Evidence of Market Anomalies in the Eurozone: a Practical Implementation

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Abstract

Previous research documented the existence of market anomalies; this work directs its focus on the possible usage of this evidence into a profitable trading strategy. It connects itself with the recent literature around the forecasting power of market anomalies over the cross-section of stock returns, in particular Lewellen (2014). Using a sample of twenty-six anomalies their pervasiveness is tested over the Eurozone (represented by the companies included in the five biggest stock indexes) in the new millennium era. A portfolio that combines the anomalies according to their past performance outperformed the main Euro stock indexes, obtaining a Sharpe ratio of 0,59 and an annualized alpha of 7,41%. Moreover the attractiveness of the portfolio is augmented by its dynamicity: due to the large amount of factors analyzed and the flexibility of the Sharpe Ratio as an indicator the portfolio is able to detect cyclicality in the economy and to wisely diversify around geographical areas.

Introduction

There has been evidence of the existence of market anomalies, variables that retain a certain forecasting power and allow an estimation of the expected stock returns. This proof does not grant certainty around the possible usage of the same variables in a profitable way. The main contribution of this thesis will be to extend the study of how an investor can use the findings around market anomalies, and then to assess how profitable this will turn out to be. Lewellen (2014) has already documented the predictive power of market anomalies in the US; I will extend this to the Eurozone. Secondly the contributions will be merely linked to the market and sample chosen: the efficiency of the euro market in the early 2000 will be tested coupled with an overview of how good the common asset pricing models capture the cross-section of returns.

Past models gave an explanation of how the stock price should be formed; according to the dividend discount model the value should be equal to the present value of all the cash flows that it pays. The capital gains produced by expected future price of the stock are incorporated by the present price, but these capital gains are mainly dependent on dividend forecasts at every point in time. A useful variation of this model, the constant-growth dividend discount model, relieves investors from making estimation of every dividend payments and introduces the constant growth of the dividends; this figure is hard to determine and it makes the analysis very sensitive.

Another model, the P/E model, asserts that the value of the stock should be decomposed in two parts: one it is linked to the present value of the company assets and their ability to generate cash flows, a second part is referred to the growth opportunities, represented by the present value of the projects that the company has. The price earnings ratio summarizes the information contained in these two parts, it reflects the market expectations around the growth opportunities of a company.

Even if extremely important, these models, as all models, have some assumptions that in practice make their implementation difficult; for example in the dividend discount model there is no clear way to estimate what is the growth rate of dividends, whereas for the P/E model the approximation of the NPV of future projects is also uncertain. Finally, both models are using the risk-adjusted rate of return as discount rate, and this figure is always hard to appraise, even when using the current asset-pricing models.

In a broad way, it is this required rate of return, which is the objective of this work. This return should reflect the risk of the security and according to the efficient market hypothesis this risk is correctly priced such that there are no possibilities for investors to generate an expected rate of return, in excess to the risk-free rate, that it is not a risk premium.

Colliding to this view several exceptions were reported, i.e. market anomalies; these anomalies were the result of observations of the relation between the stock returns and different variables related to either the fundamentals of a company or its technical analysis. This study was usually conducted using the cross-section of stock returns with the anomaly variable significant in order to explain the differences in stock returns. More specifically the anomaly variable was discovered to have an explanatory power not recognized by known risk premiums, so a trading strategy based on the anomaly was able to produce abnormal returns, meaning returns not captured by the asset pricing model in use.

The existence of market anomalies created a whole new debate in the financial world related to their explanation: those certain about the efficiency of the market pointing the finger against the validity of the asset pricing models used, believing in their inability to capture all the risk premiums demanded by investors, and those convinced about the inefficiency of the market that see market anomalies as a clear example of it.

By now the progresses made are outstanding and despite the level of uncertainty still surrounding the topic both directions produced important results. On the one side several asset pricing models were developed with an increasing rationale (not based on empirical findings) and capability to explain the components of the stock return. On the other side the recent branch of finance named behavioral finance was able to explain several anomalies with behavioral responses that every investor is affected. The resolution of this debate is far from being solved and the present work does not want to interfere with it.

Indeed it is the usage of these market anomalies for profitable trading strategies that is the aim of this thesis. In fact the pure existence of the anomaly, even if proven by some study, does not assure an investor about its efficacy in a trading strategy. This is because there are several biases that affect the validity of the discovery.

As pointed out by Hanna and Ready (2005) the anomaly might be an artifact produced by an intensive research over a database, this phenomenon is known as data snooping. Secondly the anomaly might be vanished due to its recognition by investors, this fact is also due to the increasing investing activity and the higher knowledge available to investors. Finally some market anomalies involve the usage of dynamic trading strategies that are extremely costly, then the overall gain produced by the strategy is basically nothing, entirely captured by the transaction costs that it requires.

Another relevant point is the fact that the anomalies may focus on companies in financial distress, as identified by Avramov, Chordia, Jostova and Philipov (2010) one set of anomalies is related to companies having high credit risk and deteriorating credit conditions, and another group of anomalies to companies having high credit risk but in a phase of recovery from recent financial distress.

Moreover the attention was more on how these anomalies are correlated with future returns, not on how the estimation of these returns according to the same variables are actually equal to the realized returns. The thorny point here deals with the ex-ante applicability of the trading strategy, a variable can be significant and have explanatory power but at the inception of the strategy this may not be known and predicted. In that case the practical implementation of the anomalies become relevant for an easy and tradable strategy. This work focuses on this and in particular on how to aggregate the anomaly variables into a portfolio.

Most of the academic literature is concentrated over the US market, to distinguish this work from the previous ones I decided to focus it on the Euro market; this will help to test the persistence of the anomalies in a market different from the one in which they were discovered. The dataset comprises companies in the five major stock indexes in the Euro area (France, Germany, Italy, Netherlands and Spain) and starts from the beginning of 2004 and it ends in the middle of 2014.

The usage of such database is important for two reasons: first it studies the persistency of market anomalies on companies that have a great market cap (and thus economically relevant) then it makes the trading strategies liquid and tradable, avoiding the double bias of focusing on micro-cap stocks and companies in financial distress.

There are twenty-six variables analyzed and these include values and growth factors, size, momentum, and volatility. At first, for every variable an independent trading strategy is developed, with the application of each variable linked to previous findings around its relation to the average stock return. Every trading strategy is built on a market-neutral base and uses all the securities available (conditional on the availability of data for every factor); one of the goals was to limit as much the discretion around possible variants for every strategy, so the methodology around the construction of the trading strategy was clear and simple from the beginning.

The primary results will be linked to the aggregation and upcoming analysis of the variables into a portfolio. The aggregation discriminant will be the performance obtained by the strategies based on singular factors. The portfolio is tested out-of-sample since part of the dataset is used to have the performance and then, given this information, the strategies are set in place. In this step further variants, concerning different ways to sort stocks, will be used as robustness tests for the results produced by the portfolio.

Literature review

A comprehensive literature review of the topic has to start from its inception and so this revision starts from the CAPM initially introduced by Sharpe (1964), the CAPM was the first asset pricing model, a model that explains why the return of a security is different from another one. According to this model there is only one risk: the market risk. One of the main assumptions of the CAPM is that every investor holds a fraction of the market portfolio (which is the universe of all risky assets), benefitting from the diversification the contribution of a security to the overall riskiness of the portfolio is reduced to the interaction of the security with the portfolio. This interaction is represented by the market risk, the beta, which is proportional to the covariance of the returns of a specific security and the returns of the portfolio.

The CAPM represented the first attempt to give investors a general understanding of the differences in returns and risks of securities. It remained an unproven theory though since the introduction of the computers, which made possible to test the theory in practice and to see the actual degree of truth in explaining the differences across stock returns. The CAPM gave an explanation of the difference between stock returns, but it did not provide any clarification about the stock price development in the future and the extent to which this development can be forecasted.

An initial effort to give an answer to this problem was made by Louis Bachelier (1900) who observed the unpredictability of the stock price and affirmed its "random walk" behavior. Bachelier's thesis did not receive much popularity at the time that was firstly published, nevertheless several economists recognized later its importance as a pioneering work in the field of financial mathematics. Kendall (1953) was one of the first economists to analyze the time series of prices in order to discover some kind of predictability and pattern in the series; confirming Bachelier's intuitions he found that stock prices move in an unpredictable fashion, disregarding past performance.

This discovery was at first intended as a sign of market irrationality, then Fama in his PhD thesis used these findings to affirm the complete rationality and efficiency dominating the market. According to the efficient market hypothesis the information capable of affecting the stock price is already incorporated in it and so future price movements are basically random and unpredictable. The theory also suggests that once new and relevant information is disclosed the price will immediately adjust to a new level. Formally three sets of efficiency are highlighted by Fama: a weak form, in which just past information regarding the price is incorporated in the price, a semi-strong form, in which all the publicly information is included, and a strong form, in which also privately held information is included in the price; the semi-strong form includes also the weak form and similarly the strong form includes both, the semi-strong and the weak forms. These three versions of market efficiency can be tested, with most of the tests targeted to prove or reject the weak and semi-strong form, using technical (for the weak) and fundamental indicators (for the semi-strong). From another perspective EMH affirms the impossibility to generate any higher return that is not a result of the higher risk sustained, the impossibility to use the past information makes any abnormal return impossible; as a consequence this theory was not widely accepted on Wall Street.

These two theories together set the milestones for further research in the financial markets, this was mainly related to empirical studies aimed at the confirmation or rejection of the theories. With the computer era a massive quantity of data was analyzed and the financial markets were studied in a more quantitative way. A lot of trading strategies were performed using different variables, spanning all available information, and soon some of them produced abnormal returns, i.e. returns not explained by the CAPM; these variables were identified as market anomalies.

All of the empirical tests assume the form of joint tests of both theories, the EMH and the CAPM. If the joint test is accepted, implying no abnormal returns are present after the CAPM adjustment for risk, then both theories are proven, the asset pricing model and the efficiency of the market. If the test is rejected, it can be either because the market is inefficient or because the asset pricing model is not considering some feature that is relevant in the cross-section of stock returns.

Disregarding now the debate around the nature and explanation of these anomalies, it is provided a quick overview of the most well-known market anomalies, out of which some are included in the present research. As Fama and French (2008) underlined, two are the most used approaches to detect market anomalies in the cross-section of stock returns. The simplest one is to sort stock returns on the factor analyzed to see how the average return is distributed around the anomaly variable. The main advantage of this method is its simplicity and its ability to provide a quick overview of the impact of the factor on the stock return. A more technical approach involves the use of the Fama-MacBeth regression, divided in two steps, the first one involves time series regressions for all the assets in the portfolio, the stock return of each asset is regressed over the anomaly variable; in the second step all the coefficients estimated in the first one are used as independent variable in cross-sectional regressions using again the stock return as explained variable. This method provides a more quantitative description on how the factor analyzed is impacting the stock return and how it is priced in the cross-section of stock returns.

One of the first market anomaly discovered was the size effect, Banz (1981) showed that smaller firms tend to outperform bigger ones. Basu (1977) focused on the P/E ratio and observed that stocks with low P/E have higher returns than firms with high P/E. Stattman (1980) used the book value of equity to its market value, and documented the positive relation between this variable and the stock return. Bhandari (1988) reported the positive effect of leverage on the average stock return. Loughran and Ritter (1995) showed the negative performance of companies that experienced an IPO or seasoned equity offer in the five years after the operation. Titman, Wei and Xie (2004) noticed how companies that invest more tend to have negative abnormal returns, this finding is even augmented for those companies with higher cash flows and more solid capital structure. On a similar level Cooper, Gulen and Schill (2009) documented how firms with low asset growth (measured as the yearly change in the total assets) tend to outperform firms with high asset growth. Sloan (1996) identified the negative impact of accruals on the stock price. Pontiff and Woodgate (2008) confirm findings around the positive link between long-term stock return and share repurchase announcements, stock mergers and seasoned equity offers, exploring the relation of stock issuance and the cross-section of stock returns, affirming how stock issuance is statistically more relevant in predicting returns than other well-known anomalies.

A special mention is appropriate for those anomalies that are based on the historical stock prices; this because out of the market anomalies those are the ones that contradict even with the weak form of the EMH. One of the first paper using technical indicators is the one from De Bondt and Thaler (1985), using the past three and five years stock performance they observed the stock reversal effect, meaning that the companies that performed worst were the ones that outperformed the others in the subsequent period, simultaneously the best ones underperformed the others. A similar conclusion was found by Jegadeesh (1990), who showed the negative auto-correlation of returns in the 1-month window but also the positive auto-correlation for longer lags up to one year. Moving from this last finding, Jegadeesh and Titman (1993) used the stock returns over the past three to twelve months (skipping the most recent week to avoid the negative correlation in the stock returns) and observed how the past winners outperformed the past losers also in the future, this particular anomaly gained much recognition and it was named momentum.

An interesting implication of the EMH is that whenever new information is released the stock price should immediately adjust reflecting the content of the information. This gave rise to a whole new type of study in finance, the event study, an analysis directed to understand the development of the stock price on certain event like an earnings announcement. Despite their relevance, Ball and Brown (1968) found that there are no price adjustments after an earnings announcement. Rendleman, Jones and Latané (1982) studied the phenomenon in a different way, instead of looking at the earnings announcement they observed the earnings surprise (measured as the difference between the estimated/expected earnings and the announced one) and observed not only a price adjustment but also a momentum pattern whenever the surprise was positive or negative.

The interpretation of these market anomalies is always arduous, sometimes because it is puzzling to find a rational explanation for the anomaly, in other words it appears to be difficult to explain the superior returns as a compensation for the higher risk sustained. Even if the previous statement is correct for factors like P/E or size is really hard to think that the problem is related to the overall efficiency of the market; such that strategies based on such factor are too simple to be able to produce abnormal returns, investors in the world should do this on regular basis and then the abnormal return should disappear.

Fama and French (1996) argued that for some anomalies the factor used to obtain the abnormal returns may act as a proxy for a different source of risk; for example when looking at firms with high book to market ratio they observed how these companies are usually more unstable and more likely to be in financial distress, a similar consideration is done for small firms, which are more prone to suffer variations in the business cycle.

Different asset pricing models were developed in order to explain and capture the cross-section of the returns in a more comprehensive way than what the CAPM did. Some others indeed argued that the presence of market anomalies is a distinct sign of the market inefficiency, and within this line of thought some think that this is because the market is dominated by irrational investors and that modern finance ignores some behavioral effects that are able to explain most of this irrationality.

