantage of delays in the execution of trades to make a profit.

HFT algorithms could be designed to identify and exploit market inefficiencies by analyzing large amounts of market data and executing trades quickly. This can be done using techniques such as order book analysis, statistical arbitrage, and co-integration. These algorithms can detect and take advantage of small discrepancies in prices across different markets, or even within the same market.

HFT has been linked to several market anomalies, including flash crashes, where prices can drop quickly and substantially, and liquidity crises, where there is a sudden lack of buyers or sellers in the market. Some regulators and market participants have raised concerns about the potential negative impact of HFT on market stability and liquidity.

HFT is a complex and rapidly evolving field and requires significant expertise and computational resources to implement effectively. It is worth to mention that HFT is also subject to different regulations and rules in different countries and markets.

Big data: The availability of large amounts of market data has allowed researchers to identify new anomalies and to test existing anomaly hypotheses using more data.

The availability of large amounts of market data, also known as "big data", has created new opportunities for identifying and exploiting market anomalies. Big data include information on prices, trades, orders, and other market activity, as well as news, social media, and other external data sources.

Big data analytics could be used to analyze this information to identify patterns and relationships that may indicate market anomalies. This can be done using techniques such as machine learning, natural language processing, and data visualization. For example, big data analytics can be used to identify patterns in historical market data that may indicate a market anomaly, such as a price trend or a trading strategy that has been particularly successful in the past. This information could then be used to develop trading strategies that exploit the anomaly.

Big data analytics could also be used to analyze news and social media data to identify market sentiment and predict market trends. For example, sentiment analysis can be used to determine whether market participants are bullish or bearish on a particular stock or market, which can provide insight into future price movements.

Big data analytics can also be used to identify potential risks in the market, such as the emergence of new competitors or regulatory changes that could affect market conditions.

It is worth mentioning that big data analytics is a complex field that requires significant expertise and computational resources to implement effectively. Additionally, the accuracy and quality of the data is also important to take into account, as well as the ethical and legal considerations surrounding data privacy and security.

Risk-premia: Risk-premia strategies and factor investing have become increasingly popular, leading to new research on the risk factors that drive returns and how to exploit them. Risk-premia strategies and factor investing have become increasingly popular in recent years and have led to new research on the risk factors that drive returns and how to exploit them.

Risk-premia strategies seek to identify and exploit the risk factors that drive returns in financial markets. These risk factors, also known as "premia", can include factors such as value, momentum, and volatility. By identifying these risk factors and investing in assets that have high exposure to them, investors can potentially earn higher returns.

Factor investing, which is a subset of risk-premia strategies, involves investing in a specific factor or group of factors that have been shown to have a consistent relationship with returns. For example, the value factor refers to investing in companies that are undervalued by the market, while the momentum factor refers to investing in companies that have experienced strong price gains in the recent past.

Risk-premia strategies and factor investing can be used to identify and exploit market anomalies, such as mispricing or inefficiencies. For example, if a company is undervalued by the market, it may be a good investment opportunity. Similarly, if a company has experienced strong price gains in the recent past, it may be a good investment opportunity.

It is worth mentioning that risk-premia strategies and factor investing are complex fields that require significant expertise and computational resources to implement effectively. Additionally, it's important to keep in mind that these strategies are based on historical data, and the past performance does not guarantee future results.

<u>Cryptocurrency markets</u>: The emergence of cryptocurrency markets has led to new research on the unique market anomalies present in these markets.

The emergence of cryptocurrency markets has led to new research on the unique market anomalies present in these markets. Cryptocurrency markets are relatively new and have several unique characteristics, such as high volatility and lack of regulation, that may create opportunities for market anomalies.

Some examples of market anomalies that have been identified in the cryptocurrency market include:

a) Pump and dump schemes: In this type of market manipulation, a group of traders artificially inflate the price of a cryptocurrency by buying it in large quantities and then selling it at a higher price, causing the price to crash.
b) Inside trading: Insiders with privileged information about a cryptocurrency or blockchain project may use it to make a profit in the market.
c) Whale manipulation: Large holders of a cryptocurrency, known as "whales," may have a significant impact on the market by buying or selling large amounts of a cryptocurrency, causing the price to move in their favor.
d) Market manipulation: Some market participants have been known to use a variety of tactics, such as spoofing, to manipulate the market.
e) Lack of regulation: The lack of regulation in the cryptocurrency market may create opportunities for market manipulation and fraud.

Research in cryptocurrency markets is ongoing and new market anomalies are still being discovered. It is also worth mentioning that cryptocurrency markets are highly speculative and volatile, and can be affected by a wide range of factors. It is important to keep in mind that investing in cryptocurrency is highly speculative and comes with a high level of risk.

The existence of specific conditions, where market anomalies could be evolved, motivates me to investigate this concept in European Stock Markets on a time span of 28 years. As well as it is interesting the fact that the selected companies were traded around the developed stock markets of Europe, so this research could detect the idiosyncratic characteristics of the European Stock Markets and lead to generalized conclusions.

At the end of this paper, we hope to determine how we can exploit market anomalies phenomena for investment strategy creation. As well as we expect to provide the directions and a valid methodology in order to identify such phenomena among different geographic markets with different idiosyncratic characteristics.

Briefly, the present study focusses on four market anomalies, which are relative to the difference between the change of turnover and inventories of a company, the variations of the gross profit margin, the hypothesis of negative relation between the growth in operating assets and future stock returns and the negative relation between stock returns and capital investments as proportion of total assets. These market anomalies are selected by literature and are tested in different European markets. For each of these anomalies, an index was calculated for every company of the sample. Furthermore, the sample sorted and separated according to this index. This process led to the formulation of five portfolios. The final step of methodology included the use of the Fama - French 5 Factor Model in order to examine the existence or not of the market anomalies.

At the next chapter, I present an overview of market anomalies through a literature review. Specifically, in chapter two I describe the concept of the term “market anomaly” and I explain the connection between this term and the Efficient Market Hypothesis concept. As well as, in the same chapter a set of selected generic market anomalies are included. Moreover, in the chapter two I referred to the basic research from where I chose the four market anomalies, which were included in my research.

In chapter three the methodology is described in detail. Specifically, there is a description of four market anomalies, which are under examination, along with the review of the relative literature. Furthermore, in the same chapter described the formulation of portfolios and the Fama - French 5 Factor Model.

In chapter four, the empirical data are presented in detail. As well as, at this chapter are presented and explained the results of the econometric analysis of the four estimated models.

Finally, in the fifth chapter the conclusions are included. In this chapter a set of useful and interesting results provide a holistic picture of market anomalies in European territory.

<u>Literature</u>

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Chapter 2: Literature Review

2.1: Market Anomalies

The concept of anomalies in science introduced by Kuhn (1962). According to his point of view, science is a similar process as the puzzle integration. The components of the puzzle are the inconsistent, with paradigms, phenomena which could be consistent by modifying the paradigms. In this context, an anomaly it could be defined as the failure to integrate the puzzle simultaneously with the lack of a different paradigm, which could be able to provide a solution.

The concept of anomalies in the field of Finance and in the field of Economics was introduced by Michael Jensen in 1978 and Richard Thaler in 1987, respectively. Initially, as a market anomaly could be described an observed result, which is inconsistent with the prevalent asset pricing theory. The existence of market anomalies could imply that the Efficient Market Hypothesis is not valid for the specific market or the model, which be selected for the asset pricing, is not adequate for a specific asset. According to the literature on this topic, market anomalies are not characterized by stability, it is common an anomaly to be eliminated or cause a reverse result periodically. These inconsistencies in market anomalies behavior leads the participants to examine the roots of the anomalies. In that case the question is whether a market anomaly, which have been eliminated for example, is result of the arbitrage effect or market anomalies are simply statistical deviations.

Fundamentally, the definition of a market anomaly is feasible only into the context of a "normal" returns generation mechanism. This approach was followed by Fama (1970), in order to examine the level of market efficiency, he tested simultaneously a known hypothesis of market returns equilibrium. In other words, the market inefficiency is highly correlated to abnormal returns or abnormal returns implies a market anomaly. Due to this two-way relation, which could be misleading, the selection of the "normal" returns definition model must be careful.

Another parameter for the examination of a market anomaly is the underlying economic theory, which is selected for the definition on normality. In 1978 Jensen examined the market efficiency using the profits of trading as a significant parameter. Especially, he did not characterize an abnormal return as significant if an efficient trader does not make a profit after the cost of trading deduction. This approach highlights the significance of transactional costs and the market structure.

The exponential production of data, which is supported by the evolution in computer technology field, and the gradual increase of the interest of the researchers in the field of Finance provide a plenty of findings, which could set the power of the simple models of market efficiency as a debatable topic. This hyper-analysis of the findings may lead researchers to recognize as market anomalies some random events. A deviation from what the theory defines as efficiency in market could be characterized as market anomaly if this deviation is persistent and universal among different samples.

An interesting topic is the extinction of a market anomaly after its documentation in literature. This phenomenon generates the question of how possible this observed inefficiency is a result of a biased sample, therefore another data set could not be characterized by this anomaly, or this anomaly tends to be disappeared due to market participants' investment strategies based on this anomaly.

A selected set of empirical market anomalies is described below.

1. "Size Effect"

Empirical evidence showed that the returns of small-capitalization companies listed on New York Stock Exchange exceeded on average the expected returns according to Capital Asset Pricing Model (CAPM) during the period between 1936 and 1975. The size effect was a common topic on several papers and research. Following the first publications on this market anomaly, the power of this phenomenon seems to be declined.

2. "Turn-of-the-year Effect"

The research of Keim (1983) and Reinganum (1983) implied that during the first fourteen days of the year small capitalization companies gains returns which exceed the expected returns according CAPM. A possible explanation, which is suggested by literature, connects this observed anomaly with taxation. According to this hypothesis, investors might chase temporary losses, before the closing of fiscal year for taxation reasons, by selling small capitalization stocks in December with the intention to repurchase these stocks in January. Therefore, these excess returns might be the results of the stocks regaining form the investors, who intend to retain their portfolios balances. The empirical evidence suggests that this market anomaly is not extinguished totally after its first documentation in literature.

3. “The Weekend Effect”

French (1980) pinpointed another market inefficiency which was related to the day of the week. Specifically, he observed that the returns, on an average basis, of the Standard and Poor’s composite portfolio was significantly negative during weekends between 1953 and 1977. As it is already observed with other market inefficiencies, the power of weekend effect it seems to be declining since 1980, when it was firstly documented.

4. “The Value Effect”

According to research of Basu (1977, 1983) observed that companies which are characterized by high earnings to price index gain higher returns than the normal returns which were implied by CAPM. Research, which were conducted later, suggest that exceeded returns observed in portfolios, which include equities with high dividend to price ratio or book to market ratio. On the contrary, Ball (1978) pinpointed that these abnormal returns are possible to be attributed on Capital Asset Pricing Model inadequacy rather than market anomaly. This possibility is based on the fact that Capital Asset Pricing Model ignores the transactional costs which may be occurred to an investor for portfolio restructuring or information acquisition.

Fama and French (1992, 1993) converged to the conclusion that Capital Asset Pricing Model did not take into consideration the size and the value of a company as factors of risk. Especially, they proposed the model below for the estimation of expected returns of an equity.

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it}$$

On the aforementioned model, the factor SMB is referred to the difference between small-capitalization stocks portfolio returns and large-capitalization stocks portfolio returns, with similar Book to Market ratio for the companies, which are included in these portfolios. HML factor is the difference of returns between portfolios which include stocks with high Book to Market ratio and portfolios which are formed by stocks with low Book to Market ratio, retaining the capitalization similar among these stocks. Furthermore, the parameter α_i is the measure of abnormal return and the parameters s_i and h_i are the measure of size risk and value risk respectively.

This model, which is composed by three factors, exploited by Fama and French (1993) in order to test the validity of previous mentioned market inefficiencies in literature. This research implied that using the three-factor model, instead of the Capital Management Pricing Model, for the examination of market anomalies existence on portfolios, where equities were sorted by Book to Market ratio, dividend yield, capitalization or Earnings to

Price ratio, the measure of abnormal returns (parameter $α_i$) was not statistically significant.

5. “The Momentum Effect”

In 1996 Fama and French examined two kinds of strategies which were based on momentum. The first strategy was founded on the observations of DeBondt and Thaler (1985), who detected a market inefficiency whereby stocks which gained low returns three to five year in the past resulted better returns on average than stocks which had high returns in the same period in the past. On the contrary, the second strategy was founded on the Jegadeesh ’s and Titman ‘s (1993) research, who observed that portfolios which included stocks with a good past performance had higher returns than portfolios which formed by stocks with low past performance, during a past period of one year. For the examination of the existence of market inefficiency, as referred above, Fama and French implemented the three-factor model and the results for the first strategy was not significant, the measure of abnormal returns was close to zero. Also, the three-factor model did not achieve to capture the momentum effect in the short run.

Results of Lewellen ‘s (2002) research on momentum effect, for portfolios which formed by equities ranked by size and Book to Market ratios, it seems to be in line with those of Jegadeesh and Titman (1993, 2001) and Fama and French (1996). According to him, behavioral characteristics in the way that information is processed make difficult the explanation of momentum in portfolios which are well diversified.