The first asset pricing model that tries to solve this issues is the one developed by Fama and French (1992), in this model along with the market beta also a size and value factor, represented by B/M, are added. The reasons for having this three factors is mostly empirical, given the previous findings Fama and French decided to expand the CAPM with two of the most constant market anomalies. The result is surprisingly good with the model that seems to capture the cross-section of returns for the US market from 1963 to 1990. The surprising part was though related to the poor significance of the market beta, with the size and value coefficient that were basically the only explanatory variables for the returns.

With the three-factor model most of the anomalies vanished, but one of the most important, momentum, still persisted. In order to include this variable Carhart (1997) added a momentum factor, similar to the three-factor model also the four-factor model is an empirical model, it takes as given some findings that are relevant in the cross-section of returns and it includes those in the model.

Recently Chen, Novy-Marx and Zhang (2010) developed an alternative three-factor model, this model is constituted by three explanatory variables: the market beta, an investment factor and a profitability factor (with ROA used as proxy). The introduction of these two factors is motivated by an investment reason. To infer the cost of capital (i.e. the required return demanded by investors) the level of investments is meaningful: assuming a fixed level of expected cash flows, the cost of capital determines the NPV of a project, if high the level of investment will also be high because of the profitable project to finance; the opposite is also true. So from the level of investment one can infer the cost of capital of the company; this measure is coupled with ROA. Observing a high ROA and a low level of investment means that the high ROA is offset by a high cost of capital; ROA in this sense acts like another determinant for the specification of the cost of capital.

Of all the anomalies, momentum (together with other technical factors) is one of the most deceptive and hard to explain, an attempt to solve the problem was made by Chen (1991) who gave the interpretation of momentum as a pattern emerging because risk premiums are time varying. The level of risk and risk aversion are both changing during business cycles, e.g. during a recession expected returns can be higher because of an increase in risk and risk aversion (since wealth is decreasing and we face diminishing marginal utility function). To the extent that these cycles happen with a certain frequency this can lead to the technical pattern in the stock returns, as momentum.

On a similar level, Campbell et al. (2008) declare that the size and value factors on the three-factor-model are acting as an imprecise proxy for the risk of the firm being in financial distress, this because companies having high loadings on these two factors are exhibiting high risk but not high returns. Confirming the result of this paper Avramov, Chordia, Jostova and Philipov (2010) explore commonalities across the anomalies and noted how most of them are highly related to companies being in financial distress or recovering by it. Hence they conclude that most of market anomalies are generating abnormal returns because of the inability of asset pricing models to capture the risk of financial distress.

Liew and Vassalou (2000) used portfolios based on size and B/M and found how the returns produced by these portfolios can be linked to macroeconomic risk. The main result of the paper is that these two factors have explanatory power when regressed over future GDP growth, even when controlling for other known predictors of business cycles. This result suggests that small and high B/M companies are more prone to be in financial distress when an economic downturn is approaching. The intuition is stronger because of the high persistency for companies to have either small market cap or high B/M, suggesting that investors are aware of this risk and then demand a premium for holding such stocks.

In their latest paper Fama and French (2013) developed a five-factor model, with the goal to expand the explanatory power of the three-factor model and to base this more on a rational base rather than an empirical one. They noticed how size, B/M, expected earnings and investment are all variables that are implied and included in the dividend discount model; an important model aimed to identify the intrinsic value of a stock, in the model is asserted that this value is the present value of the future dividends that the stock will pay. One of the practical issues was to find a valid proxy for profitability and investments, they then used operating profitability minus interest expense for profitability and the asset growth for investment. The model failed the GRS test, that measures if the levels of the intercept from a multiple regression model are jointly zero, nevertheless it provides a good explanation of the cross-section of returns. Interestingly, the B/M factor is not relevant in order to capture abnormal returns, because its significance is seized by the other four factors, but still it provides a good explanation of portfolio's exposure towards the size, value, profitability and investment.

Despite the growing explanatory power of such asset pricing models some academics are convinced about the irrationality and inefficiency of the market. Kahneman and Tversky (1979) in their prospect theory used tools from psychology to explain the behavior of investors, in particular they stated how an investor does not act rationally and does not make optimal decisions, instead it is biased from a series of behavioral phenomena. In their paper they enumerate three common patterns in investors' behavior: the framing effect, stating that the context in which the individual makes a choice is relevant for the outcome of this decision; the loss aversion, affirming the fact that a loss is always worse than sacrifice a gain; the isolation effect, when facing consecutive probabilities individuals tend to isolate the odd of each event without considering the overall probability.

This whole branch of study got the name of behavioral finance and it is based on two pillars: first economic agents are believed to act irrationally and secondly rational arbitrageurs cannot exploit the mispricing because of limited resources. In addition to this the arbitrage opportunities are not of the pure arbitrage nature, i.e. they are not risk free, mentioning a common sentence attributed to Keynes: “markets can stay irrational longer than you staying solvent”.

One of the most important papers in this area, by De Bondt and Thaler (1994) explained the anomalies related to some value factors (P/E for example) as under or overreactions of investors, in particular when new information is released the market participants tend to exaggerate the feelings toward a company. This explanation rapidly gained consensus and different papers after this tried to expand the initial definition, for example La Porta (1996) argued that analysts are always too optimistic or too pessimistic when giving expectations about firms’ growth rates and this gives rise to mispricing in the market.

According to Grinblatt and Han (2002) one anomaly, stock reversal in the short term, can be explained with the disposition effect, according to this investors are less likely to recognize losses than gain, so the consequence is that they will keep stocks that are underperforming and they will sell those that increased in value to lock the gains.

The critics of behavioral finance argue that it is easy to explain a market anomaly with a behavioral response when it is done after having observed the anomaly but impossible to use the same argumentations to detect it.

The present work focuses on the usages of the previous findings related to market anomalies, its primary aim is to see if these anomalies can lead to substantial profits and how can they be interpolated with each other to maximize the return. This goal will be coupled with the intent of finding what could have been possible and rational ex-ante, by this it is meant that the trading strategies are performed out of sample, with a precise method (i.e. limiting as much as possible discretionary choices) to use the information available.

There are several papers that share a similar aim, at first, Fama and French (2008) published a paper in which they revisited all the principal market anomalies with the purpose to understand which ones are the most persistent and how are they structured in different size groups. They use both portfolio sorting and cross-section regression to have a clear picture of which factor is relevant in order to explain the stock returns. The size division has to be intended for a reason of economic significance: even if they account for 3% of the total capitalization microcaps stocks are 60% of the number of stocks in the NYSE-Amex-NASDAQ universe and according to Fama and French 60% of the stocks in the extreme portfolio sorting are from microcap stocks. Having divided stocks into three size groups (micro, small and big) they found that returns associated with net stock issues, accruals and momentum are the only widespread in each group.

Haugen and Baker (1996) started their analysis with the consideration that non-risk related factors are relevant explaining the stock returns, assuming that also stocks are different in their liquidity they divided factors in five classes: risk, liquidity, price-level, growth potential and price history. They used cross-sectional regressions to estimate the expected return for the following month using all the factors available (a total of fifty variables), the payoffs are aggregated with a simple average of the past twelve months reaching the expected return for the factor analyzed. The first twelve months prior 1979 are used to make a first estimation of the payoffs, the future coefficients for each payoff are then given by a 12-month trailing mean, the whole process is repeated till the end of 1993. Together with a test with all factors other two are run to see if the results are highly dependent to the effect of some previously mentioned anomaly: first all factor besides momentum related ones are dropped, then all except the ones related to the cheapness in price (for instance B/M and P/E). The spread between the realized returns from the highest to the lowest decile is 35% and this spread is drastically decreasing when the factors are simply momentum or cheapness in price ones, the authors' deduction is that the predictive power is laying mostly on the multitude of factors used. The main results of the paper are linked to the average fundamentals of companies that are in the highest decile from the ones in the lowest one; Haugen and Baker looking at these features are trying to infer if the superior performance of decile ten is a reward for the highest risk taken. The assessment is made in two ways, at first looking at the average fundamentals across deciles, like D/E or volatility, the second using the Fama, French three-factor model. The conclusion is that it is quite difficult to argue that firms in decile ten are riskier than the ones in the lowest decile, looking at the fundamentals these companies show a more stable condition and lower volatility, regarding the model they have lower loadings on all three factors.

Hanna and Ready (2005) reexamined some of the previous findings related to market anomalies and questioned whether a dynamic trading strategy combining these anomalies would lead to substantial profits, even adjusting for transaction costs. The anomalies (B/M, six months past returns, Haugen and Baker's factors) are organized in different independent portfolios, using the same dataset (the Russell 3000 Index) but on a more extended period to the papers related to the anomalies (from 1979 to 2001) so the strategies are partially tested out-of-sample. Stocks are assigned decile rankings for each factor; for B/M and momentum the sort is done directly from the factor, whereas for the Haugen and Baker's variables the sort is done by the expected returns. The portfolios are formed using companies in decile one and ten; both equally-weighted and value-weighted, with monthly rebalancing (important to account for the transaction costs). For every strategy there is a difference in return from decile ten to decile one, with the Haugen and Baker's difference more than double than the other two portfolios (+31,2% and -6% the annualized return); this result is statistically significant different from zero at the .01 confidence level using the t-test. The excess return of each strategy is then tested using the CAPM, in order to see which weight to give for every strategy, the alpha is divided by the residual variance. Also accounting for trade delays and transaction costs the portfolio formed on B/M is the one showing the best alpha/residual variance ratio The last part of the paper concerns the portfolio optimization, to maximize the Sharpe ratio. This maximization is unfeasible in practice because it takes the ex-post distribution of the returns as given, having this in mind the optimal portfolio when only long positions are allowed is made 80% by B/M portfolio and 20% of the momentum portfolio. When short selling is permitted the HB portfolio is in the optimal one just for the short part, even excluding it the overall result doesn't change much (Sharpe ratio of 0,38 versus 0,378).

Lewellen (2014) focused on the Fama-MacBeth regression to forecast returns; using a set of fifteen firm characteristics for the US stock market from 1964 to 2009, Lewellen, in his primary test, used the slopes derived from a rolling ten years FM regression in order to predict monthly returns. These fifteen factors are organized in three different portfolios, with the most persistent factors composing the first model (like B/M or size) and the less persistent factors added to this first set in the second and third portfolio; the reason is to move from a portfolio of well-known predictors of stock returns from others that include other variables that an investor could have thought of. Stocks are then sorted on the expected return forecast. The main result concerns the overall realized return versus the forecasted one, for the first portfolio the estimated spread between the top and worst decile is 2,82% whereas the realized one is almost as large, 2,43%. The interesting result is that the forecasting power of the most important factors account for most of the success of the FM regression, in fact the last portfolio, including factors like dividend yield and sales to price ratio, does not add anything to the overall forecasting power of the model.

Following this last stream of literature I will move from analyzing the predictive power of market anomalies to the employment of the same variables in different trading strategies, trying to detect how much an investor could gain from this evidence. My effort will be concentrated on how these factors can be aggregated into a profitable and ex-ante feasible strategy. Differing from these papers I will not use cross-sectional regressions to determine the expected returns but a more practical approach, directly developing a trading strategy based on those variables. The analysis starts with the factors taken individually rather than having all of them in a portfolio; as a consequence the following step is their aggregation, rather than separation, into a portfolio. The discriminant for the aggregation will be the actual performance of every factor and not a division "per classes" as in Lewellen (2014) or Haugen and Baker (1996).

One of the main criticism related to market anomalies is the usage of the same database (US market generally) to discover and test the magnitude of the anomalies, the phenomenon is known as data snooping. Expressing this concept in the words of Ronald Coase: "if you torture the data long enough, it will confess". Some work has been done to avoid this bias and even if not widespread to all findings around market anomalies at least the most important ones were also tested using financial markets different from the US one.

Asness, Moskowitz and Pedersen (2013) extended the evidence over momentum and value in the British, European and Japanese markets; finding abnormal returns that are consistent with what documented for the US market. Using also different and uncorrelated asset classes a similar patter is discovered, since the strategies based on momentum and value have a strong correlation structure this induces the authors to conclude that momentum and value might be a premium for global risk factors.

Fama and French (2012) find a considerable persistency of size, value and momentum effects in international stock markets (North American, Europe, Japan and Asia Pacific). Using different versions of the three-factor model and the four-factor model Fama and French tried to explain the returns produced by trading strategies on size, value and momentum for each of the region; when the explanatory variables (meaning the returns produced by the factors of the asset pricing model) are taken globally the results are quite poor, contrasting partially with Asness et al. (2013) and the possibility that size, value and momentum could be linked to global risk factors.

The contributions that I am expecting will be twofold, even though very linked to each other. On one side the different data set from the original one, in which the market anomaly was discovered, acts as a double check for the persistence of the anomaly. In addition the different period analyzed adds ulterior material for this proof. On the other side studying the implementation in practice of market anomalies will function as a verification of them on a different level: even if present the anomaly could not be used because at the beginning of the period the investors do not have any tool to infer how much predictive power each variable has. Both contributions are acting in the more comprehensive environment of the efficient market hypothesis, as all these studies the main conclusion will always be related to the possibility or no to use available information to spot mispricing in the market that can lead to abnormal returns.

Data

The analysis is directed towards the Euro market; instead of picking a broad index as the EURO STOXX I preferred to create a sample of companies from the five most important Euro stock market indexes; namely the Dutch (AEX 25), French (CAC 40), German (DAX 30), Italian (FTSE MIB 35) and Spanish (IBEX 35). The complete list of companies used is presented in the appendix.

Following Fama, French (2008) I use only the bigger stocks. In fact this is what institutions actually invest in, among other things, because of liquidity concerns. As a proof of this, around all the minimum points touched by the market caps of all companies in the whole sample the median point is 3.351 billion €, just as a comparison Fama and French in the same paper identified 610 million $ the breakpoint on the NYSE to be a micro-cap stock.

The set of factors analyzed are related to previous findings surrounding their applicability to predict stock returns in the cross-section; trying to gather an acceptable number of companies reporting, the list of these factors can be found in the appendix. Broadly speaking the factors covered are mostly related to the fundamental variables of a company, highlighting different aspects from the risk, profitability or fair valuation of the stock price, but also technical indicators based on previous stock returns.