Moreover, research from Brennan, Chordia and Subrahmanyam (1998) suggests that the size of the companies and the Book to Market ratio are not significant factors for the explanation of variances in average returns, using the suggested model of Fama and French. Furthermore, Fama and French (1996) concluded to the same evidence.

To sum up, according to literature the momentum effect is not among the market inefficiencies which could be detected and explained by the three-factor model.

6. “Predictable differences in returns through time”

In the dawn of the research on topic of market efficiency there were a misperception that market efficiency and random walk on returns are parts of the same topic. Therefore, Fama (1970, 1976) clarified that the hypothesis of expected returns equilibrium is not component of efficient market concept.

Subsequently, the observation of a slight level of correlation between equities returns and prior information was appeared on many studies. Such examples are the study of

Fama snd Schwert (1977), the paper of Keim and Stanbaugh (1986) on differences yields between risky companies' bond and short-term interest rates, the study of Campbell (1987) on short-term and long-term interest rates spreads, French, Schwert and Stambaugh (1987) on equities price volatility. As well as Baker and Wurgler (2000) documented a negative relation between future stocks returns and the proportion of newly issued equities during the period 1928 until 1997.

Therefore, the question which arises from the ability to predict at some point the returns using historical data is whether we could recognize that as market anomaly or recognize a time-depending equilibrium on returns. Fama and Schwert (1977) detected some evidence that the CRSP (Center for Research in Security Prices) value-weighted portfolio of NYSE excess returns were be predicted negative.

7. "Short-term interest rates, expected inflation and stock returns"

In 1977 Fama and Schwert exploiting data between 1953 and 1971 extracted the conclusion that there was a significant negative correlation between short-term interest rates and stock returns. Two years earlier Fama documented that the major factor which leads to short-term interest rates volatility was the expectations of the inflation, so Fama and Schwert converged to the conclusion that the expected stock returns is negatively correlated with expected inflation.

To reached to this conclusion Fama and Schwert estimates the model below,

$$R_{mt} = \alpha + \gamma R_{ft} + e_t$$

Where, R_{mt} is the return on a monthly basis of the portfolio and R_{ft} is the risk-free rate. As portfolio used the CRSP value-weighted portfolio of period 1926 – 2001 and as risk-free rate considered the Treasury Bills yield.

2.2: Contemporary Research

Recent research by Muhammad A. Cheema and Frank Scrimreour (2019) aims to assess the effect of changes in oil prices on the occurrence of stock market anomalies in China. Their focus on China market is driven by three reasons, firstly, the influence of crude oil prices on the stock market in China has been well documented, as seen in studies by Zhu et al. (2016a), Zhang and Chen (2011), and Li et al. (2012). Conversely, there is limited evidence on the impact of crude oil prices on stock markets in the United

States and Europe. Secondly, a surge in oil prices caused by a demand shock has had a positive impact on the Chinese economy, as noted in research by Herwartz and Plödt (2016) and Zhao et al. (2016). However, a supply shock has had no effect on the Chinese economy. Lastly, it is crucial to examine whether the positive connection between oil prices and stock returns resulting from an oil demand shock leads to abnormal returns in the Chinese stock market.

The second reason is that China's imports of oil have steadily risen since it first became a net importer of crude oil in 1993 (Leung, 2011). In 2003, China became the largest consumer of crude oil and in 2017, it became the largest importer of crude oil as well. As a result, as the largest oil importer and consumer, China plays a significant role in determining global oil demand and price (as discussed in detail in studies by Datta and Vigfusson, 2017 and Hamilton, 2009). Therefore, a rise in global oil prices could be seen as a positive sign by Chinese investors, reflecting increased oil consumption in China due to economic growth.

The last reason is that despite being the world's second largest economy and having the second largest stock market, there is limited research on stock market anomalies in China. The current evidence on stock market anomalies in China suggests that the effect of anomalies is weaker in the Chinese stock market compared to the U.S. stock market (as seen in studies by Chen et al., 2010 and Jacobs, 2016). Therefore, investigating the relationship between oil prices and anomaly returns in China will not only shed light on the impact of oil prices on the stock market but also serve as an additional test of the anomalies identified in the U.S. market.

Building upon previous studies such as Stambaugh et al., 2012; Lu et al., 2017; Stambaugh et al., 2015; and Jacobs, 2016, Muhammad A. Cheema and Frank Scrimreour selected a set of twelve market anomalies to examine, including net stock issues, composite equity, accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, investment to assets, maximum daily return, idiosyncratic risk, and low volatility. As suggested by Stambaugh et al. (2015), they created a mispricing score based on the combined mispricing of these anomalies, as this provides stronger evidence of mispricing compared to individual anomalies. For each anomaly, a long position was taken in underpriced stocks and a short position was taken in overpriced stocks. The difference in returns between the long and short positions (long-short) demonstrates the return predictability of each anomaly.

This research indicated that among the under examination anomalies, six created positive and statistically significant long-short returns and seven anomalies led to positive and significant Fama-French alpha. Three anomalies resulted in positive and significant valued-weighted returns, while alpha was positive and significant for six anomalies. These long-short returns were consistent with the findings of Jacobs (2016), who found weaker anomalies in China compared to the US and other developed markets. However, the results of sorting stocks based on the mispricing score indicated positive and significant long-short returns and alpha, suggesting the prevalence of mispricing in the Chinese stock market. Another finding was that long-short returns of individual anomalies and their aggregate mispricing score were stronger after rising oil prices than after falling oil prices. Significantly, Muhammad A. Cheema and Frank Scrimreour discovered that long-short returns of individual anomalies and their aggregate mispricing score were stronger after rising oil prices only when the rise was driven by increased oil demand.

The outcomes of their research have three significant implications for market participants such as investors, fund managers, etc. Firstly, the findings indicate that the connection between oil prices and stock market anomalies suggests that investors and fund managers should not use oil as a mean of reducing China's stock market risk. Secondly, the research results on the potential trading strategies to yield abnormal profits after an increase in oil prices suggest that investors can capitalize on stock market anomalies when oil prices rise due to increased demand. Finally, the outcome of the study could assist policymakers in making well-informed investment decisions based on the impact of oil price changes on the stock market.

Another recent research by Javier Vidal-García and Marta Vidal (2022), using daily return data from stocks listed on the London Stock Exchange, aims to assess whether price fluctuations can be described statistically as independent random variables or if they are impacted by a calendar effect tied to the day of the week. The research is based on a data sample which spans the years 1990 to 2021, a period marked by distinct traits and strong volatility, making it ideal for examining behavioral trends. Study will look at daily seasonality in terms of returns and volatility and will compare the findings to the FTSE All-Share, FTSE 250, and FTSE Small Cap indexes. From this point of view, the fundamental contribution of this research is that it addresses the examination of the day impact with a large sample on an unstudied financial market. This indicates a particular interest for U.K. listed companies listed, but also for the various sectors of the economy in general, as well as for portfolio managers by providing information about the behavior of their investments and, thus, in the development of optimal investment strategies.

Javier Vidal-García and Marta Vidal (2022) research indicated that for many U.K. companies listed on the stock exchange a potential turning point on Wednesdays is identified, which is linked to a shift in returns. Specifically, these companies tend to have higher returns in the latter half of the week and greater volatility in the first days of the week. As for the FTSE All-Share Index, the highest volatility is seen on Fridays and the lowest on Mondays. It is important to emphasize that the results of this study demonstrate a distinct behavior of stocks on the London Stock Exchange compared to the FTSE All-Share Index, even for those companies that are part of it. Lastly, it is worth mentioning that this study has significant implications not only for the field of finance, but also in light of the crucial role that stock exchanges possess in the market economies.

In the advent of 2021 another research, which was conducted by Asheesh Pandey, Anand Mittal and Arjun Mittal, explored the size effect in four developed stock markets in Europe. Specifically, the countries France, Germany, Spain and Italy were under examination. They created a 505-company portfolio for France market, a same size portfolio for Germany market, a 427-company portfolio for Spanish market and a 503-comparny portfolio for Italian market. Furthermore, they collected the monthly returns during January 2008 to March 2018 for each selected companies of these portfolios.

The outcome of the research confirmed that the existence of the size anomaly is not clear enough. For this reason, they evaluated if the rational causes of the size effect discussed in literature could explain the anomaly. The results confirmed the presence of size effects in each of these economies as reflected in their raw returns.

Additionally, they used both single-factor and multi-factor models to assess if the size effect persist against well-known asset pricing models. Results show that the Capital Asset Pricing Model (CAPM) is an important explaining factor of the size anomaly for both Spain and Italy. However, this model failed to explain the size effect for France and Germany, for this reason researchers was led to employ multi-factor models.

Finally, they concluded on that taking into consideration the 10-year period the size effect could be explained only in Germany, Spain and Italy. On the contrary, it seems to be able for investors to create profitable investment strategies based on size effect in France Equity market.

One of the latest papers on market anomalies, which was published in 2021, is the research of Md. Imran Hossain who investigates three well-known market anomalies on US stock market. The primary goal of this research was to re-examine three established anomalies in the US stock market: the size effect (Banz, 1981), the short-term return reversal effect (Jegadeesh, 1990), and the momentum effect (Jegadeesh & Titman, 1993), with the aim of determining their ability to produce risk-adjusted abnormal returns and their impact on market efficiency. The research design involved back-testing procedures using monthly stock returns data of a random sample of 150 stocks listed in NYSE, AMEX, and NASDAQ from 2001 to 2017. The exclusion of financial and utilities stocks from the sample is an important consideration, as these sectors may have different characteristics and behaviors in the stock market.

This study took the research a step further by testing the ability of four contemporary asset pricing models to explain the abnormal returns generated by the three anomalies studied. The models were being tested were the Capital Asset Pricing Model, Fama-French Three Factor model, Liquidity augmented, Fama-French Three Factor model, and Fama-French Five Factor model. These models represent different approaches to modeling risk and return in financial markets and are commonly used to evaluate investment opportunities and to make asset allocation decisions.

The results of this empirical analysis could shed light on whether these systematic risk factors are able to explain fully the abnormal returns generated by these three anomalies. If the models are found to be insufficient in explaining the anomalies, it could imply that additional risk factors or market inefficiencies are present and must be considered in investment decision making. On the other hand, if the models are found to be effective in explaining the anomalies, it would provide further support for their use in finance and investment management.

The main finding of Md. Imran Hossai' s research is that the size effect and the short-term return reversal effect produce excess returns that are significant on a statistical view, even after accounting for the systematic risk factors included in the current asset pricing models. This conclusion suggests that the weak-form efficiency of the US stock market is not supported by the data, and that these two anomalies present opportunities for excess returns that cannot be fully explained by the systematic risk factors included in the asset pricing models. Additionally, the study found that the trading strategy based on size creates higher excess returns than the short-term return reversal and momentum strategies during the examined period. This highlights the potential for investors to benefit from a size-based investment strategy in the US stock market. These findings are significant, as they challenge the traditional view of efficient financial markets and have important implications for investment theory and practice. By highlighting the existence of these anomalies, the study provides a new perspective on how to approach investment decision making and portfolio construction.

This dissertation is based on the study of Heiko Jacobs "What explains the dynamics of 100 anomalies?" and focuses on anomalies which are related to a) Fundamental Analysis and b) Capital investment and Growth. According to this study, there are two main behavioral causes which lead to asset pricing anomalies, the first one is investors phycology and the second one is the arbitrage limitations. Theoretically, the abnormal returns are expected to be higher into an investment environment, which is characterized by the investors' irrationality and arbitrage limitations, ceteris paribus. In fact, the empirical results from different tests are not clear enough.

Therefore, the aim of the study is to reexamine this controversial topic by taking into account time series variations at a market level, instead of cross-sectional data at an anomaly or a stock level. Through this approach, the study tries to define the causes which lead to significant abnormal returns in different circumstances and the link between variance in market sentiment and market arbitrage limitations, in relation to abnormal returns.

Initially, for the purpose of research 100 already known or newly observed anomalies were identified, grouping and reproduced. These set of anomalies are concerning violation of one price law, technical analysis, price momentum, short-term and long-term reversal, date effects, lead-lag effects among economically linked firms, pairs trading, beta coefficient, financial distress, skewness, differences of opinion, industry effects, fundamental analysis, net stock and financing decisions, capital investment and firm growth, innovation, accruals, dividend payments, or earnings surprises. The database, which the study was founded, contains about 65.000 months of anomalies.

The most significant results of the study are the bellow mentioned. Exploiting the Fama and French (1993) model, a great number of anomalies lead to significant abnormal returns. The sentimental behavior of investors could predict abnormal returns. On the contrary of the previous finding, the variance during the time of arbitrage limitations is not a reliable predictor of anomaly returns.

Methodologically, the study identifies all the known anomalies, which are referred in literature. Mainly, the papers which suggests abnormal returns, either using a three-factor model or comparable benchmarks are included in the study. A zero-cost portfolio based on a short-long investment strategy, is calculated for each anomaly. Finally, a on long position portfolio, which includes undervalued assets, and a short position portfolio, which includes overvalued assets, are constructed. These portfolios were restructured on a one to twelve months basis.