Table 1 provides an overview of the factors and the descriptive statistic for the whole sample and the two sub samples. The period analyzed is from 2004 to mid 2014. The data is initially daily organized and from this the technical factors are built. All the data, from the price series to the accounting variables is downloaded from Bloomberg. Price series is retrieved using the PX_LAST ticker, which gives back the closing price of a specific day. Accounting variables are, on the other hand, linked to company reports.

More precisely the technical factors used can be divided into three categories: momentum, volatility and market beta. Momentum consists of the cumulative return of the past 20-260 and 130-260 trading days; using the same windows but the average return instead of the cumulative one other two factors are created. Similarly, volatility comprises two factors constructed using the standard deviation of the past 20-260 and 130-260 daily stock returns. Finally the market beta refers to one factor that is the slope of past 260 daily stock returns of a security and the return of the stock index in which the company is quoted on.

In order to avoid the problem of analyzing a period taking the ex-post winners (i.e. survivorship bias) the index composition is taken at the inception of the strategy. The list of companies forming the indexes is assembled again in 2009, this is necessary because some companies got delisted through time and to successfully perform the strategies I need a substantial number of companies that are alive and disclosing information. Some companies are quoted in more than one market, to not have the same security twice the stock listed in the peripheral market is deleted; these companies are just two for the 2004 index and three for the 2009 one.

A clarification: most of the companies are always reporting, but for some factors the availability is not so widespread and this is an issue with the factor itself and not with the fact that the company is not reporting at all. When a company is delisted in the trading strategy this acts in the same way as a real event and not like an ex-post manipulation; the company is available for investment purpose until the moment that it gets delisted.

Table1: descriptive statistics 2004-2014.
All the data is gathered from Bloomberg, for each factor is reported the average value (Avg), the standard deviation of the average value (Std) and the sample size (N).

	ALL			2004			2009		
	Avg	Std	N	Avg	Std	N	Avg	Std	N
ReturnOnAsset (%)	3,30	1,02	415.266	3,98	0,80	198.157	2,66	0,75	217.109
AssetGrowth (%)	8,32	5,59	415.266	11,81	4,76	198.157	5,08	4,18	217.109
SalesGrowth (%)	7,21	5,14	415.266	8,24	3,79	198.157	6,25	5,97	217.109
PriceToCash (%)	13,27	7,54	399.106	15,10	8,33	183.257	11,57	6,26	215.849
PriceToBook (%)	2,47	1,03	410.170	2,86	0,47	192.808	2,11	1,25	217.362
PriceToEarnings (%)	37,58	22,00	397.701	21,79	4,15	182.039	52,25	21,70	215.662
DebtToEquity (%)	339,78	293,44	415.270	283,00	9,23	197.907	392,55	400,40	217.363
ReturnOnEquity (%)	11,93	4,43	414.004	15,33	3,00	196.895	8,76	2,97	217.109
MarketCap (mln€)	18.495	3.114	417.486	19.434	3.565	199.360	17.621	2.306	218.126
EbitdaToRevenues (%)	21,10	1,21	337.634	20,24	0,73	159.213	21,90	1,01	178.421
DividendPerShare (€/share)	0,94	0,10	399.147	0,94	0,14	185.291	0,93	0,04	213.856
EnterpriseValueToSales	2,18	0,27	369.091	2,41	0,18	176.765	1,97	0,14	192.326
CashRatio (%)	0,34	0,04	329.715	0,33	0,03	156.782	0,36	0,04	172.933
PriceToSales (%)	1,36	0,27	410.676	1,55	0,23	193.314	1,17	0,15	217.362
EPS trail 12-month (€/share)	1,91	0,61	410.937	2,32	0,51	193.574	1,54	0,44	217.363
CashGrowth (%)	49,27	56,64	397.551	55,87	50,09	186.502	43,14	61,50	211.049
CapexGrowth (%)	26,24	24,70	394.643	27,69	18,41	180.964	24,89	29,31	213.679
TradingVolume (mln)	8,10	2,90	418.065	7,37	2,36	199.939	8,77	3,18	218.126
EPS annualized (€/share)	1,91	0,61	410.937	2,32	0,51	193.574	1,54	0,44	217.363
MovingAverage 20-260 (%)	-0,0001	0,0010	418.038	0,0001	0,0010	199.919	-0,0002	0,00109	218.119
MovingAverage 130-260 (%)	-0,0001	0,0014	418.038	0,0003	0,0010	199.919	-0,0003	0,0016	218.119
CumulativeReturn 20-260 (%)	-0,01	0,25	418.065	0,02	0,23	199.939	-0,05	0,26	218.126
CumulativeReturn 130-260 (%)	-0,01	0,18	418.065	0,03	0,12	199.939	-0,05	0,21	218.126
Std 20-260 (%)	0,02	0,01	418.031	0,02	0,00	199.918	0,03	0,01	218.113
Std 130-260 (%)	0,02	0,01	418.031	0,02	0,00	199.918	0,03	0,01	218.113
Beta	0,95	0,04	418.065	0,92	0,03	199.939	0,97	0,04	218.126
StockReturn (%)	-0,00005	0,01362	418.065	-0,00030	0,01251	199.939	0,00019	0,01458	218.126

Methodology

Given a set of proven predictors in the cross-section of stock returns, the problem is to find a profitable way to use them. Instead of using cross-sectional regressions to see to what extent each factor predicts the stock return and then make usage of this information I directly used all factors individually into trading strategies and then valued their quality based on the performance obtained.

Since daily trading would be too costly transaction wise, I extracted the data at the end of every month from the database and built all the trading strategies that are rebalanced monthly. More specifically the signal to buy or sell is given at the end of a month and then applied for the following one. This method partially differentiate this work to ones that share the same aim, mostly Lewellen (2014) and Haugen and Baker (1996), because it takes factors individually and then mixes them rather than initially start with a considerable amount of factors and then excluding some. This approach is different because it ignores the correlation between factors relying solely on the goodness of their past performance.

To not develop the strategies on information that is not yet available a lag is introduced, there is a distinction between variables though; the information regarding fundamental variables is lagged by three months due to the delay of companies to release the annual and infra annual reports. Whereas no lag is applied concerning market information since these are assumed to be easily accessible by everyone and basically at every moment.

The allocation of resources is achieved through portfolio sorting, using ranks. Specifically every security receives a rank established on the factor examined, the long position is selected using previous findings around the factors, e.g. for ROA the company displaying the highest ROA will also have the highest rank. For some factors the link is immediate since the factor is the same variable analyzed in some previous paper, for others there is no such link, I then tried to apply the intuition of the paper to the new factor.

Instead of looking at the different percentiles and select a top/worst class in which to invest in, I preferred to use the whole sample, assigning a weight based on the rank for all. At first this eliminates the discretion among the percentile to pick when an investment decision is made, i.e. there is no model that states before which percentile is better to use, so this choice is left to the preference of the investor. Then it will help to see the persistency of the anomaly variable not only in the extremes of the portfolio sorting, but using all the securities available. Roughly, at every point in time, half of the companies will compose the long position and the other half the short position.

The strategy is built on a euro-neutral base and standardized such that the long position sums up to 1 and the short position to -1. The weight given to each security is applied following the approach of Asness, Moskowitz and Pedersen (2013):

$$w_{it}^{S} = rank(S_{it}) - \frac{(\frac{N_t + 1}{2})}{c_t}$$

Where N represents the number of companies, i the company, t the time and S the factor used, c is a scaling factor:

$$for\ all\ long\ positions: c_t = \sum_i rank(S_{it}) - \frac{N_t + 1}{2}$$

At the end of this procedure I have a trading strategy for every variable in the dataset; the overview of the risk-return profile for all the individual strategies is presented in table 2. As a matter of completeness in the table are also presented all the five stock indexes plus an equal-weight composition of the five.

Table 2: summary statistics for trading strategies on singular factor, from May 2004 to May 2014.
In the first set of factors the long position is assigned to those securities having the highest values, in the second set the opposite is done. The index returns in the last panel are total returns, in excess to the risk-free rate. Momentum factors are constructed using moving averages and cumulative returns.

	Mean12	StD12	SR	T-stats	Kurt	Skew	Top month	Median month	Worst month
	Highest rank given to highest value								
ROA	8,59%	13,24%	0,65	*7,134*	1,10	0,42	14,02%	0,50%	-9,98%
SG	4,51%	9,60%	0,47	*5,173*	0,95	0,65	8,46%	-0,09%	-6,84%
DE	-6,91%	11,42%	-0,60	*-6,650*	0,69	-0,47	8,17%	-0,37%	-10,81%
ROE	7,74%	10,73%	0,72	*7,942*	-0,02	0,28	9,76%	0,51%	-5,92%
EBITDA	-2,54%	11,05%	-0,23	*-2,532*	4,11	0,52	14,55%	-0,24%	-11,69%
DPS	5,45%	11,32%	0,48	*5,297*	0,03	0,21	9,57%	0,28%	-7,67%
CR	0,49%	7,35%	0,07	*0,733*	0,90	-0,40	5,83%	0,23%	-5,78%
EPS	5,94%	11,49%	0,52	*5,692*	0,11	0,22	9,38%	0,47%	-6,80%
CG	1,72%	7,21%	0,24	*2,630*	1,76	0,09	7,53%	0,20%	-5,92%
EPS ANN	5,94%	11,48%	0,52	*5,691*	0,11	0,22	9,38%	0,47%	-6,80%
MA 20-260	7,52%	16,00%	0,47	*5,232*	7,46	-0,83	15,02%	0,57%	-24,61%
MA 130-260	10,05%	12,93%	0,78	*8,659*	2,15	0,94	14,29%	0,21%	-7,51%
CR 20-260	7,92%	16,03%	0,49	*5,501*	7,62	-0,86	15,02%	0,62%	-24,81%
CR 130-260	10,28%	12,94%	0,79	*8,844*	2,10	0,93	14,32%	0,21%	-7,64%
	Highest rank given to lowest value								
AG	-2,79%	7,72%	-0,36	*-3,970*	2,78	-0,87	4,49%	-0,08%	-9,92%
PC	-2,65%	12,08%	-0,22	*-2,409*	1,04	-0,44	8,37%	0,16%	-13,04%
PB	-5,50%	14,24%	-0,39	*-4,248*	1,06	-0,28	11,85%	-0,26%	-12,89%
PE	-0,71%	9,46%	-0,08	*-0,827*	3,72	-1,07	7,59%	0,21%	-12,71%
EV	3,81%	9,35%	0,41	*4,478*	2,95	0,34	12,27%	0,23%	-8,67%
PS	-0,33%	13,65%	-0,02	*-0,262*	2,50	-0,11	16,23%	0,11%	-12,49%
CAPEX	-0,69%	6,81%	-0,10	*-1,108*	0,83	-0,25	5,33%	0,05%	-6,52%
MK	-4,28%	11,47%	-0,37	*-4,151*	0,83	-0,21	9,50%	-0,05%	-10,36%
VOL	4,43%	8,52%	0,52	*5,794*	1,67	0,32	9,11%	0,45%	-5,62%
STD 20-260	7,99%	15,90%	0,50	*5,593*	1,33	0,58	18,22%	0,43%	-10,05%
STD 130-260	6,93%	14,94%	0,46	*5,163*	3,92	1,05	21,33%	0,27%	-9,89%
BETA 260	6,05%	15,74%	0,38	*4,594*	3,25	0,65	20,71%	0,15%	-15,74%
FTSEMIB	0,10%	21,14%	0,00	*0,828*	0,90	-0,43	19,27%	0,98%	-17,85%
DAX	7,81%	18,46%	0,42	*5,515*	3,18	-1,11	15,49%	1,73%	-21,32%
CAC	4,19%	16,77%	0,25	*3,711*	0,97	-0,76	12,51%	1,04%	-14,65%
IBEX	6,44%	20,03%	0,32	*4,334*	1,22	-0,43	15,79%	0,90%	-18,42%
AEX	3,97%	18,65%	0,21	*3,215*	4,17	-1,41	11,52%	1,27%	-22,03%
EW Indexes	3,00%	17,65%	0,17	*3,722*	1,76	-0,83	14,69%	1,20%	-17,66%

Last remark: in table 2, I highlighted the Sharpe ratio which in this case is not considering the excess risk premium but just divides the mean with the standard deviation, this is because the strategies are constructed on a cash neutral base and so the risk-free rate can be ignored.

Results

Support the evidence: abnormal returns for the twenty-six factors

Before going through the analysis of the factors and their employment into a composite trading strategy it is worth to first test the results of the simple trading strategies on singular factors. This will provide the preliminary results around the persistency of these anomalies over the new period and, more importantly, a new market.

Table 3: alphas for trading strategies on singular factors, returns from May 2004 to May 2014.
* indicates statistical significance at the 10% level **=5% level and *** at the 1% level.

	ROA	AG	SG	PC	PB	PE	DE	ROE	EBITDA	DPS	EV	CR	PS
α CAPM	0,009	-0,004	0,002	-0,005	-0,009	-0,004	-0,008	0,007	-0,001	0,004	0,000	-0,001	-0,005
t-stat	*3,085 ****	*-2,034 ***	*0,852*	*-1,786 **	*-2,939 ****	*-1,702 **	*-2,880 ****	*2,976 ****	*-0,398*	*1,365*	*0,004*	*-0,700*	*-1,720 ***
α 3FM	0,009	-0,004	0,002	-0,005	-0,009	-0,003	-0,008	0,007	0,000	0,004	0,000	-0,002	-0,005
t-stat	*4,158 ***	*-2,113 ***	*0,877*	*-2,101 ***	*-4,293 ****	*-1,746 **	*-3,450 ****	*3,640 ****	*-0,211*	*1,679 **	*-0,051*	*-0,815*	*-2,175 ***

	EPS	CG	CAPEX	EPS ANN	MK	VOL	MA1	MA2	CR1	CR2	STD1	STD2	BETA
α CAPM	0,004	0,000	-0,002	0,004	-0,007	0,003	0,009	0,010	0,009	0,010	0,009	0,008	0,000
t-stat	*1,379*	*0,247*	*-1,294*	*1,379*	*-2,290 ***	*1,452*	*2,420 ***	*2,981 ****	*2,497 ***	*3,007 ****	*3,214 ****	*2,981 ****	*0,059*
α 3FM	0,004	0,001	-0,003	0,004	-0,007	0,003	0,009	0,010	0,009	0,010	0,010	0,008	-0,001
t-stat	*1,634*	*0,266*	*-1,462*	*1,634*	*-3,262 ****	*1,359*	*2,603 ***	*3,229 ****	*2,693 ****	*3,260 ****	*4,041 ****	*3,704 ****	*-0,269*

The models used to observe the alphas are the ones mostly used in the papers where the anomaly was discovered. Even if a more complete model could be used this choice is prevalently linked to the interest of observing the anomaly in a different context with the same instruments. In table 3 it is provided evidence of the abnormal returns produced by the strategies, the coefficients are not highlighted since when further processing the variables into a portfolio they are not considered.

Despite the usage of the same variables as in related papers, a major difference could be the different methodology used to build the trading strategies, once again, not investing just in the top-worst decile but in all the securities with a weight proportional to the rank.

Table 3 depicts a controversial scenario: out of twenty-six factors thirteen obtained a positive alpha according to both asset pricing models, and from this group eight are statistically significant; even if the group represents the majority of the variables it is still not high enough to conclude that the market anomalies are mostly pervasive in the Eurozone. It should also be noticed that in the same group several factors are very similar to each other (for example the variants of momentum or volatility).

It is also true to affirm that not even the most well-known ones are present in Europe; starting with P/B the alpha is not just negative but also highly significant even when correcting for the Fama French three-factor-model. A similar situation is displayed by asset growth, a variable that is used as a proxy of investments in the new five-factor-model of Fama and French (2013). D/E also represents an important contradiction to the evidence, firm that showed a lower leverage actually gained a premium that is hardly explainable as risk premium as it is indeed the high leverage since it can be easily linked to the likelihood of a firm to be in financial distress or more vulnerable if a recession is approaching.

From the group of variables that exhibited a negative alpha MK is one of the most evident example. Big stocks outperformed small stocks, and generated a positive abnormal return, statistically significant at the 10% level for CAPM and 1% for the three-factor-model. Indeed it should be mentioned that most of the American literature considers bigger indexes, like the Russell 3000, and so the spanning market cap is more accentuated that the one I have in my sample; so this difference can partially explain the different result.

It is most likely, though, that the difference is rooted in the sample, and this consideration is valid for all the anomalies; some anomalies may not be pervasive because of the distressed period analyzed, so the bad performance can be partially tied to this and the fact that these strategies are cyclical rather than that they are not applicable to the Eurozone market. Going back again on size and value, because of their popularity among the anomalies, it should be noticed that the poor result that they obtained during this period is also clearly shown in the returns of the SML and HML factors of the three-factor model for Europe.

Moreover, anomalies are usually discovered using an extended period, since this study uses a 10-year period the pervasiveness of the anomalies can be rejected for sure for the period considered but since this is not tremendously high their presence in the Eurozone cannot be fully assessed.

Afterwards, when correcting for common risk factors, I will use a more complete asset pricing model, the four-factor-model. Consequently, the alphas of the individual strategies will be lower (especially the ones related to momentum and profitability, so the ones having the highest alphas).

Factors aggregation: Sharpe ratio's screening

The considerations around the results obtained by each individual strategy will come together with the ones obtained by the portfolio made by combination of factors.

The idea of aggregating the factors is linked to the belief that the performance will improve because of the higher degree of information used and taken advantage of; in other words it introduces the benefits of diversification. The problematic point copes with the aggregation of the factors, meaning to have a rationale for having a particular set of factors together.

Since one of the goal is to leave as much of the heterogeneity around investors' beliefs and preferences out, instead of aggregating factors using an artificial division by classes I used their past performances. The tool used to build the different portfolios is the Sharpe ratio produced by the strategies based on singular factors. This indicator is chosen because it summarizes the information regarding the risk-return profile of a particular strategy and mostly, it makes every strategy comparable and easily classified. A higher Sharpe ratio, even if produced by a strategy that has a low average return, is always preferable to a lower one with a high average return because of the possibility to leverage the first strategy and magnify the returns.

In order to have a stable outlook of the Sharpe ratios, the first twenty-four months of the sample are used to observe the development of this figure and used to invest from month twenty-five (April 2006) onwards. When I am calculation the Sharpe ratio I always use all the history available, such that the sample used for this computation is enlarged every month by one unit.

Technically the trading strategy is performed using the same rules as before, the difference is now that the rank is not a direct product of the factor but is a combined rank, having each factor weighted differently according to their Sharpe ratio. For every security i, the formula to obtain the ranks later used to sort the securities is the following:

$$Rank(F_{it}) = \sum_{s=1}^{23} w_s \cdot Rank(S_{it})$$

Where w represent the weight placed to the factor s.

To not have in the portfolio two identical factors I discarded the EPS annualized factor and the two momentum factors with moving averages. This because in the first twenty-four months they performed slightly worse than their counterparts, respectively the trail 12-months EPS and momentum factors built using cumulative returns.

In view of the fact that the factors suffer from different number of observations I adopted the same approach as in Haugen and Baker (1996). I modified the database so to have all factors with the same amount of observations: when the company is alive but a certain factor is missing the mean sample value is assigned to that company. The aim is not to throw away valid data reducing the sample to companies having all factors. Nonetheless this step may bias the accuracy of the results, this is certainly true for those factors that exhibit a serious lack of data but in general this is not the case, having most of the factors with quite equal observations (close to the totality of companies).

Since investors care more about the performance and less about what past academic evidence have proved I took a similar point of view, treating all the variables in an equal way, using the Sharpe ratio that they produced as the only discriminant. This consideration then induces to include the factors that underperformed and question if the long position was chosen wrongly, i.e. the factor was showing an opposite relation to returns than the one initially thought.

Using the past performance as only driver to aggregate the factors has a main downside: it ignores the correlation between the factors. In fact it might happen that most of the portfolio's returns are resting on variables that are positively correlated with each other. The risk is that the portfolio could be more vulnerable to sudden changes in the profitability of the same variables; in other words it looses in terms of diversification.

A simple way to aggregate the factors moves from the consideration that the ones having the highest Sharpe would be the factors most attractive to use; then using a formula to give a weight to the factor that is proportional to its Sharpe ratio should reflect this consideration.
A possible procedure to do it would be to simply divide the individual Sharpe by the sum of all the Sharpe ratios of the strategies:

$$w_i = \frac{|S_i|}{\sum_n S_n}$$

Where w represents the weight placed to the factor and S the Sharpe ratio that it produced.

In this view factors are observed for their absolute Sharpe ratio value: if the sign is positive it means that the relation is the one initially assumed and if it is negative it means that the ranking may be given incorrectly and should be changed into the new order (e.g. instead of sorting stocks using a descending order sort them in an ascending one). Expanding this idea, if the Sharpe ratio is negative an investor could have thought about the misuse of a factor and that if he had invested following an inverted order he would have got a positive ratio. In this case this presumption is certainly true because the specific formula that gives weight to securities assures that if the highest rank would be given to the lowest value instead of the highest the return would be the same as before but with a different sign. Therefore the Sharpe would be the same in absolute terms but with a plus instead of a minus in front.

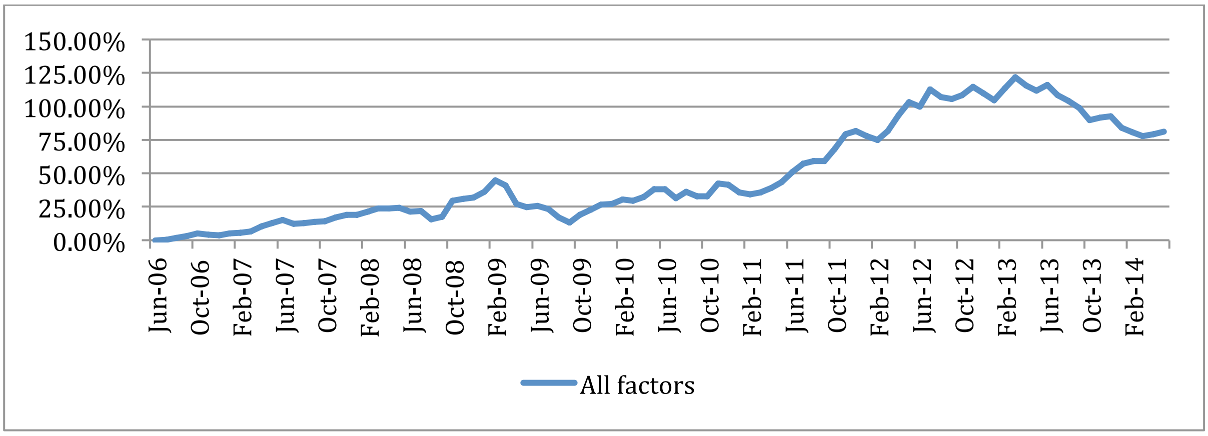
At first glimpse changing the belief towards a factor just because the Sharpe ratio is negative may be too drastic, but it should not be forgotten that the metric is built from, at least, the past twenty-four months performance and so it should capture something more than a pure deviation from the relation expected. Even if the previous statement is true this will not compromise the results of the portfolio: if the Sharpe ratio changes from positive to negative in a specific month it is fair to assume that it was close to zero until the month before. Therefore the factor will receive, in both, previous and current portfolio rebalancing a weight that is very low.

Table 4 reports the results of this portfolio, it is useful to have a first idea around its performance. The risk-return profile obtained was above the five indexes that act as a benchmark; the average return was above the one offered by the indexes and the volatility was slightly lower. The cumulative return of the strategy denotes a clear upward trend, with most of the returns that are coming from the after crisis period.

Table 4: summary statistics for portfolio created using all the 23 variables. The starting point is May 2006 and it goes till May 2014.

	Mean12	StD12	SR	Kurt	Skew	Top month	Median month	Worst month	Months positive
All factors	10,03%	17,07%	0,588	0,425	0,070	12,86%	1,04%	-13,74%	61,86%

Figure 1: cumulative return of the portfolio, from May 2006 to May 2014.



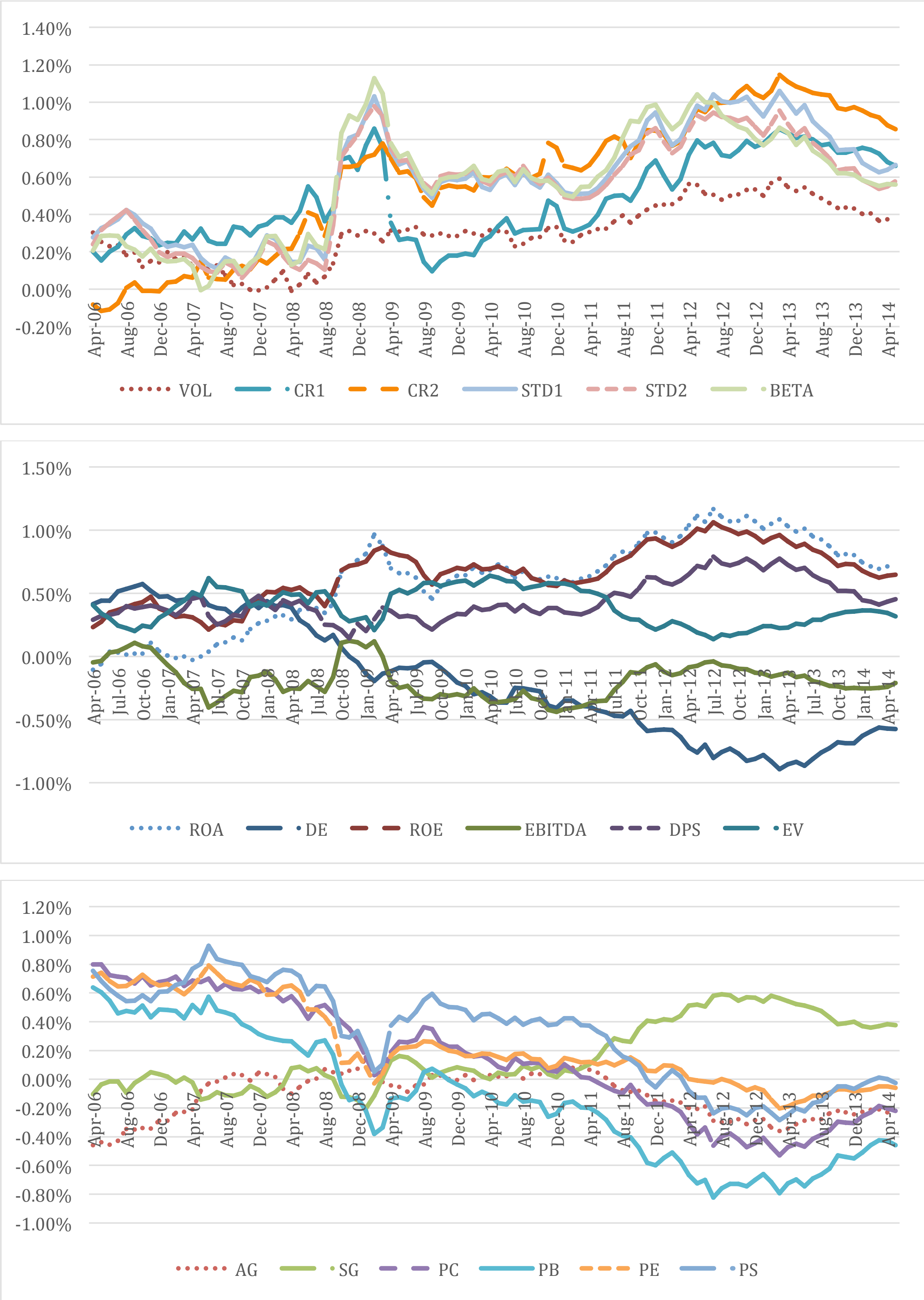
I will now focus on the interpretation and further analysis of the results earned by the simple strategies and for the portfolio on all factors. Given the fact that the effect of the financial crisis of 2008 in this sample is really relevant and due to the shortness of the period analyzed, I will provide a separate picture for its effects on the trading strategies.