As far as the fundamental analysis is concerned, this study examines as a signal of anomaly a) the difference between the change of turnover and inventories of a company and b) the variations of the gross profit margin. In respect of anomalies which are relative to capital investment and growth, the study tests a) the hypothesis of negative relation between the growth in operating assets and future stock returns and b) the negative relation between stock returns and capital investments as proportion of total assets.

Especially, the dataset which was taken under consideration for the difference between the change of turnover and inventories anomaly includes observations from November 1975 to December 2011. The anomalies which derived from changes in gross profit margin was examined between February 1975 and December 2011. In relation to the negative correlation between the growth in operating assets and future stock returns anomaly, a period between July 1965 to December 2011 was examined. Finally, for the examination of capital investments anomaly taken into account observations from July 1952 to December 2011.

2.3: Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) is a theory in financial economics that states that financial markets are "informationally efficient," meaning that the prices of publicly traded assets reflect all publicly available information at any given time. The EMH has three forms: weak, semi-strong, and strong. The weak form states that past prices and trading volume have no effect on future prices. The semi-strong form states that prices reflect all publicly available information, including financial statements and news. The strong form states that prices reflect all information, including insider information. The EMH is a widely debated theory and has been the subject of much empirical research. Some evidence supports the EMH, while other evidence contradicts it.

The Efficient Market Hypothesis (EMH) originated in the 1960s with the work of economist Eugene Fama. Fama's early research focused on testing the relationship between stock prices and various types of publicly available information, such as financial statements and news. He found that stock prices tended to reflect all publicly available information, leading him to propose the EMH. The theory suggests that it is impossible to consistently achieve higher returns than the market average by using publicly available information, as the prices of securities already reflect all such information. Subsequently, the EMH became a central idea in the field of financial economics, and has been widely studied and debated by economists, finance professionals, and academics.

According to Samuelson (1965), a competitive market characterized by the perfect match of buyers and sellers, so if the participants anticipate a price of an asset would rise, this price increase would have been already done. Based on Samuelson’s concept of

Efficient Market Hypothesis, which be examined from a microeconomic view, Fama (1970) reviewed both the theoretical and empirical components of this hypothesis.

According to Fama (1970) an efficient market is a market where the prices are characterized by the full adoption of all relative information or as Malkiel (1992) suggests, a market is efficient if the prices remain steady after the disclosure of all relative information to all participants.

On a theoretical basis, Efficient Market Hypothesis suggests that participants are not able to achieve abnormal returns by trading on available information, into an efficient market. According to theory, there are three levels of market efficiency, the Weak Form, the Semi-strong Form and the Strong Form.

The weak form of the Efficient Market Hypothesis (EMH) states that historical stock prices and trading volume data have no effect on future stock prices. This means that it is not possible to consistently achieve higher returns than the market average by analyzing past prices and trading volume data, such as using technical analysis.

In simple terms, it means that it is not possible to predict future stock prices by looking at past prices and trading volume data, because the current market price already reflects all historical data.

It is important to note that the weak form of the EMH does not take into account any other type of information such as company fundamentals, news, and economic indicators, which are considered in the semi-strong and strong form of the EMH.

The semi-strong form of the Efficient Market Hypothesis (EMH) states that stock prices reflect all publicly available information, including financial statements, news, and other publicly available information. This means that it is not possible to consistently achieve higher returns than the market average by using publicly available information such as financial statements and news, as the prices of securities already reflect this information.

It implies that it is impossible to beat the market by analyzing publicly available information, as the prices already reflect all the information available to the public.

This form of EMH is considered more realistic than the strong form, as it acknowledges that some information may be difficult to access or analyze, and thus, investors may have an edge over others with more information or better analysis.

The strong form of the Efficient Market Hypothesis (EMH) states that stock prices reflect all information, including insider information. This means that it is not possible to consistently achieve higher returns than the market average by using any type of information, including insider information. In other words, it is impossible to consistently beat the market through any means, including insider trading. This form of EMH is considered the most extreme and least realistic, as it implies that no one can have an informational advantage over anyone else, including insiders, who have access to non-public information.

It is important to note that the strong form of EMH is highly debated among academics and practitioners, and many argue that it is impossible for markets to be perfectly efficient and reflect all information, as there are many factors that can affect prices, including insider trading, market manipulation, and irrational behavior.

It is also important to note that EMH is just a theory, it is not a law and it's a subject to empirical testing, which have shown mixed results, some studies support it and others don't.

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Chapter 3: Methodology

The present study focusses on four market anomalies which are relative to the difference between the change of turnover and inventories of a company, the variations of the gross profit margin, the hypothesis of negative relation between the growth in operating assets and future stock returns and the negative relation between stock returns and capital investments as proportion of total assets. The computational approaches which were adapted for the purposes of the study are described below for each anomaly, separately.

3.1: Market anomaly indexes

3.1.1: Difference between the change of turnover and inventories

According to the main paper, the approach was based on Abarbanell and Bushee (1998). The purpose of the study of Abarbanell and Bushee (1998) is to investigate the relation between current changes of fundamental financial statements elements and future changes of earnings. Specifically, the aforementioned paper focusing on changes of fundamental elements Sales and Inventories, tests the correlation between a) the one-year-ahead earnings change and b) the percentage change in Inventory minus the percentage change in Sales.

Index: Δ Inventory – Δ Sales ⇔

$$\frac{Inventories_t - E(Inventories_t)}{E(Inventories_t)} - \frac{Sales_t - E(Sales_t)}{E(Sales_t)}$$

Where: E → Expected

t → time indicator

Abarbanell and Bushee (1997) in their paper explore the connection between the data which are depicted on financial statements and the stock earnings. They try to define if changes of the fundamental measures of a firm contain information which could enable the participants to predict the future earning of its stock. Theirs paper is in line with the Penman 's (1992) and others' perspective, according to which the main scope of fundamental analysis should be the estimation of earning on account basis. The detection of the connection between financial statement data and future earnings enables the researcher to testify the fundamental economic rationale which lead to these financial data. A less straight approach, which was proposed by Lev and Thiagarajan

(1993), suggests the detection of the connection between changes in fundamentals and contemporary returns.

According to Lev and Thiagarajan (1993), fundamental analysis seeks to determine the value of company stocks by a thorough evaluation of critical value drivers such as profits, risk, growth, and competitive position. In the framework of their research, they define a collection of financial indicators (fundamentals) claimed by markets participants to be relevant in security valuation and investigate these assertions by evaluating their additional value relevance over profits. Findings corroborate that the incremental value-relevance of the majority of the identified financial measures; in fact, for the 1980s, the fundamentals provide about 70% to the explanatory power of excess profits on average. Also, their research documented that when the relationship between the returns and fundamentals is conditioned on macroeconomic factors, it becomes significantly stronger, emphasizing the relevance of context - specific capital market analysis. Several fundamentals, for example, that seem to be only slightly value-relevant or even irrelevant in the unconditional analysis have a considerable correlation with returns under certain economic situations, such as the accounts receivable and the provision for doubtful receivables signals during high inflation.

Also, a standard for evaluating how well analysts use the fundamental signals while studying the relationships between the fundamental signals and anticipated earnings is developed. The correlations between the signals and the current anomalous returns cannot be used to answer the question of how well analysts use this information. The proposed method is intended to identify those signals analysts claim to use or researchers claim analysts use that truly have an impact on their profit estimates. According to their approach, they determine whether the information contained in fundamental signals about future earnings is fully exploited in analysts' revisions by comparing the relations between the signals and earnings changes to the analogous relations between the signals and forecast. The findings of this research imply that the information about future earnings included in fundamental signals is not fully captured by analysts' projection revisions, and tests based on stock return data reveal that investors generally seem to be aware of this fact.

The majority of the economic intuition that has been employed to relate changes in earnings to current accounting information is validated by the findings of this papers. However, certain prominent outliers show that applying mechanical norms of basic analysis should be done carefully. Similar to this, is discovered that many, but not all, of the signals that anticipate future earnings are connected with analysts' revisions of their earnings projections.

Tests based on recent securities returns show that fundamental signals transmit information orthogonal to forecast revisions that is relevant to value. One argument is because the signals include value-relevant data that is unrelated to earnings, such as risk indicators that are left out of experts' short-term estimates. This argument reflects an alternate interpretation of their findings and runs against to the future returns-based logic that Lev and Thiagarajan employed to support the development of the basic signals.

It's also feasible that investors don't believe experts' projection adjustments completely replace the information in the signals. According to this paper are documented relationships between analysts' forecast revisions, financial statement data, and future earnings changes that are consistent with analysts' failure to undertake totally efficient fundamental evaluations, giving support for such beliefs. Abarbanell and Bushee 's investigation of forecast mistakes by analysts reveals a generalized underreaction to comprehensive accounting information, which, if eliminated, would also reduce analysts' apparent underreaction to yearly earnings announcements.

To summarize, the research of Abarbanell and Bushee (1997) investigates the basic relationships between accounting-based fundamental signals and stock prices. There is an economic reason for analysts and investors to depend on many, but not all, of the basic signals described by Lev and Thiagarajan (1993) when judging future business performance based on relationships between the individual signals and future earnings changes. Furthermore, certain basic signals on financial statements only explain long-run profits growth, implying that they may reflect both structural shifts and temporary profitability changes.

Abarbanell and Bushee (1997) discovered that experts' projections do not fully incorporate the information that investors believe is present in fundamental signals. Because analysts' prediction revisions are closely related to many of these signals in the same manner as returns are, the question of why these revisions fail to incorporate value-relevant information emerges. One possible reason for this outcome is that the signals may capture information about the business that has little to do with short-term profitability, such as changes in corporate risk. Because analysts' projections are limited to conveying information about profits over a short time horizon, value-based information regarding remaining future earnings will be removed from their estimations, even if it may be reflected in price.

Another interpretation supported by the data is that analysts' projection revisions fail to fully internalize the information in fundamental signals concerning future earnings changes. As a result, even when analyst projections are available, investors may gain from utilizing the signals. The study's findings call into question the accuracy of analysts' estimates considering the information in basic signals. An assessment of analyst prediction mistakes finds that analyst inefficiency takes the form of generalized underreaction, and that this underreaction to specific fundamental signals appears to explain for analyst underreaction to prior year earnings news reported in early-year projections.

The findings of researchers on analyst underreaction to financial statement information suggest that investors in general may be inefficient in the analysis of financial statements. Previous study has shown that investors do not use in depth the earnings information (see Bernard and Thomas (1990)). Abarbanell and Bushee (1996) investigate whether investors fully utilize the information in fundamental signals and discover evidence consistent with underreaction. Because previous research indicates that analysts' inefficient use of prior earnings information does not fully explain investors' underreaction to this information (e.g., Jacob and Lys (1993) and Abarbanell and Bernard (1992)), it is vague to what extent the analyst underreactions reported in this study contribute to slow-moving price changes.

Finally, Abarbanell and Bushee (1997) demonstrated that firm ’s characteristics like as historical earnings and expected earnings growth, as well as macroeconomic variables such as inflation and GDP, condition some of the relationships between fundamental signals and future earnings, revisions, and forecast errors. Preliminary information on the effect of industry participation implies that more theory can be used to enhance the core analysis undertaken in this study (see, e.g., Bernard and Noel (1991) and Stober (1993).

3.1.2: Variations of the gross profit margin

The computational approach was based on Piotroski (2000). Piotroski (2000) considers the change of gross margin ratio as operating efficiency of a company. Exploiting this metric among others an overall score per company was calculated. Based on these scores two portfolios formulated, one which included companies with high score and one which included low score companies. Finally, the paper compares the returns of these two portfolios.

Index: Δ Margin ⇔

$Margin_t – Margin_{t-1} \Leftrightarrow$

$$\frac{Gross\ Margin_t}{Sales_t} - \frac{Gross\ Margin_{t-1}}{Sales_{t-1}}$$

Where: t → time indicator

Piotroski ‘s (2000) research investigates whether a basic accounting-based fundamental analysis method may affect the distribution of returns received by an investor when applied to a large portfolio of high book-to-market businesses. Considerable research has been conducted to demonstrate the benefits of a high book-to-market investing strategy (e.g., Rosenberg, Reid, and Lanstein (1984), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994)). However, the strategy's effectiveness is dependent on the excellent performance of a few firms while tolerating the low performance of numerous failing ones.

According to this research, fewer than 44% of all high book-to-market enterprises have positive market-adjusted returns in the two years after portfolio formation. Given the different outcomes attained within that portfolio, investors may gain by anticipating the forthcoming strong and poor firms. This research investigates whether a basic, financial statement-based bias, when be realized to these out-of-favor companies, can distinguish between enterprises with strong and bad prospects. In the process, a set of intriguing regularities is uncovered about the performance of the high book-to-market portfolio and some evidence to corroborate the expectations of contemporary behavioral finance models are presented.