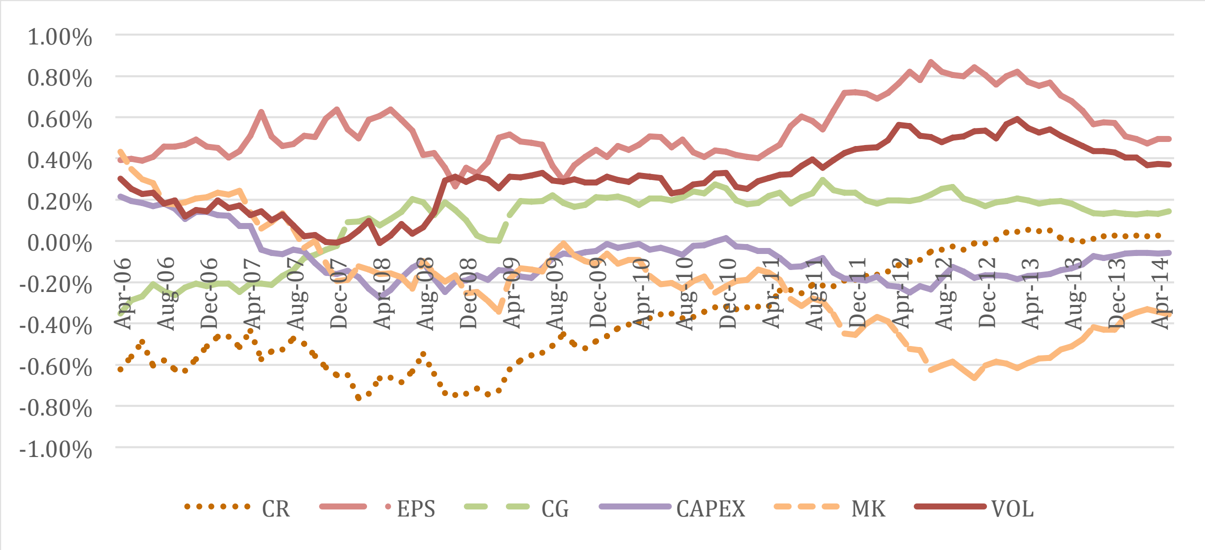
Data Analysis

Interpretation: strategies on singular factors

From the evolution of the average monthly return obtained by each strategy some considerations can be made around the factors and their relation to the realized returns. I highlight now the most evident trend in this matter. A graph in this sense would be clearer and more efficient than words, in figure 1 all the individual strategies' average monthly returns are displayed.

Figure 2: average monthly return (from month 24) for all 23 factors.





At first not many factors had a stable pattern over time, one of the causes could be the impact of the crisis and its effects that were able to change the entire trend showed until that moment. Out of twenty-three factors eleven had a positive average monthly return, in line with the past evidence, for at least 90% of the months. From this group of twenty-three factors profitability factors, ROA and ROE, DPS, both momentum factors, volatility and earnings-per-share are included.

One of the most recent anomalies, asset growth, did not confirm any negative relation with the stock return, having the strategy going long on low asset growth companies two-thirds of the times a negative average return. Another variable EBITDA/Sales that, in theory, should be similar to a profitability indicator, highlighting how good a firm is doing in managing the operative costs, produced a very poor performance in the sample analyzed. Most of the factors related to the fairness in pricing exhibited a negative trend, meaning that from mid 2006 they were producing good performance but from that had a constant decline, with the inception of the crisis culminated in negative results. Linking to this, again the crisis had a disrupting effect for most of the strategies, for some changing the trend from positive to negative, for some other representing the main source of gain.

It is hard to find a general explanation for these changes in the performances when looking at factors individually, but when aggregating them into groups some useful considerations can be made. Out of the group of strategies that lost a lot, D/E, MK and P/B changed drastically their trend with the abruption of the crisis; the preference from small and leveraged firms switched to bigger and more equity financed companies. Also P/B highlights the new preference of investors for firms that are highly recognized and successful, reflecting this success with an higher valuation of their equity compared to its book value; discarding, on the other hand, those firms that have a cheaper valuation of their title. In general it is possible to affirm that the aptitude towards risk busted, with most of the investors searching for stable and solid companies, able to save their money even in a period of financial turmoil. Related to this, the positive peak reached by the volatility strategies can be explained. Companies that had the lowest volatility were awarded for this stability in a period of great uncertainty. A similar conclusion can be inferred from the momentum strategies, in particular for companies that performed poorly before the crisis, the beginning of the downturn represented a major issue than for the others.

Impact of the financial crisis

This section investigates the role of the 2008 financial crisis as a game changer for most of the individual trading strategies. Considering the peak of the downturn of the financial markets as a metric, table 5 displays the returns of the individual trading strategies over the beginning of the crisis. As clear from the table the highest values are positive and then it is important to further study the determinants of this result also to understand if they represented the main source of gain for the overall period.

Table 5: monthly returns from July 2008 to February 2009.
Panel A: cumulative return for the whole period.

Cumulative return from July 2008 to February 2009

ROA	37,11%	**EBITDA**	16,66%
AG	2,26%	**CR**	-8,89%
SG	-9,35%	**PS**	-26,47%
PC	-19,33%	**EPS**	-7,21%
PB	-30,29%	**CG**	-6,74%
PE	-25,90%	**CAPEX**	-1,98%
DE	-23,44%	**MK**	-8,41%
ROE	23,59%	**VOL**	13,86%
		BETA	9,95%

Panel B: monthly returns for momentum and volatility strategies, division between return produced by long position and short position.

	CR 20-260		CR 130-260		STD 20-260		STD 130-260	
	SHORT	LONG	SHORT	LONG	SHORT	LONG	SHORT	LONG
31/07/08	2,64%	-5,25%	3,21%	-3,72%	3,49%	-3,91%	3,46%	-4,35%
29/08/08	-7,56%	1,10%	-6,97%	1,44%	-5,56%	2,44%	-4,86%	3,15%
30/09/08	13,82%	-9,35%	16,68%	-8,80%	19,12%	-5,67%	19,38%	-5,98%
31/10/08	28,46%	-13,44%	27,35%	-13,68%	28,85%	-10,62%	31,56%	-10,22%
28/11/08	7,38%	-5,89%	6,83%	-6,17%	8,48%	-2,05%	8,07%	-4,07%
30/12/08	-0,66%	-2,79%	1,46%	-0,36%	2,36%	-0,35%	4,16%	0,01%
30/01/09	12,71%	-4,10%	8,83%	-5,50%	11,74%	-4,92%	11,49%	-5,10%
27/02/09	16,09%	-9,92%	14,22%	-12,59%	17,31%	-10,05%	15,81%	-11,03%
Total	72,89%	-49,64%	71,61%	-49,38%	85,79%	-35,14%	89,06%	-37,60%

The strategies that mostly gained out of this financial turmoil were the ones related to momentum and volatility. From table 5, panel B, it can be seen how the gain is coming from the short position.

This result is a bit contradicting the evidence since momentum historically performed bad in the US, having suffered a lot from the downturn. As a matter of comparison I analyze the WML factors for Europe and US together with the factor I built, CR 20-260. In this case I use a broader period to include also the final part of the recession.

Table 6: return during the crisis (June 2008 to June 2009) for momentum US, EU and the two cumulative return factors that I included in the analysis. The momentum factors for US and EU are retrieved from Kenneth French Data Library. US from Momentum consists of the returns of the average past winners from the big companies and the small companies minus the returns of the average past losers from the small companies. The previous return is measured from month two to month twelve.

	Momentum US	CR 20-260	Momentum EU
Jun-08	12,53%	7,40%	9,66%
Jul-08	-5,29%	-2,60%	-2,13%
Aug-08	-3,81%	-6,46%	-4,92%
Sep-08	0,33%	4,47%	3,83%
Oct-08	7,77%	15,02%	9,87%
Nov-08	7,19%	1,50%	2,71%
Dec-08	-5,03%	-3,44%	-0,85%
Jan-09	-1,90%	8,61%	3,41%
Feb-09	4,22%	6,17%	4,50%
Mar-09	-11,36%	-5,24%	-10,03%
Apr-09	-34,72%	-24,81%	-25,96%
May-09	-12,46%	-5,45%	-7,72%
Jun-09	5,33%	0,84%	2,50%
Total	-37,20%	-4,01%	-15,13%

Table 6 depicts a different scenario, with momentum factors in the Eurozone also producing a negative return. Curiously the momentum factor that I am using outperforms the ones retrieved from Kenneth French Database, the sources of the difference might be the different sample used (my sample should be smaller since considering just a part of the Eurozone) and maybe also the discard of the first twenty trading days in order to avoid mean reversal in the short term. In conclusion from table 6 it can actually be affirmed that the effects of the financial crisis were not so negative in Europe as in the US.

With a broader view the impact of the crisis is also analyzed with respect to the portfolio's returns. The recession period is the one identified by the Euro Area Business Cycle Dating Committee and goes form the first quarter of 2008 until the end of the second quarter of 2009. Concluding this section, table 7 displays the performance of the portfolio when either including or when excluding the crisis. The recession period represented a negative period overall for the portfolio, having a lower average return and higher volatility when including the crisis. Despite this, there is no capital loss having the cumulative return for the same period equal to 6,47%.

Table 7: summary statistics for portfolio on combination of factors, excluding and including the crisis (January 2008 - June 2009).

	Mean12	StD12	SR	Kurt	Skew	Top month	Median month	Worst month	Months positive
All factors	10,03%	17,07%	0,588	0,425	0,070	12,86%	1,04%	-13,74%	61,86%
All factors (Excluding crisis)	11,34%	16,72%	0,678	-0,083	0,231	12,86%	1,06%	-9,35%	62,03%

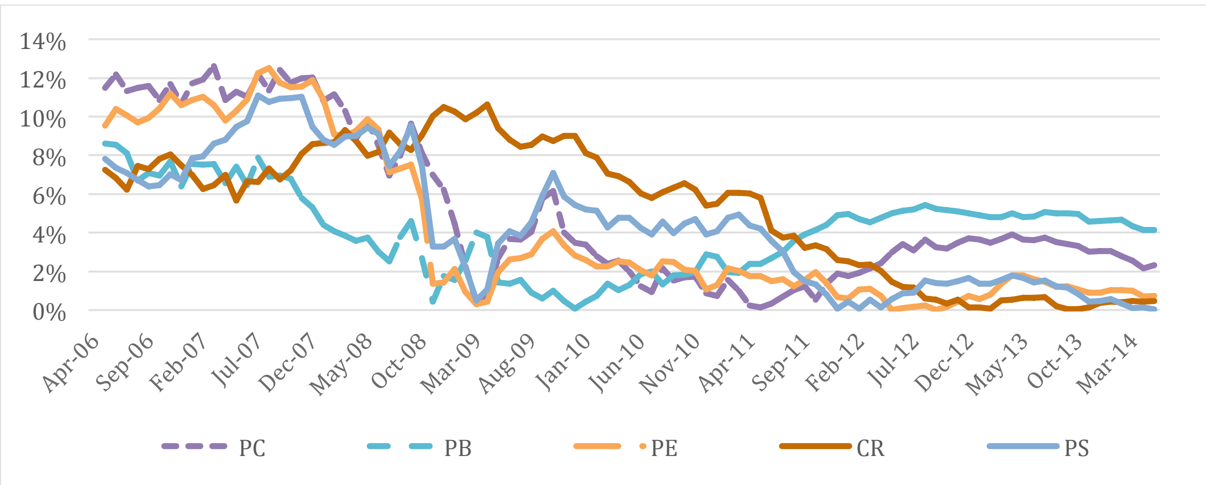
Interpretation: strategies with multitude of factors

For the combination of factors it makes sense to look at the different weights given to each factor to see the composition of the final portfolio. For the sake of simplicity I will look at the first ten factors; this because these ten factors will be the ones receiving the highest weights for the final rank composition used to sort stocks and so they provide a valid representation on how the final weight is formed.

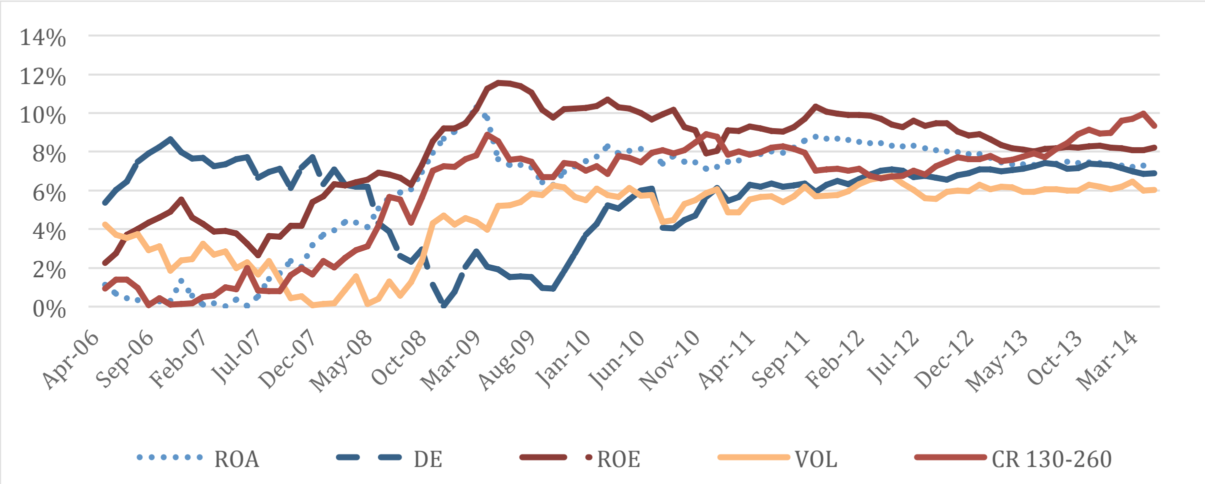
Overall, for most of the time factors changed positions frequently and without maintaining it for a considerable amount of months; here position means the specific weight that each factor will have for the computation of the ranks to sort stocks. Despite this high degree of change if just looking at the top factors (first four-five) two tendencies can be defined across the years. Until the inception of the crisis the dominating factors were the ones related to the fairness in price: P/B, P/E, P/S, P/C for the first years were the factors having the highest weights in the portfolio. After the crisis the profitability factors, ROA and ROE, together with momentum (especially the 130-260 past cumulative return) got the highest ranks, together with these two a lot of factors changed positions.

These factors were used as initially assumed because their Sharpe ratio was positive, it is nevertheless interesting to mention those factors that had a negative Sharpe and then they were used with an inverted order. In general the factors having a positive Sharpe ratio from the beginning were the ones with the highest weights; even so, the exceptions exist and in three cases they were relevant. Debt over equity reflecting the good performance of investing in companies highly leveraged got one of the highest weights in the pre-crisis period, after that, since it was one of the factor most affected by the crisis, still got a relevant weight but assigning the long position to less leveraged companies. Cash ratio represents the second relevant exception and in this case it is clear how the usage of the variable was misused until the beginning. Because of its highly negative Sharpe ratio, the long position was assigned to companies having low cash ratio rather than a high one. The abruption of the crisis changed the trend for this variable, making the weight assigned to it constantly declining until the end of 2012, from which the variable was used also in the opposite way. The least important exception is represented by P/B, because this variable was used as initially assumed until the end of 2009. Afterwards the usage of P/B was directed to invest in companies having a high price to book value but this usage did not get a great consideration in terms of weight on the factor.

Figure 3: weights assigned to factors, from April 2006 to May 2014.
Panel A: development of weights assigned to the initial top five factors (starting with highest weights).



Panel B: development of weights assigned to the final top five factors (finishing with highest weights).



Dissecting the portfolio returns: decile and quartile divisions

A valid perspective to analyze the discriminant of the final portfolio returns is to look at the performances produced by companies positioned into different percentiles according to the different ranks. More analytically the returns displayed in table 8 are the ones referring to long positions taken into companies placed in that specific percentile; the division is made using deciles and quartiles.

Table 8: returns produced by different deciles and quartiles, only long position analyzed. Panel A refers to returns from May 2006 to May 2014, Panel B excludes the months from September 2008 to February 2009.

PANEL A: WHOLE PERIOD

	Deciles				Quartiles		
	Mean12	**STD12**	**SR**		**Mean12**	**STD12**	**SR**
1 *(lowest)*	-12,97%	32,77%	-0,40	1 *(lowest)*	-11,48%	29,06%	-0,39
2	-11,95%	28,81%	-0,41	2	-10,26%	22,09%	-0,46
3	-10,80%	25,68%	-0,42	3	-2,68%	18,92%	-0,14
4	-12,70%	23,98%	-0,53	4 *(highest)*	-1,74%	16,78%	-0,10
5	-5,75%	21,80%	-0,26				
6	-0,91%	19,60%	-0,05				
7	-6,62%	20,46%	-0,32				
8	-0,59%	18,83%	-0,03				
9	-1,55%	17,91%	-0,09				
10 *(highest)*	-1,18%	15,81%	-0,07				

PANEL B: Excluding CRISIS

	Deciles				Quartiles		
	Mean12	**STD12**	**SR**		**Mean12**	**STD12**	**SR**
1 *(lowest)*	-2,03%	30,23%	-0,07	1 *(lowest)*	-2,24%	26,91%	-0,08
2	-2,98%	26,46%	-0,11	2	-2,25%	20,10%	-0,11
3	-4,19%	24,64%	-0,17	3	3,76%	17,23%	0,22
4	-3,66%	21,09%	-0,17	4 *(highest)*	4,32%	15,41%	0,28
5	1,93%	20,31%	0,10				
6	4,85%	18,69%	0,26				
7	1,01%	17,93%	0,06				
8	6,64%	16,30%	0,41				
9	3,89%	17,09%	0,23				
10 *(highest)*	4,03%	14,61%	0,28				

The deciles are more volatile than usual because the decile composition is usually made by fifteen companies and thus very exposed to big drawdowns. Despite this, the usual clear upward trend of the average monthly return is showed, moving from the lowest to the top decile. Since deciles can be a noisier proxy for the division of the sample I also display in table 8 the quartiles. This figure confirms, in a clearer way, the trend already stated before.

Looking at the standard deviations the result partially confirms what Haugen and Baker (1996) stated about companies in their top deciles: they exhibit a lower volatility, and that induces them to affirm that they are GARP (Growth At a Reasonable Price) stocks. Not developing further this observation the result is indeed curious. Nonetheless keeping in mind that the huge standard deviation for companies in lowest decile/quartile may be due to some outliers (companies in financial distress).

The impact of the crisis is once again remarked because of its tremendous impact, investing in equity if considering those six months is basically a loss every time. The exclusion of those six months is then motivated by the fact that this scenario is not generally the case and once again the impact is so big because of the shortness of the sample. Moreover also to demonstrate how the portfolio returns are not coming solely from the short position but also from having selected companies that had a positive average return.

Analysis of the performance: correlation with main indexes

One important feature for an equity portfolio is the correlation with the stock indexes of the markets in which it is exposed to; this gives an idea of how much the portfolio is vulnerable to cyclical variations that impact the same stock markets. The comparison is made using all the five stock indexes of the countries analyzed, plus an equal-weight combination of the same five, for the returns it is used the total return index, simulating a buy-and-hold strategy for the whole period.

Despite the fact that all the companies are gathered from these five indexes it should be recalled that over the selected time-period the index compositions are rebalanced twice a year, for most of them. Contrary to this, the companies I use are rebalanced just twice over the whole sample, so this inevitably gives rise to some differences concerning the companies that are forming the indexes and the ones I utilized.

Table 9: correlation of portfolio returns with trading strategies on individual factors and stock indexes.

Correlation coefficients with portfolio returns					
PB	-0,888	VOL	0,553	FTSEMIB	-0,677
PC	-0,820	BETA	0,699	IBEX	-0,631
PS	-0,814	MA2	0,708	EW Indexes	-0,534
MK	-0,799	CR2	0,713	CAC	-0,445
DE	-0,790	EPS	0,716	AEX	-0,355
PE	-0,612	EPS ANN	0,716	DAX	-0,328
EV	-0,562	MA1	0,764		
CAPEX	-0,529	CR1	0,765		
AG	-0,504	DPS	0,775		
CR	-0,060	ROE	0,783		
CG	0,008	STD2	0,796		
SG	0,325	STD1	0,843		
EBITDA	0,447	ROA	0,918		

Correlations with individual strategies and portfolio returns confirm the previous analysis over the weights given to the factors, denoting immediately which factors are mostly used to compose the final ranks used to sort stocks. From table 9 it is also evident how the correlations are, most of the time, either really positive or negative; this might suggests the fact that the portfolio is made mostly by factors that are positively correlated with each other and negatively correlated with the ones that are discarded. This result is highlighting the main drawback of the portfolio, ignoring correlation between factors leads to a lower diversification and thus higher risk. I remark here the surprising fact that the portfolio appears to be tilted over big and highly valued (high P/B) stocks, having a negative correlation with strategies that are short on these stocks.

As immediately seen from the table, all the correlations estimated with the stock indexes are negative, the intuition is that the portfolio is acting mainly in a countercyclical way. This result can be studied further to understand what the determinants of this behavior are. The starting point could be the correlation between the individual strategies and the same indexes, to link then the overall behavior of the portfolio with the weight given to each factor.

Table 10: correlation between indexes and trading strategies with individual factor.

	FTSEMIB	DAX	CAC	IBEX	AEX	EW Indexes
ROA	-0,73	-0,49	-0,56	-0,67	-0,49	-0,64
AG	0,30	0,18	0,19	0,21	0,22	0,24
SG	-0,04	0,11	0,06	-0,02	0,02	0,03
PC	0,61	0,30	0,39	0,58	0,28	0,47
PB	0,73	0,47	0,56	0,66	0,45	0,62
PE	0,56	0,44	0,49	0,60	0,45	0,55
DE	0,47	0,11	0,22	0,54	0,11	0,32
ROE	-0,61	-0,45	-0,51	-0,50	-0,49	-0,55
EBITDA	-0,51	-0,59	-0,57	-0,41	-0,59	-0,57
DPS	-0,40	-0,06	-0,16	-0,34	-0,16	-0,25
EV	0,59	0,58	0,57	0,45	0,53	0,59
CR	0,19	0,23	0,26	0,03	0,30	0,22
PS	0,72	0,58	0,62	0,64	0,52	0,66
EPS	-0,32	0,04	-0,08	-0,28	-0,09	-0,17
CG	-0,13	-0,11	-0,15	-0,14	-0,13	-0,14
CAPEX	0,23	0,09	0,10	0,19	0,15	0,17
MK	0,45	0,16	0,30	0,42	0,30	0,36
VOL	-0,51	-0,26	-0,35	-0,49	-0,31	-0,42
CR 20-260	-0,62	-0,43	-0,51	-0,61	-0,41	-0,56
CR 130-260	-0,48	-0,22	-0,34	-0,49	-0,34	-0,40
STD 20-260	-0,79	-0,63	-0,70	-0,71	-0,64	-0,75
STD 130-260	-0,78	-0,64	-0,70	-0,70	-0,67	-0,75
BETA 260	-0,84	-0,79	-0,82	-0,78	-0,76	-0,86

From table 10 it is clear how the majority of the factors were actually positively correlated with the indexes; then the negative correlation of the portfolio should be explained entirely by the weights given to each factor. In fact remembering the portfolio composition from the inception of the crisis (so for most of the period studied) the ranks were basically made by those factors having negative correlation (those are, foremost, ROA, ROE, momentum and volatility). So it is probably also true that before the crisis the portfolio was positively correlated with the indexes since it is dominated by factors that are displaying this relation (mainly P/B, PE, PC).

It is interesting to notice how the set of factors used for the portfolio's weights are positively correlated with each other denoting the aspect of the cyclicality and different usage of factors. Then it seems that using this set of factors somehow recognizes the cyclicality implicit in the stock market and picks the best combination given the state of the economy. Unfortunately the period analyzed is too short to analyze further any changes in the portfolio weights and observe these switches from different set of factors.

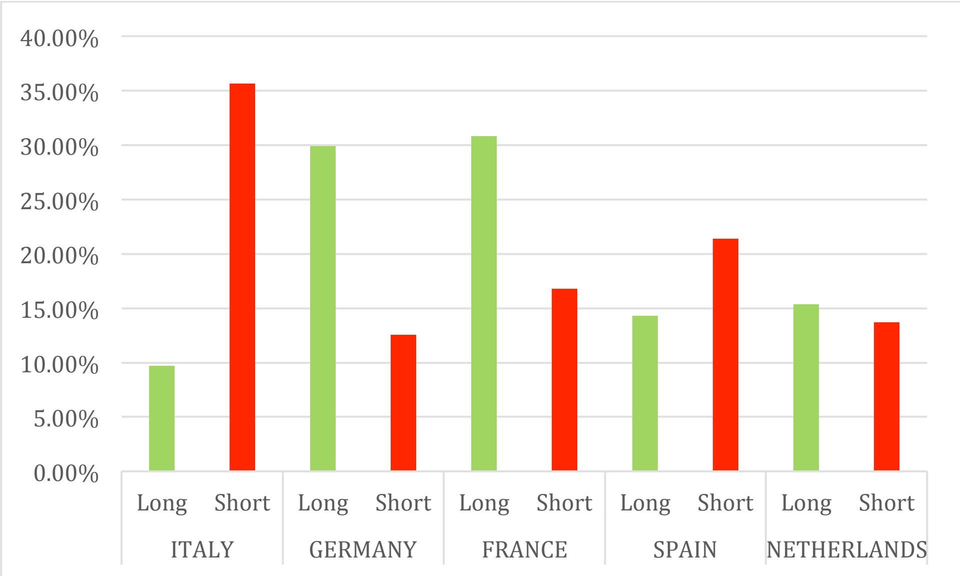
Analysis of the performance: geographical composition

Since investing in stocks of different countries, another analysis would be related to the geographical composition of the portfolio. This relates to the previous analysis of the correlation with the stock indexes aimed at understanding to which markets the portfolio is more exposed. The fact that makes this useful is that, despite the high integration in the Eurozone, the different stock indexes had different performances in the sample (as testified in table 2).

The object of the analysis is the weight given to each security, the weights are then aggregated by country and inside each country there is a division between weights referred to the long position of the portfolio and the short position. This division actually helps to understand how companies of a country are mostly used.

Overall the weight given to each country is stable, without big changes over time and the magnitude reflecting the different number of companies included in each stock index (so bigger index leads to bigger weight). Very different indeed are the weights if long and short positions are divided. Actually from this it is clear how the portfolio allocates “wisely” to the funds, having the companies of the countries that performed poorly mainly used for the short part and companies from countries that performed good on the long part. This allocation also gets important in absolute terms, having for example two countries that alone represented the core long and short part of strategy: Italy is, by far, the country out of which companies are included in the short part, for a relevant part of the period even above 40% of the overall position, and Germany for the long part, with peaks above 35%.

Figure 4: Average division of long/short weight assigned for each country from April 2006 to May 2014, this weight is the sum of the weights given to securities of the same country.



Correction for common risk factors: employing the four-factor model

The last step to evaluate the performances of the portfolio somehow restarts from the analysis of its composition but now to see to what extent the portfolio is exposed to common risk factors, in other words to which risk the portfolio is exposed and in which terms.

This procedure is also aimed at the identification of possible abnormal returns, this figure has a particular importance for at least two reasons. First it represents an award obtained by the portfolio without "paying" the price of higher risk. Secondly it is contradicting either the asset pricing model in use or the efficient market hypothesis, given the fact that using past information an abnormal return is generated.

The correction for common risk factors is achieved using the following regression equation:

$$R_{i,t} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \varepsilon_t$$

Table 11: results of the regression, t-stats are showed for each variable. * = significant at the 10% level, **= significant at the 5% level, ***= significant at the 1% level.

	Alpha	MKT	SMB	HML	WML	Adj R2
AbsAll	0,006	-0,013	-0,498	-1,346	0,260	0,681
t-stat	*2,085* **	*-0,218*	*-3,386* ***	*-8,404* ***	*3,253* ***	

The relevant result is that the abnormal return is present and statistically significant at the 5% level. From the economic aspect its magnitude is also really important, given the fact that the alpha is expressed monthly and then annualized it means that its level is 7,41%.

Moving to the analysis of the coefficients, the market beta is basically insignificant from the statistical and the economic aspects; this may be related to the fact that the explanatory power of this coefficient is captured by the SMB and HML ones, as already noted by Fama and French when they proposed their three-factor-model. HML and SMB are, on the other hand, highly significant from both perspectives. Both factors performed quite poorly from the beginning of the crisis, and it has been already stated how the portfolio changed composition from value and small stocks to bigger and highly valued stocks; since this time represents the major part of the period analyzed, it is explained in these terms the negative sign on both coefficients. WML was the only coefficient to be positive and highly significant, this result is not surprising since it has already been noticed how the portfolio was tilted towards profitability factors, which have a high correlation with momentum factors. Despite this the magnitude of this coefficient is still small enough to affirm that this risk factor only partially explains the returns obtained by the portfolio.