Companies with a high book-to-market ratio provide an exceptional chance to examine the capacity of simple fundamental analysis bias to differentiate companies. First, value stocks are frequently overlooked. As a group, these firms are thinly watched by analysts and characterized by low levels of investors’ interest. Analyst estimates and stock recommendations for these companies are unavailable due to a lack of coverage. Second, due to their poor recent performance, these enterprises have restricted access to most "informal" information dissemination channels, and their voluntary disclosures may not be perceived as reliable. As a result, financial statements are the most trustworthy and easily available source of information on these companies. Third, high book-to-market enterprises are more likely to be in financially distress, therefore their value is based on financial statements measures such as leverage, liquidity, profitability trends, and cash flow sufficiency. These key qualities may be determined most easily from past financial accounts.

The purpose of this article is to demonstrate how basic screens based on previous financial performance may help investors build a stronger value portfolio. If successful, the distinction between future "winners" and "losers" should affect the distribution of a value investor's profits. The findings indicate that such differentiation is conceivable. To begin, the research reveals that selecting financially sound high BM businesses can boost the mean return gained by a high book-to-market investor by at least 7.5% yearly. Second, the entire realized return distribution is stressed to the right. Although the portfolio's mean return is the essential benchmark for performance measurement, this article also shows that when fundamental filters are applied, the left-tail of the return distribution (i.e., the 10th percentile, 25th percentile, and median) sees a considerable positive change. Third, between 1976 and 1996, an investing strategy that buys projected winners and sells expected losers generated a 23% yearly return. These returns of this strategy are proven to be robust over time and to controls for competing investing techniques. Fourth, the capacity to distinguish organizations is not limited to a single technique to financial statement examination. Additional experiments show that employing alternate, but complementing, indicators of previous financial performance is successful. Fifth, this research contributes to the finance literature by offering data on current behavioral model predictions (such as Hong and Stein (1999), Barbaris, Shleifer, and Vishny (1998), and Daniel, Hirshleifer, and Subrahmanyam (1998)). Similar to the momentum-related results reported in Hong, Lim, and Stein (2000), I find that in rapid information dissemination contexts, the positive market-adjusted return gained by a general high book-to-market approach vanishes (large firms, firms with analyst following, high share-turnover firms). More crucially, the fundamental analysis technique is most effective at differentiating value organizations in sluggish information dissemination contexts.

Finally, Piotroski demonstrates that the strategy's effectiveness is dependent on the capacity to forecast future business performance and the market's inability to detect these predictable patterns. Businesses with weak present signals have lower future profit realizations and are five times more likely than firms with strong current signals to delist for performance-related reasons. Furthermore, he shows evidence that the market is systematically "surprised" by these two organizations' future profit statements. When the three-day market responses around the next four quarterly earnings releases are added together, the announcement-period returns for expected "winners" are 0.041 greater than identical values for predicted losers. This one-year announcement return differential is equivalent in magnitude to LaPorta et al. four-quarter "value" vs "glamour" announcement return difference (1997). Furthermore, only 12 trading days account for around one-sixth of the overall yearly return differential between ex ante strong and weak businesses.

This study adds to our understanding of the returns obtained by small, financially troubled enterprises, as well as the relationship between these returns and their prior financial performance. Given the significance of these corporations in many of the "anomalies" described in the present literature (see Fama (1998)), this finding is intriguing. The findings imply that high performers can be distinguished from future underperformers by making use of contextually relevant previous knowledge. The capacity to distinguish between future successful and failed enterprises ex ante and profit from the technique shows that the market does not efficiently absorb previous financial signals into present stock prices.

One of signals which is explored in the Piotroski ‘s research is the Operating Efficiency of a firm. Especially, the metric exploited by the researcher is the change in gross margin “ΔMARGIN”. This ratio is significant because illustrates two essential characteristics underpinning a return on assets decomposition. ΔMARGIN is defined as the current gross margin ratio (gross margin divided by total sales) less the previous year's gross margin ratio. An increase in margins indicates a probable improvement in costs elements, a decline in inventory expenses, or a rise in the company’s product prices.

3.1.3: Negative relation between the growth in operating assets and future stock returns

The computational approach was broadly based on Fairfield (2003). Fairfield (2003) tested the hypothesis that the accrual earnings and the growth of net operating assets on a long-term basis are negatively correlated to future Return on Asset (ROA).

Index: ROA = $\frac{Operating\ Income\ after\ Depreciation\ and\ Amortization\ _t}{[Total\ Assets_{t-1}+Total\ Assets_t]/2}$

Where: t → time indicator

According to Fairfield (2003) financial statement analysis research has revealed indicators that might help forecast profitability. Regression toward the mean in return on equity, for example, as documented by Freeman, Ohlson, and Penman (1982). Other study has found that financial statement components and ratios convey information regarding future earnings changes (Ou and Penman 1989, Ou 1990 and Abarbanell and Bushee 1997) as well as future return on assets (Fairfield and Yohn 2001). Furthermore, research has been conducted to determine if information in previous financial statements seems to be accurately represented in equity market valuations. Market mispricing has been established in studies based on basic variables such as business size (Fama and

French 1992), recent earnings surprises (Bernard and Thomas 1989), and previous sales growth (Lakonishok, Shleifer, and V ishny 1994).

The discovery of unequal persistence of the accrual and cash flow components of earnings performance, as well as the mispricing of the accrual and cash flow components, is a recent noteworthy contribution to both streams of research (Sloan 1996; Collins and Hribar 2000; and Xie 2001). Sloan (1996) shows that the accrual component of earnings is less consistent than the cash flow component and that investors fail to fully comprehend the differences between accruals and cash flows.

The concept explored in this study is whether the results regarding lower persistence and market mispricing of accruals can be extended to long-term growth in net operating assets, and whether the lower persistence of accruals stems from the differential impact of net operating assets growth relative to cash flows on the earnings performance measure's denominator. The basis of this research is the suggestion that earnings performance, as defined by Sloan (1996), is operating income divided by contemporaneous average total assets translates operating income into return on assets (ROA). Furthermore, accruals are defined as the increase in operating working capital minus depreciation and amortization expenditures. Accruals thus represent not just a component of operating income in the numerator of current ROA, but also a component of net operating asset growth, which affects average total assets in the denominator of one-year-ahead ROA. According to Fairfield accruals, as a component of net operating asset growth, are more closely tied to average total assets than cash flows from operational activity. So, suggested that the observed lower durability of accruals vs cash flows is due to variations in correlations between the two components and the future ROA denominator.

Another interpretation of accruals' differential persistence is that, conditioned on present ROA, accruals are inversely related with one-year-ahead ROA. This paper suggests that the observed negative relationship between accruals and one-year-ahead ROA is due to the disproportionate influence of increase in net operating assets relative to cash flows on the ratio's denominator. Furthermore, is expected that the negative connection would be absent when the profits performance measure's deflator is lagged rather than contemporaneous average total assets.

The results of Fairfield ‘s research confirms the initial hypotheses. The paper suggests that, given the present ROA, growth in long-term net operating assets correlates adversely with one-year-ahead ROA. Moreover, there are not differences in the implications for one-year-ahead ROA between accruals and long-term increase in net operating assets. Also, discovered that the negative connections between one-year-ahead ROA and both types of net operating asset growth (accruals and long-term net operating asset growth) are attributable to the influence of growth on the denominator of ROA rather than their implications for one-year-ahead operating income.

These findings are critical for financial statement analysis. According to the results, present ROA and current increase in net operating assets are related to one-year-ahead ROA. The conclusion is consistent with the valuation models of Ohlson (1995) and Feltham and Ohlson (1995), which show that profitability and growth are the key determinants of valuation. Findings indicates that disaggregating current ROA into its accrual and cash components provides no additional explanatory power on average.

The findings are also significant for future study. Earnings, ROA, and profitability are frequently used interchangeably by researchers. The findings shows that the relationship between growth and one-year-ahead ROA is not the same as the relationship between growth and one-year-ahead operating income. As a result, the choice of deflator is critical in interpreting data about the persistence of accruals for future income vs future ROA.

The researcher analyzes whether the market inefficiency reported in Sloan (1996) applies to growth in long-term net operating assets, given that there are similar connections between accruals and growth in long-term net operating assets and one-year-ahead ROA conditioned on present ROA. The Mishkin (1983) test is implemented to see if there is a discrepancy between the predictive capacity of long-term net operating asset growth for one-year-ahead ROA and the weight on long-term net operating asset growth inherent in stock prices. She discovers that, similar to the market mispricing of accruals, investors seem to overestimate the consequences of long-term net operational asset growth for one-year-ahead ROA. The two mispricing impacts appear to be distinct but statistically equal. The findings imply that the apparent market mispricing of accruals may be extended to a single fundamental variable, net operating asset growth.

3.1.4: Negative relation between stock returns and capital investments as proportion of total assets

The computational approach was based on Stambaugh et al. (2012). According to Stambaugh et al. (2012) the set of market anomalies, which are considered, are related to investor sentiment. Among others, this article examines the negative relation between the level of past capital investments and future returns. Specifically, the capital investment be defined as the yearly change in capital assets proportional to previous year’s book value of assets.

Index: $\dfrac{\frac{Capital\ Assets_t - Capital\ Assets_{t-1}}{Capital\ Assets_{t-1}} + \frac{Inventories_t - Inventories_{t-1}}{Inventories_{t-1}}}{\frac{Assets\ Book\ Value_t - Assets\ Book\ Value_{t-1}}{Assets\ Book\ Value_{t-1}}}$

Where: t → time indicator

Economists have long been interested in whether investor mood influences stock prices. A lot of researchers have examined the idea that a considerable presence of sentiment-driven investors might lead prices to deviate from fundamental values as early as Keynes (1936). The fundamental argument against emotion effects is that they would be eradicated by rational traders attempting to profit from mispricing. However, if sensible traders are unable to completely capitalize on such chances, sentiment impacts become more frequent.

The study of Stambaugh, Jianfeng and Yu (2012) looks at the occurrence of sentiment effects by merging two ideas that are popular in the related literature on their own. The first assumption is that investor sentiment has a market-wide component that has the capacity to move several securities' values in the same direction at the same time. The second idea, which comes from Miller (1977), is that obstacles to short selling play a substantial role in restricting rational traders' capacity to exploit overpricing. As Miller argues "A market with a large number of well-informed investors may not have any grossly undervalued securities, but if those investors are unwilling to sell short (as they often are) their presence is consistent with a few investments being overvalued.".

When Miller's reasoning is combined with the existence of market-wide sentiment, the few overvalued investments are replaced with possibly many such investments when market-wide characterized by high sentimental level. Miller's argument holds that periods of poor market sentiment should not be accompanied by significant undervaluation.

This paper investigates sentiment-related overvaluation as at least a partial explanation for 11 asset-pricing anomalies that persist after adjusting for exposure to the three Fama and French components (1993). Financial hardship, net stock issues, composite equity issues, total accruals, net operational assets, momentum, gross profit-to-assets, asset growth, return-on-assets (ROA), and investment-to-assets are all examples of anomalies. Also, the strategy that goes long the stocks in the highest-performing decile and short the stocks in the lowest-performing decile are investigated for each aberration. In addition, the researchers investigate sentiment impacts using Baker and Wurgler's (2006) market-wide investor sentiment index.

According to the paper, three possibilities arise from combining market-wide sentiment with the Miller short-sale argument. The first hypothesis is that, to the degree that they reflect mispricing, the anomalies should be stronger after a period of high emotion. If overpricing is the most common type of mispricing, then mispricing should be more likely when sentiment is strong. Also, discovered that after high levels of investor sentiment, each of the 11 anomalies becomes stronger (i.e., levels of sentiment above the median value). When the benchmark adjusted earnings from a long-short strategy are averaged across anomalies, 70% occur in months following levels of market sentiment above the median value. Time series analysis supports the existence of a substantial positive correlation between investor sentiment and long-short anomaly profits.

The second premise is that when sentiment is strong, the returns on the short leg portfolio of each market anomaly should be lower. To the degree that the anomaly indicates mispricing, the stocks in the short leg are comparatively expensive compared to the equities in the long leg. Furthermore, when sentiment is high, the equities in the short leg should be more overvalued. The results indicate that the return on the short leg is lower following strong emotion for each of the 11 anomalies. When the earnings from shorting that leg are averaged over anomalies, 78% of the benchmark-adjusted profits come in the months after strong sentiment. Time series regressions indicate a substantial negative relationship between investor mood and short leg performance.

The third hypothesis is that investor sentiment should not have a significant impact on any anomaly of long leg portfolio results. If there is no underpricing, as in the Miller argument, then the returns on the long leg should not be higher after low sentiment than following high sentiment. When market sentiment is high, equities in the long leg may be overvalued, but the long leg should be the least overpriced. Overall, is anticipated that sentiment to have a minor impact in long-term results. This theory has also been validated. There is no significant difference between high and low sentiment times in any of the 11 lengthy legs. When the benchmark-adjusted returns on the long leg are averaged over anomalies, there is only a 4 basis point monthly difference between high and low sentiment periods. Time series regressions show that there is no relationship between benchmark-adjusted long-leg returns and investor mood.

Stambaugh, Jianfeng and Yu (2012) broaden their investigation of sentiment impacts by looking at four long-short spreads that are frequently linked with systematic risk. they showed that spreads depending on market beta or company size have sentiment-related relationships that are highly similar to the eleven anomalies, implying that these return spreads at least largely reflect sentiment-related mispricing along the lines suggested. The same emotional relationships for spreads based on book-to-market ratios or betas in connection to market liquidity is not discovered.

Stambaugh, Jianfeng and Yu (2012) concluded that considering the restrictions on short selling, it becomes more difficult to eradicate overpricing, thus a company's stock price may reflect the opinions of too optimistic investors. Overpricing could happens occur for many equities during moments of strong sentiment due to marketwide fluctuations in investor mood.

Strategies based on long-short practice reveal empirical features consistent with a mix of short-sale obstacles and market-wide sentiment over a wide range of anomalies in cross-sectional returns. Because overpricing is more common in predicted scenario of their research than underpricing, anomalies should be higher after periods of high emotion, to the degree that the anomalies reflect mispricing. Also, they discovered that long-short strategies were more profitable when sentiment is strong. If overpricing is the major source of those higher gains, the short legs of the strategies should be more profitable when sentiment is high, and that inference was well confirmed by the data. Sentiment had no discernible influence on earnings from the lengthy legs of the techniques. The latter conclusion was also consistent with the hypothesis that underpricing should be less common in their research simplified context, where short-sale barriers were the primary hindrance to traders looking to exploit mispricing.

According to the researchers of this paper, this study does not seek comprehensive answers for all of the oddities investigated. Numerous studies investigate the individual abnormalities in greater depth and give more narrowly focused settings and explanations. The goal, given the considering of the ramifications when market-wide sentiment interacts with short-sale barriers, is to paint the collection of anomalies with a deliberately broad brush. The main goal was to investigate the potential that sentiment has a long-term influence on the degree of mispricing that occurs in a variety of specific scenarios. There was no attempt to be explained the causes, in the cross section, more mispricing was related with more extreme values of a certain attribute used to construct an anomaly. While this technique uncovered new evidence compatible with overpricing as at least a partial explanation for many anomalies, much more research is needed to create a more comprehensive knowledge of how sentiment influences financial asset pricing.

3.2: Portfolio Formulation

The sample of companies, which were examined for the purposes of this study, were traded in European Stock Markets. The aforementioned indexes were calculated on an annual basis for each company of the sample. Following, the companies were sorted in ascending order according to this index. Finally, five portfolios (d1, d2, d3, d4, d5) were formed, where the d1 includes the 20 % of the companies with lowest index result and the d5 includes the companies of the upper 20 %. These portfolios were rebalanced on an annual basis when the recalculation of the index took place. The returns of each portfolio were calculated on a monthly basis, for a 28-year period, from July 1990 to June 2018.

3.3: Tested Model

In order to examine the existence and the power of these four market anomalies the Fama - French 5 Factor Model were used as the pricing model.

The Fama-French 5-factor model is a widely used asset pricing model developed by Eugene Fama and Kenneth French. This model is an extension of the original 3-factor model developed by Fama and French, which included market beta, size, and value as factors that could explain the cross-section of stock returns.

The 5-factor model includes these three original factors, and adds two additional factors: profitability and investment. The profitability factor represents the long-term earnings power of a firm, and the investment factor represents the level of physical and intangible investments made by the firm. The purpose of the Fama-French was to provide a more comprehensive explanation of the cross-section of stock returns. By incorporating additional factors that capture important characteristics of firms, the Fama-French 5-factor model aims to explain a larger portion of the variation in stock returns.

Empirically, the Fama-French 5-factor model has been found to provide a better explanation of the cross-section of stock returns compared to the original 3-factor model. This has led to the widespread adoption of the Fama-French 5-factor model in academic research and investment management.

So, as a dependent variable is defined the portfolio risk premium, which is calculated as the difference between the monthly return of each portfolio and the risk-free rate of the reference period. The model is described below.

Model: $R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$

Where:

R_{it} = Portfolio returns

R_{Ft} = Risk-free rate

a_i = Intercept

b_i, s_i, h_i, r_i, c_i = Regression coefficients of each independent variable

e_{it} = *Residuals*

The source of the explanatory variables, which are described below, is Kenneth R. French data library (source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Developed). Especially, the historical data, which were used, referred to the monthly returns of Fama/French 5 factors for the Developed European Economies during the period July 1990 to June 2018

Market Risk Premium $(R_{Mt} - R_{Ft})$: Is the difference between the market portfolio return and risk-free rate.

SMB: Is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios

HML: Is the average return on the two value portfolios minus the average return on the two growth portfolios.

RMW: Is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios.

CMA: Is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios.

Finally, the estimation of each coefficient of the Fama/French 5 Factor model derives from the regression on the relative time series. Following the model estimation, as the measure of each Market Anomaly defined the abnormal returns (CAR).

$$AR = (a_i + e_i) \Leftrightarrow$$

$$AR = (R_{it} - R_{Ft}) - [b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t)]$$

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Chapter 4: Empirical Results

4.1: Explanatory Variables – Descriptive Statistics

Regarding the data set and the statistical analysis assumptions, the sample includes monthly observation from July 1990 to June 2018. During this period, a set of 336 observations was formed. The econometric analysis and the statistical testing procedure considered a 95 % level of confidence.

The statistical analysis of independent variables, which is presented on table 1, for the reference period shows that the average return of small stocks portfolio is equal to the average return of big stocks portfolio. On the other side, the statistical significance of the mean of HML, RMW and CMA suggests that the high value stocks outperform growth stocks, robust operating profitability portfolios outperforms low operating profitability portfolios and conservative portfolio outperforms the aggressive one, respectively. Also, the market risk premium is different to zero on average, something which is reasonable under normal market conditions.

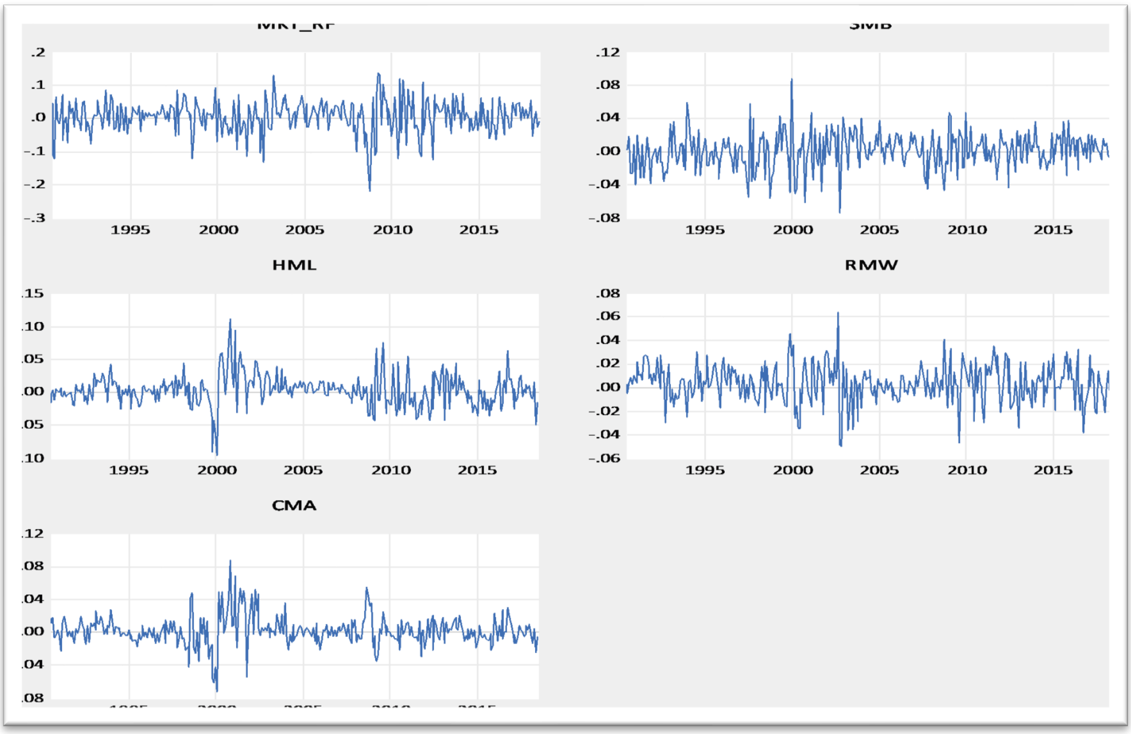

Diagram 1: Independent variables time-series (extract from EViews)

Table 1: Independent variables descriptive statistics

	Mkt-RF	SMB	HML	RMW	CMA
Mean	0.004995	0.000728	0.003149	0.003854	0.001892
P-value of Mean*	0.03063	0.26764	0.00835	0.00000	0.02806
Median	0.007200	0.001500	0.003350	0.004200	0.000700
Maximum	0.136700	0.088300	0.111600	0.064000	0.087700
Minimum	-0.220200	-0.073300	-0.095000	-0.050000	-0.073000
Standard Deviation	0.048759	0.021502	0.023999	0.016053	0.018096
Skewness	-0.602807	-0.071251	0.302685	-0.272806	0.376358
Kurtosis	4.635665	3.975978	5.919585	3.893519	6.655767
Jarque-Bera	57.80467	13.61975	124.4663	15.34495	195.0370
Probability	0.00000	0.001103	0.00000	0.000465	0.00000
Sum	1.678400	0.244600	1.058100	1.295100	0.635800
Sum Sq. Dev	0.796458	0.154886	0.192947	0.086326	0.109700
P-value of ADF**	0.00000	0.00000	0.00000	0.00000	0.00000
Observations	336	336	336	336	336

*** Null Hypothesis: Mean = 0**

**** Null Hypothesis: Time series has Unit Root**

Furthermore, the Jarque-Berra distribution normality test (table 1) indicates that the time series of all the factors are not normally distributed. The Augmented Dickey-Fuller test, as it represented on the tables 2, 3 ,4, 5 and 6, which tests the existence of unit root on time series, suggests that none of the time series of 5 factors has Unit Root. This unit root test assumes that the time series have no trend and intercept, something which is reasonable examining the Diagram 1.

Table 2: MKT_RF unit root test (extract from EViews)

Null Hypothesis: MKT_RF has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.39859	0.0000
Test critical values:	1% level	-2.571883	
	5% level	-1.941773	
	10% level	-1.616066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(MKT_RF)
Method: Least Squares
Date: 06/20/22 Time: 20:19
Sample (adjusted): 1990M08 2018M06
Included observations: 335 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MKT_RF(-1)	-0.890862	0.054326	-16.39859	0.0000

R-squared	0.446020	Mean dependent var	-0.000161
Adjusted R-squared	0.446020	S.D. dependent var	0.065477
S.E. of regression	0.048735	Akaike info criterion	-3.201878
Sum squared resid	0.793267	Schwarz criterion	-3.190493
Log likelihood	537.3146	Hannan-Quinn criter.	-3.197339
Durbin-Watson stat	1.962129		

Table 3: SMB unit root test (extract from EViews)

Null Hypothesis: SMB has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.11879	0.0000
Test critical values:	1% level	-2.571883	
	5% level	-1.941773	
	10% level	-1.616066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(SMB)
Method: Least Squares
Date: 06/20/22 Time: 20:21
Sample (adjusted): 1990M08 2018M06
Included observations: 335 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SMB(-1)	-0.991628	0.054729	-18.11879	0.0000

R-squared	0.495689	Mean dependent var	-3.28E-05
Adjusted R-squared	0.495689	S.D. dependent var	0.030340
S.E. of regression	0.021546	Akaike info criterion	-4.834294
Sum squared resid	0.155050	Schwarz criterion	-4.822909
Log likelihood	810.7443	Hannan-Quinn criter.	-4.829755
Durbin-Watson stat	1.998858		

Table 4: HML unit root test (extract from EViews)

Null Hypothesis: HML has a unit root
Exogenous: None
Lag Length: 2 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.976517	0.0000
Test critical values:	1% level	-2.571925	
	5% level	-1.941778	
	10% level	-1.616062	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(HML)
Method: Least Squares
Date: 06/20/22 Time: 20:22
Sample (adjusted): 1990M10 2018M06
Included observations: 333 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HML(-1)	-0.484525	0.069451	-6.976517	0.0000
D(HML(-1))	-0.142360	0.063396	-2.245551	0.0254
D(HML(-2))	-0.245906	0.053874	-4.564426	0.0000

R-squared	0.357342	Mean dependent var	-6.01E-05
Adjusted R-squared	0.353447	S.D. dependent var	0.027357
S.E. of regression	0.021997	Akaike info criterion	-4.786821
Sum squared resid	0.159682	Schwarz criterion	-4.752513
Log likelihood	800.0057	Hannan-Quinn criter.	-4.773140
Durbin-Watson stat	2.020131		

Table 5: RMW unit root test (extract from EViews)

Null Hypothesis: RMW has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.60595	0.0000
Test critical values:	1% level	-2.571883	
	5% level	-1.941773	
	10% level	-1.616066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RMW)
Method: Least Squares
Date: 06/20/22 Time: 20:23
Sample (adjusted): 1990M08 2018M06
Included observations: 335 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RMW(-1)	-0.779509	0.053369	-14.60595	0.0000

R-squared	0.389769	Mean dependent var	-1.31E-05
Adjusted R-squared	0.389769	S.D. dependent var	0.020645
S.E. of regression	0.016127	Akaike info criterion	-5.413620
Sum squared resid	0.086871	Schwarz criterion	-5.402234
Log likelihood	907.7813	Hannan-Quinn criter.	-5.409081
Durbin-Watson stat	1.991260		

Table 6: CMA unit root test (extract from EViews)

Null Hypothesis: CMA has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=16)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.94120	0.0000
Test critical values:	1% level	-2.571883	
	5% level	-1.941773	
	10% level	-1.616066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CMA)
Method: Least Squares
Date: 06/20/22 Time: 20:23
Sample (adjusted): 1990M08 2018M06
Included observations: 335 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CMA(-1)	-0.667530	0.051582	-12.94120	0.0000

R-squared	0.333961	Mean dependent var	-4.99E-05
Adjusted R-squared	0.333961	S.D. dependent var	0.021045
S.E. of regression	0.017175	Akaike info criterion	-5.287713
Sum squared resid	0.098526	Schwarz criterion	-5.276328
Log likelihood	886.6920	Hannan-Quinn criter.	-5.283174
Durbin-Watson stat	2.068067		

4.2: Estimated Models & Results Analysis

In order to investigate the existence of forecasting power among the market anomalies we regressed the excess returns of each portfolio with the five factors returns, which are indicated for the European equity market. Specifically, for each market anomaly index we estimated five models. Prior to regression, all the portfolios return time-series were tested for Unit Root (see appendix). Further the estimation of the model, I calculate the

Regarding the first index, the estimated parameters are presented in the table 7 below.