It is nevertheless unexpected how the portfolio outperformed the indexes and obtained high Sharpe ratios without having a particular exposure to well-known risk factors. The striking conclusion from table 11 is that the four-factor model only partially explains the returns of the portfolio and what is the underlying risk factor that is implicitly taking. Even if not really considered a relevant figure the R2 lies on a lower level than most of the tests of the four-factor model (see for instance the level reported by Fama and French (2012) in their tests using global factors of the four-factor model). This indicates that the part of returns not explained by the model is the one that makes the strategy profitable, i.e. it has a significant positive return.

Portfolio turnover

Portfolio turnover provides a useful picture to determine the transaction costs that the portfolio may face. These costs are generated by the changes in weights given to each security. Following Boons (2014) I apply the following formula to estimate the portfolio turnover:

$$\frac{\sum_i \left| w_{i,t-1}\left(\frac{1}{2}\sum_i \left| w_{i,t-2}\left(1 + r_{i,t-1}\right)\right|\right) - w_{i,t-2}\left(1 + r_{i,t-1}\right)\right|}{\sum_i \left| w_{i,t-2}\left(1 + r_{i,t-1}\right)\right|}$$

The numerator accounts for the returns produced by the security between the two rebalances and compares it with the general return produced by the portfolio, which is scaled to allow long and short position to grow equally. The denominator then adjusts for the size of the portfolio.

The resulted (annualized) average turnover for an investor who is long and short one euro in the portfolio is 2,27, which combined with an average half-spread of 25 basis points (Chordia et al. (2011)) leads to an average yearly transaction cost of 56 basis points. More specifically using the estimated monthly transaction costs the overall return seized by transactions is equal to 4,56%. This result proves the attractiveness of the portfolio, having its performance intact after adjusting for transaction costs.

Robustness tests

Other portfolio formation

The performance of the portfolio created should be tested in a more direct comparison using the same dataset but different approaches. A first series of robustness tests involves the usage of portfolios that are formed using different set factors; this exercise will try to spot if the performance is mostly driven by those factors that are displaying the greatest Sharpe ratios, even though these factors are already receiving the highest weights eliminating totally the other will imply weights even higher for them.

As a consequence the formula that assigns weights to different factors will be changed. The variable modified will be the number of factors to include into the portfolio:

$$w_i = \frac{S_i}{\sum_n S_n}$$

There is also a division between two different perspectives: the one adopted so far that uses all factors disregarding the previous evidence and a different one that indeed considers just those factors that displayed a positive Sharpe ratio following the past evidence. For both methods ulterior restrictions forming are the followed portfolios just on the factors that had the highest one, three, five and ten Sharpe ratios.

Having an approach that considers just those factors that obtained a positive Sharpe ratio following past evidence has the only rationale of not contradicting this same evidence. Short selling the individual strategies is not permitted even if they displayed a negative Sharpe ratio, they will simply be discarded from the weights calculation. It can be affirmed that the weight given to each factor is given according to the past Sharpe ratio obtained, conditional on the fact that this performance was achieved sorting stocks in a way that was previously documented by research.

Table 12: summary statistics for all portfolios, returns are from May 2006 to May 2014.

	Using just positive Sharpe ratio					**Using absolute Sharpe ratio**				
	1 factor	**3 factors**	**5 factors**	**10 factors**	**All positive**	**1 factor**	**3 factors**	**5 factors**	**10 factors**	**All factors**
Mean12	2,87%	7,44%	7,59%	10,17%	10,22%	2,07%	6,99%	7,28%	9,38%	10,03%
StD12	11,32%	13,51%	15,12%	16,06%	15,95%	11,32%	13,99%	15,72%	16,67%	17,07%
SR	0,25	0,55	0,50	0,63	0,64	0,18	0,50	0,46	0,56	0,59
Kurt	0,32	0,01	0,63	0,12	0,21	-0,09	0,06	0,68	0,47	0,42
Skew	0,34	0,32	0,00	0,05	0,08	0,27	0,30	0,09	-0,05	0,07
Top month	9,95%	10,28%	11,06%	11,62%	11,57%	8,07%	10,28%	11,44%	11,78%	12,86%
Median month	-0,05%	0,79%	0,68%	0,78%	0,91%	-0,16%	0,48%	0,74%	0,71%	1,04%
Worst month	-7,48%	-8,16%	-13,66%	-12,27%	-12,21%	-7,48%	-8,66%	-14,37%	-14,50%	-13,74%
Months positive	48,45%	57,73%	58,76%	63,92%	63,92%	47,42%	56,70%	57,73%	60,82%	61,86%

Portfolios not using all the positive factors are inserted to investigate whether the performance improves including more factors or not. Ex-ante the most viable way for an investor would be to use all factors, since they are also weighted according to the criteria used.

The initial belief that the superior information obtained using multiple factors lead to a better performance was actually true for the period considered: moving from the Sharpe ratio of the portfolio formed on one factor to the ones using all positive and all factors it is clear how the figure is trending up. This result is actually a good sign also from the fact that using more factors grants more protection to the swings that affect every factor.

If using more factors yielded better results inside each approach (all positive Sharpe and all factors) the idea of using the factors in a different way than the one initially assumed did not. Still, the difference is so marginal that it impairs from saying that one approach is clearly better than the other. It does not surprise that the performances of these two portfolios are very similar, as already noticed previously the factors that had a negative Sharpe ratio generally did not get a relevant weight.

Focusing on the transaction costs the difference is not in the amount of companies selected for investment purpose, having all portfolios the same sample, but on the volatility of weight given to each security. This weight might be more stable if more factors are included in the analysis, such that it is more likely that the weight will remain the same for consecutive months.

Despite the relevant difference in the ranks assigned to each factor the returns produced by the portfolios are all highly correlated (the minimum value is 0,8 and it is obtained with portfolios formed on one factor); one explanation could be the weighting formula for the securities, because of using all the spanning dataset the difference from the weight given to one rank and the higher/lower one is very small.

Enhancing the differences: top/worst decile approach

A final robustness test includes a different methodology to invest in stocks, instead of assign a weight to all the securities just the extremes of the sample are considered to form the long and the short position. This method involves the usage of deciles, even if previously criticized due to the discretion surrounding the approach this effect is limited simply following the main literature and focusing only on the top/worst decile for each strategy.

The securities are ranked as before, the difference is now that the companies used for investment purpose are just the ones in the top decile (for the long position) and in the worst one (for the short position). Inside the long and short position equal weights are given to the companies, such that in the end the long position is still scaled to 1 and the short position to -1.

Table 13: summary statistics portfolios formed using the decile approach, from May 2006 to May 2014. As a comparison I included again the results of the portfolios formed using all positive Sharpe factors and all factors.

	Decile approach		Standard approach	
	All positive	**All factors**	**All positive**	**All factors**
Mean12	16,72%	14,00%	10,22%	10,03%
StD12	26,79%	28,57%	15,95%	17,07%
SR	0,62	0,49	0,64	0,59
Kurt	0,64	0,81	0,21	0,42
Skew	0,45	0,24	0,08	0,07
Top month	27,90%	28,81%	11,57%	12,86%
Median month	0,86%	0,90%	0,91%	1,04%
Worst month	-15,07%	-21,39%	-12,21%	-13,74%
Months positive	57,73%	54,64%	63,92%	61,86%

The returns produced by the decile approach are sensibly higher than the standard one; as a counterbalance there is also a big increase in the standard deviation; but it is not the higher standard deviation that makes this approach riskier in conceptual terms. It is more the fact that the difference between the Sharpe ratio of the portfolio with all positive factors and the one with all factors is definitely higher than the same difference produced by the same portfolios using the standard approach. This higher difference induces the consideration that the decile approach is less stable to changes in the assumptions regarding the usage of the factors, leading to very different results and not assuring that stability that investors would seek.
This stability is indeed offered by the standard approach (recalling the results of table 12) with differences in the Sharpe ratios not incredibly high.

Abnormal returns for all the portfolios

Finally as a matter of completeness the four-factor model is applied to all the new portfolios to investigate whether the determinants of the returns are the same.

Table 14: results of the regression for all portfolios, t-stats are showed for each variable. * = significant at the 10% level, ** = significant at the 5% level, *** = significant at the 1% level.

	Alpha	MKT	SMB	HML	WML	Adj R2
Pos1	0,002	0,039	-0,158	-1,094	-0,039	0,5428
t-stat	*0,888*	*0,836*	*-1,350*	*-8,590 ****	*-0,621*	
Pos3	0,005	0,058	-0,273	-1,273	0,042	0,5778
t-stat	*1,922 **	*1,093*	*-2,034 ***	*-8,723 ****	*0,572*	
Pos5	0,004	0,047	-0,366	-1,249	0,222	0,6302
t-stat	*1,470*	*0,839*	*-2,614 ***	*-8,191 ****	*2,920 ****	
Pos10	0,007	-0,015	-0,452	-1,324	0,189	0,6683
t-stat	*2,397 ***	*-0,274*	*-3,205 ****	*-8,628 ****	*2,467 ***	
PosAll	0,007	-0,022	-0,490	-1,286	0,202	0,6747
t-stat	*2,432 ***	*-0,393*	*-3,537 ****	*-8,525 ****	*2,683 ****	
Abs1	0,001	0,014	-0,315	-1,003	-0,001	0,5328
t-stat	*0,548*	*0,305*	*-2,666 ****	*-7,803 ****	*-0,009*	
Abs3	0,004	0,065	-0,267	-1,272	0,091	0,5793
t-stat	*1,584*	*1,178*	*-1,927 ***	*-8,432 ****	*1,260*	
Abs5	0,004	0,028	-0,368	-1,238	0,274	0,6539
t-stat	*1,277*	*0,506*	*-2,616 ****	*-8,072 ****	*3,593 ****	
Abs10	0,006	-0,003	-0,410	-1,353	0,244	0,6818
t-stat	*1,974 ***	*-0,059*	*-2,925 ****	*-8,674 ****	*3,129 ****	
AbsAll	0,006	-0,013	-0,498	-1,346	0,260	0,681
t-stat	*2,085 ***	*-0,218*	*-3,386 ****	*-8,404 ****	*3,253 ****	
DecPos	0,014	-0,378	-0,849	-1,518	0,190	0,6113
t-stat	*2,730 ****	*-3,748 ****	*-3,379 ****	*-5,484 ****	*1,379*	
DecAbs	0,010	-0,358	-0,837	-1,607	0,416	0,6828
t-stat	*2,036 ***	*-3,675 ****	*-3,417 ****	*-6,024 ****	*3,130 ****	

The most salient result is that the portfolios using the standard approach generally produced a positive alpha and in five out of ten cases this alpha is at least significant at the 10% level; the magnitude of the alpha is always around 0,5-0,7% which is quite an important result given the fact that this figure is expressed as monthly.

The analysis of the coefficients for portfolios different from the one using all factors simply confirms what was affirmed before. Moving from portfolios formed on a limited number of factors to the ones employing more is clear how the economic and statistical significance of the coefficients increases; this fact might be due to the fact that the factors used to rank the securities are more stable.

The two portfolios formed using the decile approach were the ones having the highest alphas; the common risk-factor correction highlights some differences with the other portfolios. These two portfolios have higher negative loads on MKT, SML and HML, with MKT statistically significant for the first time. WML is strangely different when comparing the two portfolios formed with the decile approach, having one not statistically significant and the magnitude of these two coefficients quite different from each other.

Conclusion

The aim of the thesis was to provide a useful method and proof on how market anomalies can be used in practice. The results are particularly interesting for actual investors because of the practical implications of this thesis.

The preliminary contributions link the persistency of market anomalies over the Eurozone, the first part of the present work documents how simple trading strategies on these variables taken individually are able to produce abnormal returns; replicating the results of the paper that firstly documented the existence of these market anomalies. Specifically, out of the twenty-six variables analyzed just thirteen had a positive abnormal return and eight of them statistically significant; as already noticed the failure of some trading strategies to produce an abnormal return can be partially explained with the distressed period analyzed. In addition variables like size or P/B are likely to be cyclical and then, once again, the distressed period undermined their predictive power; this conclusion is somehow similar to the one reached by Liew and Vassalou (2000) related to the fact that size and value factors might be a proxy for future macroeconomic risk.

Despite the relevance of the alpha, as a figure for indicating the attractiveness of a security, its magnitude is intrinsically linked to the model used to assess it. This basically gives rise to a degree of uncertainty surrounding the real effect of this alpha, meaning to what extent its magnitude can be really linked to an abnormal return not rewarded by risk and to what indeed it is linked to some hidden risk factor that is not included in the asset pricing model used.

Moving further, having observed the results of trading strategies on singular factors the issue of their practical implementation comes into play. This issue rotates around two basic questions: is it possible to predict and seize that performance with the information available at the beginning of the strategy? And further, what should be the discriminant that allows an appropriate aggregation of anomaly variables into a composite trading strategy?

When a market anomaly is discovered an implicit assumption is that an investor could have taken advantage of it, but this assumption has a major caveat. This is because the performance is observed ex-post but it is rarely likely to be exploited ex-ante, at the inception of the investing period. The fact is that all the variables are regarded in the same way, as market anomalies they were all proven to be meaningful in explaining the cross-section of stock returns, and so the rationale around the usage of a variable instead of another is the same. The existence of several market anomalies then makes it difficult for an investor to choose which one to use. It is this problem that I tried to deal with, aggregating the factors with a precise rationale, trying to capture the variables that had the highest predictive power over the cross-section of stock returns, inferring the predictive power using the Sharpe ratio. This approach can be seen as a more practical version of cross-sectional regression, instead of analyzing the predictive power of a variable over subsequent stock returns it is inferred with the past performance of the trading strategy using the same variable.

In the core part of the thesis I proceed to the aggregation of the variables into a portfolio, the variables were used to produce ranks to sort stocks afterwards. The tool used to assess the weight to give to each variable was the Sharpe ratio produced by trading strategies on individual factor. As previously mentioned the Sharpe ratio was considered the best figure that represents the risk-return profile of each security and its maximization is the goal of every investor. To assume the investor's perspective the absolute Sharpe ratio is considered, meaning that the usage of a certain variable (high rank to high value or opposite) was suggested by the Sharpe ratio: if the Sharpe was negative then the variable will be still considered but it will be used in an opposite way to the one used to generate the negative Sharpe ratio.