Table 7: Turnover / Inventories Index econometric estimation

Index1_Turnover_Inventories										
Portfolio	***a***	***b***	***s***	***h***	***r***	***c***	***Adj. R Square***	***F stat.***	***Significance F***	***Observations***
d1	0,0043	0,6041	0,5966	0,1148	-0,1718	-0,2176	0,7897	252,5188	0,0000	336
p-value (95%)	0,0000	0,0000	0,0000	0,0484	0,0171	0,0021	-	-	-	-
d2	0,0019	0,5210	0,4366	0,2449	-0,0342	-0,2050	0,7883	250,4369	0,0000	336
p-value (95%)	0,0308	0,0000	0,0000	0,0000	0,5824	0,0008	-	-	-	-
d3	0,0020	0,5886	0,4703	0,2850	0,0344	-0,1491	0,8110	288,4965	0,0000	336
p-value (95%)	0,0271	0,0000	0,0000	0,0000	0,5886	0,0173	-	-	-	-
d4	0,0025	0,6483	0,4787	0,3004	-0,0207	-0,1677	0,8179	301,8617	0,0000	336
p-value (95%)	0,0116	0,0000	0,0000	0,0000	0,7633	0,0132	-	-	-	-
d5	0,0010	0,6933	0,5183	0,2898	-0,0849	-0,1983	0,8270	321,2731	0,0000	336
p-value (95%)	0,3409	0,0000	0,0000	0,0000	0,2379	0,0051	-	-	-	-

The results of the statistical significance test for portfolio d1 suggests that all the coefficients are significant that for the portfolio d1, on a 95% level of confidence. Also, the level of the adjusted R squared metric, which implies that about 79 % of the variance of the dependent variable is explained by the model, is satisfying.

According to the regression results for the rest portfolios d2, d3, d4 & d5, the estimated coefficient of the RMW factor is not important on a statistical view. Considering p-value, we can set these coefficients to zero.

In general, a positive relation is observed among the excess returns of portfolios and the parameters Market risk premium, SMB, HML. On the other hand, the relation of the dependent variable and parameter CMA in negative. As well as, negative or neutral is the relation between the excess returns of portfolios and the parameters RMW.

On the table 8 below are presented the results of regression regarding the gross profit variation index.

Table 8: Gross / Profit Margin Index econometric estimation

Index2_Gross_Profit_Margin										
Portfolio	***a***	***b***	***s***	***h***	***r***	***c***	***Adj. R Square***	***F stat.***	***Significance F***	***Observations***
d1	0,0027	0,6267	0,6321	-0,0360	-0,5655	-0,4028	0,7329	184,8301	0,0000	336
p-value (95%)	0,0454	0,0000	0,0000	0,6392	0,0000	0,0000	-	-	-	-
d2	0,0034	0,6184	0,5431	0,1188	-0,1853	-0,2659	0,8201	306,3707	0,0000	336
p-value (95%)	0,0003	0,0000	0,0000	0,0282	0,0057	0,0001	-	-	-	-
d3	0,0041	0,5847	0,5154	-0,1307	-0,2979	-0,4041	0,7891	251,6209	0,0000	336
p-value (95%)	0,0001	0,0000	0,0000	0,0254	0,0000	0,0000	-	-	-	-
d4	0,0036	0,6353	0,5425	0,1661	-0,1278	-0,1770	0,8011	270,9154	0,0000	336
p-value (95%)	0,0003	0,0000	0,0000	0,0042	0,0739	0,0116	-	-	-	-
d5	0,0033	0,6710	0,6248	-0,0863	-0,4731	-0,2180	0,7649	219,0205	0,0000	336
p-value (95%)	0,0072	0,0000	0,0000	0,2191	0,0000	0,0106	-	-	-	-

On a first review, we could say the most of estimated parameters are statistically significant, apart from the HML for portfolios d1 and d2 and the parameter RMW for the portfolio d4.

For the first three variables, the a, the Market risk premium and the SMB, a positive relation between them and the dependent variable is implied by the regression. On the contrary, the relation among the last two explanatory variables and the dependent variable is negative. Finally, the direction of correlation between the dependent variable and HML is not consistent across all the portfolios, especially for portfolios d2 and d4 is positive, for portfolio d3 is negative and for the rest is neutral.

Regarding the third index, which is relative to the growth of operating assets, the results are exhibited below on table 9.

The correlation of the parameter “a” is positive for the portfolios d3, d4 and d5. As well as the relation between the dependent variable and the market risk premium is positive and statistically significant across all the portfolios. Also, the results suggest that SMB factor is positively correlated with portfolios excess returns.

Table 9: Operating Assets / Future Stock Returns Index econometric estimation

Index3_Op_Assets_Future_Stock_Returns										
Portfolio	***a***	***b***	***s***	***h***	***r***	***c***	***Adj. R Square***	***F stat.***	***Significance F***	***Observations***
d1	0,0014	0,6135	0,8011	-0,2783	-0,8765	-0,2833	0,6845	146,3802	0,0000	336
p-value (95%)	0,3662	0,0000	0,0000	0,0019	0,0000	0,0089	-	-	-	-
d2	0,0011	0,4966	0,4809	0,1621	-0,2545	-0,1191	0,7509	202,9830	0,0000	336
p-value (95%)	0,2528	0,0000	0,0000	0,0034	0,0002	0,0746	-	-	-	-
d3	0,0021	0,5958	0,5046	0,2249	-0,1545	-0,2302	0,7954	261,5165	0,0000	336
p-value (95%)	0,0365	0,0000	0,0000	0,0001	0,0285	0,0009	-	-	-	-
d4	0,0041	0,6373	0,5210	0,1118	-0,0468	-0,2874	0,8099	286,5023	0,0000	336
p-value (95%)	0,0000	0,0000	0,0000	0,0461	0,4983	0,0000	-	-	-	-
d5	0,0043	0,6482	0,5448	-0,0245	-0,1313	-0,3927	0,7405	192,1906	0,0000	336
p-value (95%)	0,0006	0,0000	0,0000	0,7296	0,1356	0,0000	-	-	-	-

According to the estimated parameters, for the portfolio d1 is implied that the variable HML affects the excess returns negatively. On the contrary, this variable has a positive impact for the portfolios d2, d3 and d4.

Relative to explanatory variable, it seems to be correlated negatively with the dependent variable for portfolios d1, d2 and d3. The same correlation suggested by regression for variable CMA across portfolios, except for d2, where it seems to be neutral.

Finally, the results for the fourth index, which is examines in this study, are presented below on table 10. This index incorporates the capital investments as proportion of total assets.

In general, a positive correlation suggested by the results between dependent variable and explanatory variables Market risk premium and SMB across the portfolios. In contrast, the variable CMA correlated negatively with the portfolio excess returns.

Furthermore, the results suggest that the variable RMW has a negative impact on dependent variable and is statistically significant for portfolios d1, d2, d3 and d4. On the other hand, the variable HML is correlated positively with portfolios excess returns for portfolios d2, d4 and d5.

Table 10: Stock Returns / Capital Investments Index econometric estimation

Index4_Stock_Returns_Capital_Investments										
Portfolio	***a***	***b***	***s***	***h***	***r***	***c***	***Adj. R Square***	***F stat.***	***Significance F***	***Observations***
d1	0,0056	0,6809	0,5066	0,1508	-0,2497	-0,1882	0,7805	239,3043	0,0000	336
p-value (95%)	0,0000	0,0000	0,0000	0,0234	0,0025	0,0195	-	-	-	-
d2	0,0069	0,7217	0,5412	0,0967	-0,2336	-0,3236	0,8228	312,1393	0,0000	336
p-value (95%)	0,0000	0,0000	0,0000	0,1181	0,0024	0,0000	-	-	-	-
d3	0,0060	0,7297	0,5735	-0,0524	-0,4445	-0,5263	0,8153	296,6830	0,0000	336
p-value (95%)	0,0000	0,0000	0,0000	0,4395	0,0000	0,0000	-	-	-	-
d4	0,0046	0,6944	0,5864	0,1621	-0,1927	-0,3649	0,8109	288,3322	0,0000	336
p-value (95%)	0,0000	0,0000	0,0000	0,0106	0,0139	0,0000	-	-	-	-
d5	0,0019	0,6865	0,5512	0,1777	-0,1734	-0,3595	0,7497	201,7236	0,0000	336
p-value (95%)	0,1418	0,0000	0,0000	0,0172	0,0598	0,0001	-	-	-	-

Chapter 5: Conclusions

The purpose of this paper is to identify the existence and the power of a set of market anomalies, which are examined in literature. Specifically, the data derived from the European Equity Markets. The European Equity Markets are an important component of the global financial landscape and examining market anomalies in this context is crucial for understanding the behavior of these markets for identifying investment opportunities. In this paper, we aim to use data from the European Equity Markets to identify the presence of market anomalies and to evaluate their power as investment strategies. Furthermore, there is a growing body of research in finance that suggests the existence of market anomalies, which can be used to generate excess returns over time. In conclusion, the purpose of this paper is to contribute to the existing literature on market anomalies by providing a comprehensive analysis of the European Equity Markets. The results of this analysis may be of interest to academic researchers, as well as to practitioners in the investment community who are looking for opportunities to generate excess returns in these markets.

Regarding the first market anomaly, which suggests that there is a relation between the percentage change of the difference of inventories and sales and the future returns, we could conclude a set of interesting implications. Firstly, the econometric analysis shows that the excess returns of portfolios which are include stocks from the lowest 20 % index score are less sensitive to Market Risk Premium than portfolios which includes stocks from the upper 20 % of the examined index score. On the contrary, the size parameter (SMB) affected the excess returns of lowest 20 % portfolios more than the excess returns of highest 20 % portfolios. As well as the analysis implied that the explanatory variable CMA, which has a negative effect on excess returns across all the portfolios, has a less negative impact on portfolios which are in the middle of the ranking (d3 and d4).

In relation to the second market anomaly, which suggests that the change of the gross margin as proportion of sales could predicts the future returns of an equity, several implications are derived. The estimated parameters of Market Risk Premium are statistically significant and depict a positive relation. Therefore, the range of the estimations varied between 0.5857, estimation of middle portfolio (d3), and 0.6710, estimation of upper portfolio (d5), which indicates the lack of a consistent relation. Especially, is implied a U shape relation, the value of the estimated parameter declines from d1 portfolio to d3 portfolio and then increases gradually from d4 portfolio to d5 portfolio. Regarding the size parameter (SMB) parameter, a same behavior is identified.

Regarding the third market anomaly, which suggests that there is a negative relation between the growth in operating assets as percentage of total assets and the future returns, provide the bellow implications. The econometric analysis shows a higher dependency ratio of the excess returns of portfolios, which are include stocks from the lowest 20 % index score to the size parameter (SMB) than portfolios, which includes stocks from the upper 20 % of the examined index score. On the contrary, the parameter of aggressiveness has a lower negative impact on the excess returns of lowest 20 % portfolios than the excess returns of highest 20 % portfolios.

In relation to the last examined market anomaly, which implied a negative connection between capital investments and future stock returns, we could conclude a set of interesting implications. The estimated parameters of Market Risk Premium are statistically significant and depict a positive relation. As well as the range of the estimations varied between 0.6865, estimation of upper portfolio (d5), and 0.7297, estimation of middle portfolio (d4), which indicates a consistent relation. Furthermore, a steady positive relation is clear for the size parameter (SMB). Finally, for the parameter of portfolio aggressiveness is showed a negative correlation with excess returns.

In general, the examination and the analysis of the data of the sample provides insights for the formulation of investments strategies exploiting these market anomalies. The limitations of these insights are related to the idiosyncratic characteristics of European Equity Markets, a case for further research it would be the replication of this methodology in other equity markets. Apart from developed equity markets, such as European, the methodology for investigation of existence of market anomalies may be focused on developing equity markets. Recommendation for future research could be the use different asset pricing model, such as the Market Model, Capital Asset Pricing Model, Fama - French 3-Factor model for the abnormal return calculation.

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Appendix

Market anomaly 1

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,574936927
R Square	0,330552471
Adjusted R Square	0,327558459
Standard Error	0,035583924
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,208822847	0,208822847	164,9188627	6,13505E-31
Residual	334	0,422916031	0,001266216		
Total	335	0,631738877			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d1	-0,660795372	0,051455503	-12,84207392	5,9184E-31	-0,762013078	-0,559577666	-0,762013078	-0,559577666

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,582803343
R Square	0,339659737
Adjusted R Square	0,336665725
Standard Error	0,030709875
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,162023819	0,162023819	171,799841	6,15997E-32
Residual	334	0,314994213	0,000943096		
Total	335	0,477018032			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d2	-0,678573712	0,051770892	-13,10724384	5,92872E-32	-0,780411818	-0,576735605	-0,780411818	-0,576735605

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,570912624
R Square	0,325941224
Adjusted R Square	0,322947212
Standard Error	0,033072657
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,176655092	0,176655092	161,5057512	1,94172E-30
Residual	334	0,365329409	0,001093801		
Total	335	0,5419845			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d3	-0,651423964	0,051258953	-12,7084913	1,87528E-30	-0,752255039	-0,550592889	-0,752255039	-0,550592889

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,589967222							
R Square	0,348061323							
Adjusted R Square	0,345067311							
Standard Error	0,03698274							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,243889812	0,243889812	178,3181243	7,18842E-33			
Residual	334	0,456819505	0,001367723					
Total	335	0,700709317						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d4	-0,695970309	0,052118627	-13,35358096	6,90323E-33	-0,798492442	-0,593448176	-0,798492442	-0,593448176

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,595588427							
R Square	0,354725575							
Adjusted R Square	0,351731563							
Standard Error	0,039397292							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,284988446	0,284988446	183,6092325	1,28283E-33			
Residual	334	0,518416964	0,001552147					
Total	335	0,80340541						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d5	-0,709481229	0,052359278	-13,55024843	1,2297E-33	-0,812476745	-0,606485714	-0,812476745	-0,606485714

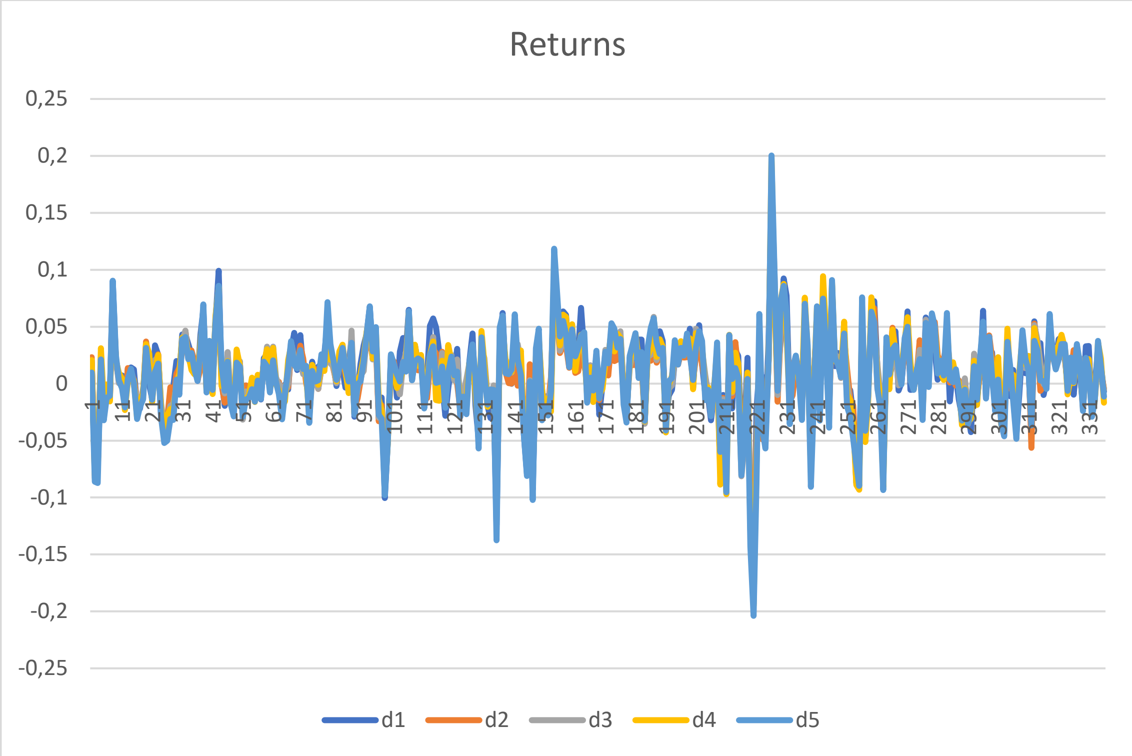
	Model 0 - no constant, no trend				Model 1 - constant, no trend				Model 2 - constant, trend			
N	0.01	0.025	0.05	0.10	0.01	0.025	0.05	0.10	0.01	0.025	0.05	0.10
25	-2.661	-2.273	-1.955	-1.609	-3.724	-3.318	-2.986	-2.633	-4.375	-3.943	-3.589	-3.238
50	-2.612	-2.246	-1.947	-1.612	-3.568	-3.213	-2.921	-2.599	-4.152	-3.791	-3.495	-3.181
100	-2.588	-2.234	-1.944	-1.614	-3.498	-3.164	-2.891	-2.582	-4.052	-3.722	-3.452	-3.153
250	-2.575	-2.227	-1.942	-1.616	-3.457	-3.136	-2.873	-2.573	-3.995	-3.683	-3.427	-3.137
500	-2.570	-2.224	-1.942	-1.616	-3.443	-3.127	-2.867	-2.570	-3.977	-3.670	-3.419	-3.132
>500	-2.567	-2.223	-1.941	-1.616	-3.434	-3.120	-2.863	-2.568	-3.963	-3.660	-3.413	-3.128

Prior to the estimation of a model, we should test the stability of the time series in order to secure the validity of the regression. A widely used test is that which proposed by David Dickey and Wayne Fuller.

Shortly, the test supposes that any time series d (1, 2, 3, 4, 5) is a stochastic process which could described by the model:

$y_i = \varphi * y_{i-1} + \varepsilon_i \Rightarrow y_i - y_{i-1} = (\varphi-1) * y_{i-1} + \varepsilon_i \Rightarrow \boldsymbol{\Delta y_i = (\varphi-1) * y_{i-1} + \varepsilon_i}$.

Following, the parameter (φ-1) is estimated by linear regression and its statistical significance is examined through a hypothesis test, where the null hypothesis is the parameter is zero. In case of an acceptance of null hypothesis, we could not consider the time series as stable, and the estimation of the model is not valid.



From the regression of parameter (**φ-1**) for each portfolios return is observed that, t-statistic (tStat) is lower than the t critical (model without trend and intercept) in a 95% confidence level (-1,942) according to the relevant table for a 250 to 500 observations sample. This result leads us to reject null hypothesis, so the time series are stable.

Market anomaly 2

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,575438049							
R Square	0,331128948							
Adjusted R Square	0,328134936							
Standard Error	0,040945021							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,277206508	0,277206508	165,348864	5,30917E-31			
Residual	334	0,559949258	0,001676495					
Total	335	0,837155766						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d1	-0,662037246	0,05148513	-12,85880492	5,12096E-31	-0,763313232	-0,560761261	-0,763313232	-0,560761261

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,566451128
R Square	0,32086688
Adjusted R Square	0,317872868
Standard Error	0,035272631
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,196332484	0,196332484	157,8034333	6,83824E-30
Residual	334	0,415548941	0,001244159		
Total	335	0,611881425			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d2	-0,641352352	0,051055022	-12,56198365	6,61234E-30	-0,741782276	-0,540922429	-0,741782276	-0,540922429

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,569814071
R Square	0,324688076
Adjusted R Square	0,321694064
Standard Error	0,03510556
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,197906565	0,197906565	160,5862616	2,65208E-30
Residual	334	0,411621717	0,0012324		
Total	335	0,609528282			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d3	-0,649189116	0,051229137	-12,67226348	2,56211E-30	-0,749961539	-0,548416693	-0,749961539	-0,548416693

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,575261029
R Square	0,330925252
Adjusted R Square	0,32793124
Standard Error	0,036295842
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,217628364	0,217628364	165,19684	5,58753E-31
Residual	334	0,44000765	0,001317388		
Total	335	0,657636014			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d4	-0,661602708	0,051475006	-12,85289228	5,38972E-31	-0,762858778	-0,560346637	-0,762858778	-0,560346637

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,578795983
R Square	0,33500479
Adjusted R Square	0,332010778
Standard Error	0,040127494
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,270933712	0,270933712	168,259257	2,00207E-31
Residual	334	0,537812073	0,001610216		
Total	335	0,808745785			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d5	-0,669886413	0,051643026	-12,9714786	1,92921E-31	-0,771472995	-0,56829983	-0,771472995	-0,56829983

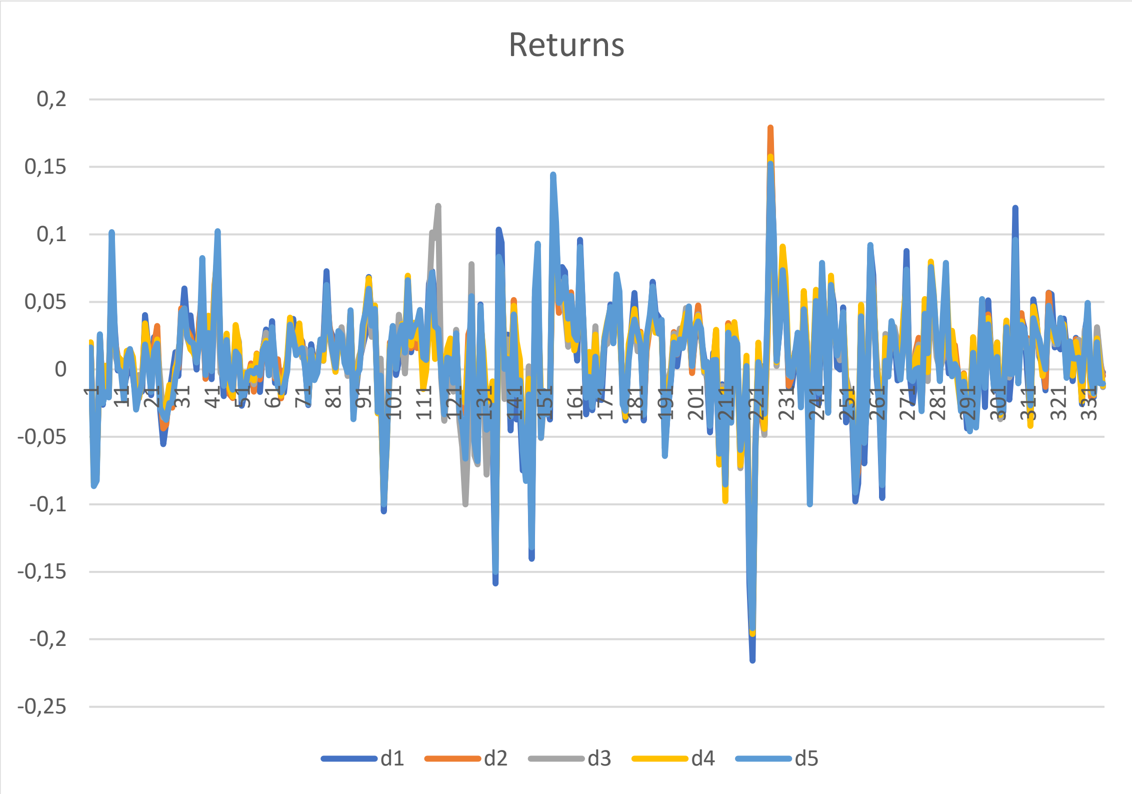
	Model 0 - no constant, no trend				Model 1 - constant, no trend				Model 2 - constant, trend			
N	0.01	0.025	0.05	0.10	0.01	0.025	0.05	0.10	0.01	0.025	0.05	0.10
25	-2.661	-2.273	-1.955	-1.609	-3.724	-3.318	-2.986	-2.633	-4.375	-3.943	-3.589	-3.238
50	-2.612	-2.246	-1.947	-1.612	-3.568	-3.213	-2.921	-2.599	-4.152	-3.791	-3.495	-3.181
100	-2.588	-2.234	-1.944	-1.614	-3.498	-3.164	-2.891	-2.582	-4.052	-3.722	-3.452	-3.153
250	-2.575	-2.227	-1.942	-1.616	-3.457	-3.136	-2.873	-2.573	-3.995	-3.683	-3.427	-3.137
500	-2.570	-2.224	-1.942	-1.616	-3.443	-3.127	-2.867	-2.570	-3.977	-3.670	-3.419	-3.132
>500	-2.567	-2.223	-1.941	-1.616	-3.434	-3.120	-2.863	-2.568	-3.963	-3.660	-3.413	-3.128

Prior to the estimation of a model, we should test the stability of the time series in order to secure the validity of the regression. A widely used test is that which proposed by David Dickey and Wayne Fuller.

Shortly, the test supposes that any time series d (1, 2, 3, 4, 5) is a stochastic process which could described by the model:

$y_i = \varphi * y_{i-1} + \varepsilon_i \Rightarrow y_i - y_{i-1} = (\varphi-1) * y_{i-1} + \varepsilon_i \Rightarrow \boldsymbol{\Delta y_i = (\varphi-1) * y_{i-1} + \varepsilon_i}$.

Following, the parameter (φ-1) is estimated by linear regression and its statistical significance is examined through a hypothesis test, where the null hypothesis is the parameter is zero. In case of an acceptance of null hypothesis, we could not consider the time series as stable, and the estimation of the model is not valid.



From the regression of parameter (**φ-1**) for each portfolios return is observed that, t-statistic (tStat) is lower than the t critical (model without trend and intercept) in a 95% confidence level (-1,942) according to the relevant table for a 250 to 500 observations sample. This result leads us to reject null hypothesis, so the time series are stable.

Market anomaly 3

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,571825703
R Square	0,326984635
Adjusted R Square	0,323990623
Standard Error	0,043213214
Observations	335

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,30302745	0,30302745	162,2739592	1,49713E-30
Residual	334	0,623705546	0,001867382		
Total	335	0,926732996			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d1	-0,653985192	0,051338538	-12,73867965	1,44553E-30	-0,754972817	-0,552997566	-0,754972817	-0,552997566

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,57065804
R Square	0,325650599
Adjusted R Square	0,322656587
Standard Error	0,030361034
Observations	335

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,148677922	0,148677922	161,2922022	2,08742E-30
Residual	334	0,307878653	0,000921792		
Total	335	0,456556575			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d2	-0,651177554	0,051273473	-12,7000867	2,01614E-30	-0,75203719	-0,550317917	-0,75203719	-0,550317917

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,572933668
R Square	0,328252988
Adjusted R Square	0,325258976
Standard Error	0,03491395
Observations	335

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,198951571	0,198951571	163,2109948	1,09083E-30
Residual	334	0,407140615	0,001218984		
Total	335	0,606092186			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d3	-0,656471777	0,051385591	-12,77540586	1,05291E-30	-0,75755196	-0,555391595	-0,75755196	-0,555391595

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,569351835
R Square	0,324161512
Adjusted R Square	0,3211675
Standard Error	0,035922124
Observations	335

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,206723104	0,206723104	160,2009163	3,02278E-30
Residual	334	0,43099327	0,001290399		
Total	335	0,637716374			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d4	-0,648381132	0,051226876	-12,65705006	2,92061E-30	-0,749149108	-0,547613156	-0,749149108	-0,547613156

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,576083033
R Square	0,33187166
Adjusted R Square	0,328877648
Standard Error	0,038976019
Observations	335

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0,252029686	0,252029686	165,9039559	4,40606E-31
Residual	334	0,50738944	0,00151913		
Total	335	0,759419126			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d5	-0,663824319	0,051537671	-12,88037095	4,24907E-31	-0,765203657	-0,562444981	-0,765203657	-0,562444981

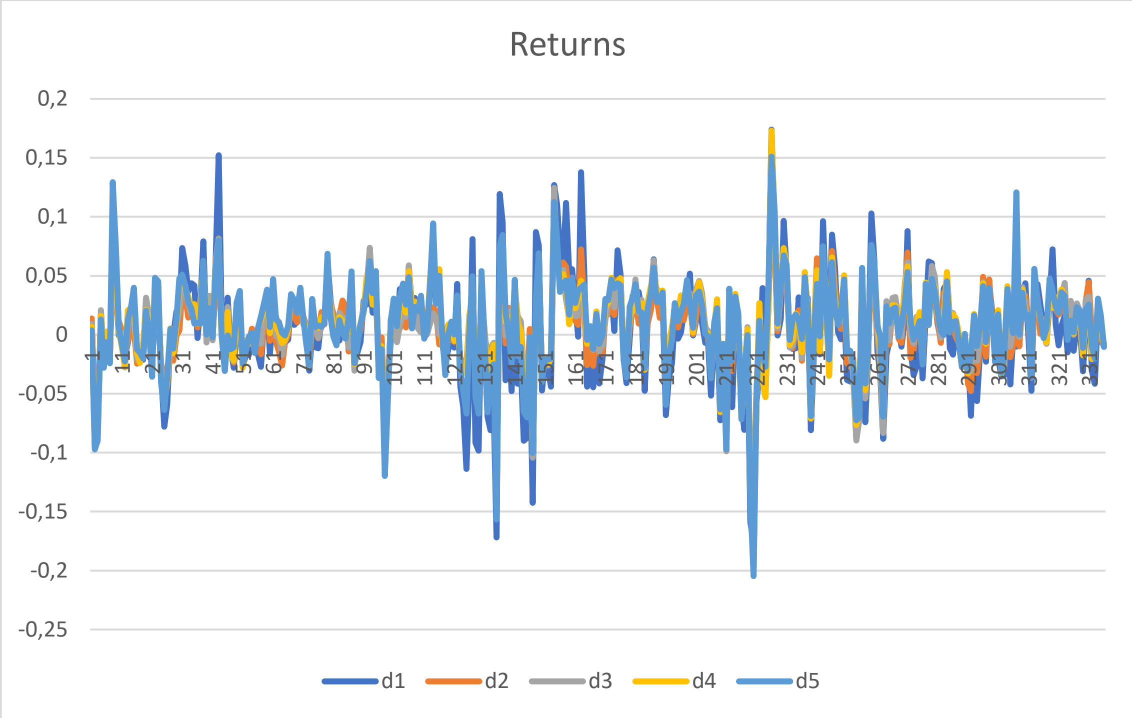
	Model 0 - no constant, no trend				Model 1 - constant, no trend				Model 2 - constant, trend			
N	0.01	0.025	0.05	0.10	0.01	0.025	0.05	0.10	0.01	0.025	0.05	0.10
25	-2.661	-2.273	-1.955	-1.609	-3.724	-3.318	-2.986	-2.633	-4.375	-3.943	-3.589	-3.238
50	-2.612	-2.246	-1.947	-1.612	-3.568	-3.213	-2.921	-2.599	-4.152	-3.791	-3.495	-3.181
100	-2.588	-2.234	-1.944	-1.614	-3.498	-3.164	-2.891	-2.582	-4.052	-3.722	-3.452	-3.153
250	-2.575	-2.227	-1.942	-1.616	-3.457	-3.136	-2.873	-2.573	-3.995	-3.683	-3.427	-3.137
500	-2.570	-2.224	-1.942	-1.616	-3.443	-3.127	-2.867	-2.570	-3.977	-3.670	-3.419	-3.132
>500	-2.567	-2.223	-1.941	-1.616	-3.434	-3.120	-2.863	-2.568	-3.963	-3.660	-3.413	-3.128

Prior to the estimation of a model, we should test the stability of the time series in order to secure the validity of the regression. A widely used test is that which proposed by David Dickey and Wayne Fuller.

Shortly, the test supposes that any time series d (1, 2, 3, 4, 5) is a stochastic process which could described by the model:

$y_i = \varphi * y_{i-1} + \varepsilon_i \Rightarrow y_i - y_{i-1} = (\varphi-1) * y_{i-1} + \varepsilon_i \Rightarrow \boldsymbol{\Delta y_i = (\varphi-1) * y_{i-1} + \varepsilon_i}$.

Following, the parameter (φ-1) is estimated by linear regression and its statistical significance is examined through a hypothesis test, where the null hypothesis is the parameter is zero. In case of an acceptance of null hypothesis, we could not consider the time series as stable, and the estimation of the model is not valid.



From the regression of parameter (**φ-1**) for each portfolios return is observed that, t-statistic (tStat) is lower than the t critical (model without trend and intercept) in a 95% confidence level (-1,942) according to the relevant table for a 250 to 500 observations sample. This result leads us to reject null hypothesis, so the time series are stable.

Market anomaly 4

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,572671995							
R Square	0,327953214							
Adjusted R Square	0,324959202							
Standard Error	0,039892669							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,259385104	0,259385104	162,9892082	1,17565E-30			
Residual	334	0,531535957	0,001591425					
Total	335	0,790921062						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d1	-0,655337206	0,051331671	-12,76672269	1,13486E-30	-0,756311323	-0,554363089	-0,756311323	-0,554363089

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,577130509							
R Square	0,333079624							
Adjusted R Square	0,330085612							
Standard Error	0,041697863							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,290033483	0,290033483	166,8094103	3,25208E-31			
Residual	334	0,580729726	0,001738712					
Total	335	0,870763209						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d2	-0,665869049	0,051555922	-12,91547174	3,13525E-31	-0,767284288	-0,56445381	-0,767284288	-0,56445381

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,573298511							
R Square	0,328671183							
Adjusted R Square	0,325677171							
Standard Error	0,043932112							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,315599976	0,315599976	163,5207252	9,82571E-31			
Residual	334	0,644630163	0,00193003					
Total	335	0,960230139						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d3	-0,65727457	0,051399681	-12,78752225	9,48316E-31	-0,75838247	-0,55616667	-0,75838247	-0,55616667

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,569771312							
R Square	0,324639348							
Adjusted R Square	0,321645336							
Standard Error	0,040437409							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,262529739	0,262529739	160,550577	2,68439E-30			
Residual	334	0,546151466	0,001635184					
Total	335	0,808681205						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d4	-0,648994299	0,051219454	-12,67085542	2,59336E-30	-0,749747675	-0,548240922	-0,749747675	-0,548240922

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,591273451							
R Square	0,349604293							
Adjusted R Square	0,346610281							
Standard Error	0,041744703							
Observations	335							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	0,312858748	0,312858748	179,5335252	4,83074E-33			
Residual	334	0,582035148	0,00174262					
Total	335	0,894893897						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
d5	-0,699079992	0,052173995	-13,3990121	4,63715E-33	-0,801711039	-0,596448946	-0,801711039	-0,596448946

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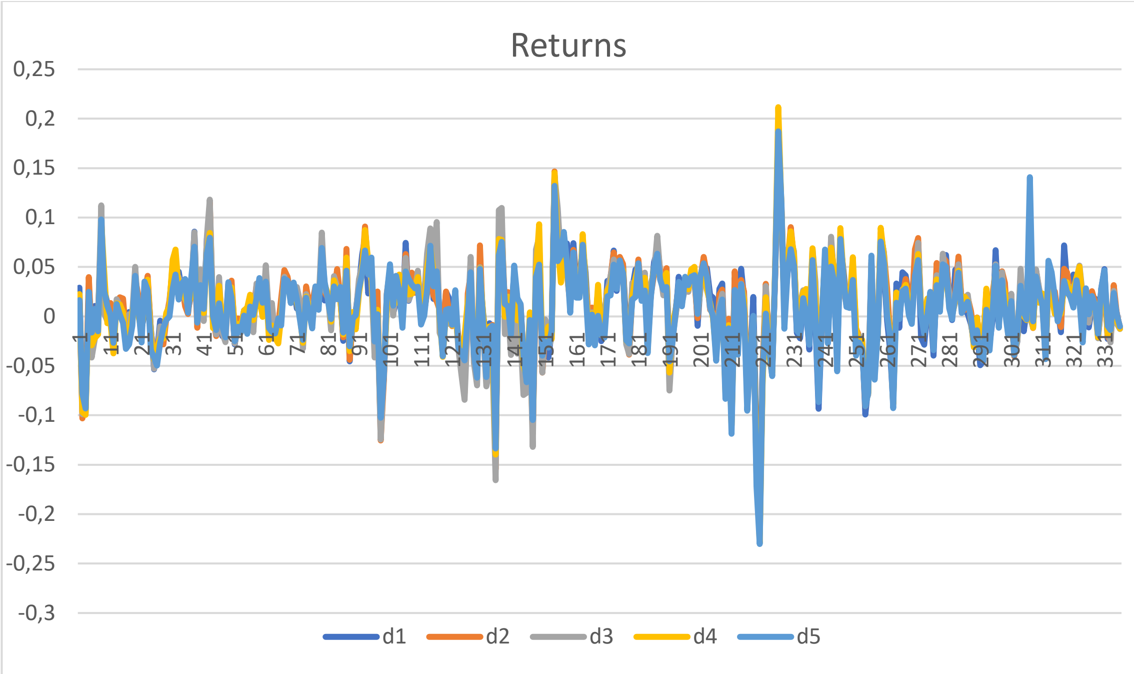

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