The goodness of this method can be entirely assessed from the analysis of the portfolio performance. Firstly the portfolio obtained a performance that is way above the average of the individual strategies, affirming the possibility to get a risk-return profile that dominates most of the anomalies and gets closer to the ones having the best Sharpe ratios. In other words it is better to use the Sharpe ratio's forecasting power than randomly select a strategy out the basket made by twenty-six anomalies.

The outstanding performance of the portfolio can be hardly explained, the asset pricing model used only partially captured the risk components of the portfolio, leaving then unsolved the nature of the returns obtained. It cannot be affirmed if these returns are a product of mispricings in the market or either a higher risk.

Not surprisingly I documented in my robustness tests how a portfolio that is formed just using the factor that had the highest Sharpe ratio fails to resemble the performance of the trading strategies that outperformed all the others. This point remarks again the fact that the observation of the performance does not imply that an investor could have seized that at the inception of the period.

Finally using all factors allows the portfolio to have a greater diversification, this diversification proves to be really relevant in affecting the dynamicity of the portfolio. This practically translates in a portfolio capable of detecting the state of the economy and the geographical diversities around the stocks of the sample. The success of this diversification has to be found in the very high heterogeneity around the different anomaly variables (as proven by table 12, highlighting the correlation between trading strategies on individual factors and the stock indexes).

Usually when using market anomalies into trading strategies it was suggested to divide the companies into deciles (according to the different ranks given using the anomaly variable) and then to make usage of the top decile for the long position and the worst one for the short position. This approach excludes then most of the companies, preferring to focus only on the extremes. Furthermore, apart from following this rule of thumb of investing in the top/worst decile there is no other motivation for discarding most of the companies, meaning that no rule indicates which decile is better following a precise methodology.

Developing new trading rules Cooper, Gulen and Vassalou (2002) provide a guideline for further research, in their paper they implement a method that allow the portfolio decile composition to change over time, this is achieved imposing filters on the expected return of the stocks, if the return is higher/lower than a certain threshold then the stock will be automatically included into the portfolio. Even if this paper shed light on new applications for trading strategies it is more concerned on eliminating a usual problem when dealing with deciles, which is the risk that companies that are forming the short position have a positive expected return, that is why the filter is established to be zero or negative.

In the present work I used a simple formula to use all the securities available for investment purpose; the weight placed on each security is proportional to the rank that it receives. A similar intuition is then applied when it came to aggregate the factors using their Sharpe ratio: the weight placed on the factor for the final rank was proportional to its Sharpe ratio. Further variants should be studied as long as different metrics to aggregate the factors. In particular it should be studied a new metric to couple with the Sharpe ratio in order to account for correlation among variables and then optimally diversify across factors.

Moving to the limitations I will highlight the major drawbacks of the present study. First of all, concerning the magnitude of the alpha, Fama and French (2013) have already developed a five-factor model that improves the explanatory power over the cross-section of stock returns, this increase in the explanatory power is mainly due to the addiction of a profitability factor. As already noted the main factors used to give ranks to securities, from the crisis onwards, are related to profitability variables, like ROA or ROE and then it makes easy to affirm that testing the portfolio returns on such model the out coming alpha should be smaller than the one reported.

Another limitation is linked to the performance of the portfolio, as clear from the cumulative returns of the portfolio in the most recent years the returns were negative. There are several different hypotheses on the explanation of this. It could be that the portfolio does not perform well in a period of reassessment of the economy, in between a recession and the subsequent recovery. This might be because of the change in weights happening in a gradual way and so it may be that the portfolio still considers anti-cyclical variables in a relevant way even if they are already losing their predictive power over the future cross-section of stock returns. A possible solution would be to use a smaller window than the cumulative Sharpe ratio, but this will probably give rise to instability problems in distressed period, considering this last issue as more dangerous I preferred to focus just on cumulative Sharpe ratios. Having for example a moving Sharpe ratio would probably allow the portfolio to be more dynamic, not having in fact a declining marginal effect of the last month performance, but similarly it will make it more volatile to changes in the stock market (and consequently more costly due to higher turnover). Another possible explanation could be the crowding out effect, investors might have realized that using the Sharpe ratio as a tool to aggregate variables produce a good performance and so the extensive usage of this strategy deployed its profitability. Even though it might be possible this option seems implausible, since this thesis does not claim to have discovered a new methodology to use market anomalies, mostly for its simplicity, it seems that is more reasonable to assume that investors were already aware of the goodness of this method and simply invested more into it in the latest years.

In conclusion I have provided evidence over the usage of market anomalies in the Eurozone, with their successful employment into a composite trading strategy. The obtained risk-return profile is above the stock market indexes used as benchmark and most of the trading strategies on singular anomalies. The portfolio nonetheless proven to be able to spot cyclicality in the economy due to the heterogeneity of the factors used; given the distressed period I analyzed a negative correlation of the portfolio with the main stock indexes.

Appendix

List of variables

All variables used, Bloomberg ticker is expressed if the variable is retrieved from Bloomberg:

Name	**Shortcut**	**Bloomberg ticker**
Return on asset	ROA	RETURN_ON_ASSET
Asset growth	AG	ASSET_GROWTH
Sales growth	SG	SALES_GROWTH
Price to cash	PC	PX_TO_CASH_FLOW
Price to book	PB	PX_TO_BOOK_RATIO
Price to earnings	PE	PE_RATIO
Debt to equity	DE	TOT_DEBT_TO_COM_EQY
Return on equity	ROE	RETURN_COM_EQY
Market capitalization	MK	CUR_MKT_CAP
EBITDA to revenues	EBITDA	EBITDA_TO_REVENUE
Dividend per share	DPS	EQY_DPS
Enterprise value to sales	EV	EV_TO_T12M_SALES
Cash ratio	CR	CASH_RATIO
Price to sales	PS	PX_TO_SALES_RATIO
Trail 12-months EPS	EPS	TRAIL_12M_EPS
Cash growth	CG	CASH_FLOW_GROWTH
CAPEX growth	CAPEX	TOT_CAP_EXPEND_GROWTH
Trading volume	VOL	PX_VOLUME
Annualized EPS	EPS ANN	EPS_ANNUALIZED
Moving average 20-260	MA 20-260	-
Moving average 130-260	MA 130-260	-
Cumulative return 20-260	CR 20-260	-
Cumulative return 130-260	CR 130-260	-
Standard deviation 20-260	STD 20-260	-
Standard deviation 130-260	STD 130-260	-
Beta	BETA 260	-

List of companies

The ticker is as indicated and used in the Bloomberg Terminal. Highlighted in red the companies that were discarded.

2004 Indexes composition					
Ticker	**#**	**Ticker**	**#**	**Ticker**	**#**
AGL IM Equity	1	IFX GY Equity	58	ACS SM Equity	114
AL IM Equity	2	LHA GY Equity	59	ACX SM Equity	115
ATL IM Equity	3	LIN GY Equity	60	ALT SM Equity	116
BEN IM Equity	4	MAN GY Equity	61	ANA SM Equity	117
BFI IM Equity	5	MEO GY Equity	62	BBVA SM Equity	118
BMPS IM Equity	6	MUV2 GY Equity	63	BKT SM Equity	119
BNL IM Equity	7	RWE GY Equity	64	ELE SM Equity	120
BPVN IM Equity	8	SAP GY Equity	65	ENG SM Equity	121
BUL IM Equity	9	SCH GY Equity	66	FCC SM Equity	122
CAP IM Equity	10	SIE GY Equity	67	GAM SM Equity	123
CPR IM Equity	11	TKA GY Equity	68	GAS SM Equity	124
EDN IM Equity	12	TUI1 GY Equity	69	IBE SM Equity	125
ENEL IM Equity	13	VOW GY Equity	70	IBLA SM Equity	126
ENI IM Equity	14	AC FP Equity	71	IDR SM Equity	127
ES IM Equity	15	ACA FP Equity	72	ITX SM Equity	128
F IM Equity	16	AGF FP Equity	73	LOR SM Equity	129
FNC IM Equity	17	AI FP Equity	74	MAP SM Equity	130
FWB IM Equity	18	AIR FP Equity	75	MVC SM Equity	131
G IM Equity	19	ALU FP Equity	76	NHH SM Equity	132
ISP IM Equity	20	AVE FP Equity	77	POP SM Equity	133
IT IM Equity	21	BN FP Equity	78	REE SM Equity	134
LUX IM Equity	22	BNP FP Equity	79	REP SM Equity	135
MB IM Equity	23	CA FP Equity	80	SAN SM Equity	136
MED IM Equity	24	CAP FP Equity	81	SCYR SM Equity	137
MN IM Equity	25	CO FP Equity	82	SGC SM Equity	138
MS IM Equity	26	CS FP Equity	83	TEF SM Equity	139
NTV IM Equity	27	DG FP Equity	84	TEM SM Equity	140
PC IM Equity	28	DX FP Equity	85	TPI SM Equity	141
PG IM Equity	29	EN FP Equity	86	TRR SM Equity	142
PMI IM Equity	30	FP FP Equity	87	UNF SM Equity	143
R IM Equity	31	GLE FP Equity	88	ZEL SM Equity	144
RCS IM Equity	32	HO FP Equity	89	3577044Z NA Equity	145
SPI IM Equity	33	KER FP Equity	90	AGN NA Equity	146

SRG IM Equity	34	LG FP Equity	91	AH NA Equity	147
STM IM Equity	35	LOR FP Equity	92	AKZA NA Equity	148
TIM IM Equity	36	MC FP Equity	93	ASML NA Equity	149
TIS IM Equity	37	ML FP Equity	94	CXP NA Equity	150
TIT IM Equity	38	MMB FP Equity	95	DSM NA Equity	151
UBI IM Equity	39	OR FP Equity	96	FORA NA Equity	152
UCG IM Equity	40	ORA FP Equity	97	GTN NA Equity	153
ADS GY Equity	41	RI FP Equity	98	GUC NA Equity	154
ALT GY Equity	42	RNO FP Equity	99	HEIA NA Equity	155
ALV GY Equity	43	SAN FP Equity	100	HGM NA Equity	156
BAS GY Equity	44	SGO FP Equity	101	INGA NA Equity	157
BAYN GY Equity	45	STM FP Equity	102	KPN NA Equity	158
BMW GY Equity	46	SU FP Equity	103	LOG NA Equity	159
CBK GY Equity	47	SW FP Equity	104	MOO NA Equity	160
CON GY Equity	48	SZE FP Equity	105	NUM NA Equity	161
DAI GY Equity	49	TCHNR FP Equity	106	PHIA NA Equity	162
DB1 GY Equity	50	TFI FP Equity	107	PNL NA Equity	163
DBK GY Equity	51	UG FP Equity	108	RDA NA Equity	164
DPW GY Equity	52	VIE FP Equity	109	REN NA Equity	165
DTE GY Equity	53	VIV FP Equity	110	SBMO NA Equity	166
EOAN GY Equity	54	3465593Q SM Equity	111	UNA NA Equity	167
FME GY Equity	55	3593258Q SM Equity	112	VNUA NA Equity	168
HEN3 GY Equity	56	ABE SM Equity	113	WKL NA Equity	169
HVM GY Equity	57				

2009 Indexes composition					
Ticker	**#**	**Ticker**	**#**	**Ticker**	**#**
A2A IM Equity	1	LHA GY Equity	58	ACS SM Equity	114
AGL IM Equity	2	LIN GY Equity	59	ACX SM Equity	115
AL IM Equity	3	MAN GY Equity	60	ANA SM Equity	116
ATL IM Equity	4	MEO GY Equity	61	BBVA SM Equity	117
BMPS IM Equity	5	MRK GY Equity	62	BKT SM Equity	118
BP IM Equity	6	MUV2 GY Equity	63	BME SM Equity	119
BUL IM Equity	7	RWE GY Equity	64	BTO SM Equity	120
BZU IM Equity	8	SAP GY Equity	65	CABK SM Equity	121
ENEL IM Equity	9	SDF GY Equity	66	ENG SM Equity	122
ENI IM Equity	10	SIE GY Equity	67	FCC SM Equity	123
ES IM Equity	11	SZG GY Equity	68	FER SM Equity	124
F IM Equity	12	TKA GY Equity	69	GAM SM Equity	125
FNC IM Equity	13	VOW GY Equity	70	GAS SM Equity	126

FWB IM Equity	14	AC FP Equity	71	GRF SM Equity	127
G IM Equity	15	ACA FP Equity	72	IBE SM Equity	128
GEO IM Equity	16	AF FP Equity	73	IBLA SM Equity	129
GTK IM Equity	17	AI FP Equity	74	IBR SM Equity	130
ISP IM Equity	18	AIR FP Equity	75	IDR SM Equity	131
IT IM Equity	19	ALO FP Equity	76	ITX SM Equity	132
LUX IM Equity	20	ALU FP Equity	77	MAP SM Equity	133
MB IM Equity	21	BN FP Equity	78	OHL SM Equity	134
MED IM Equity	22	BNP FP Equity	79	POP SM Equity	135
MN IM Equity	23	CA FP Equity	80	REE SM Equity	136
MS IM Equity	24	CAP FP Equity	81	REP SM Equity	137
PC IM Equity	25	CS FP Equity	82	SAB SM Equity	138
PG IM Equity	26	DG FP Equity	83	SAN SM Equity	139
PLT IM Equity	27	DX FP Equity	84	SCYR SM Equity	140
PMI IM Equity	28	EDF FP Equity	85	TEF SM Equity	141
PRY IM Equity	29	EI FP Equity	86	TL5 SM Equity	142
SAL IM Equity	30	EN FP Equity	87	TRE SM Equity	143
SPM IM Equity	31	FP FP Equity	88	UNF SM Equity	144
SRG IM Equity	32	GLE FP Equity	89	AGN NA Equity	145
STM IM Equity	33	GSZ FP Equity	90	AH NA Equity	146
TEN IM Equity	34	KER FP Equity	91	AKZA NA Equity	147
TIT IM Equity	35	LG FP Equity	92	ASML NA Equity	148
TRN IM Equity	36	MC FP Equity	93	BAMNB NA Equity	149
UBI IM Equity	37	ML FP Equity	94	CORA NA Equity	150
UCG IM Equity	38	MMB FP Equity	95	DSM NA Equity	151
UNI IM Equity	39	MTP FP Equity	96	FORA NA Equity	152
US IM Equity	40	OR FP Equity	97	FUR NA Equity	153
ADS GY Equity	41	ORA FP Equity	98	HEIA NA Equity	154
ALV GY Equity	42	RI FP Equity	99	INGA NA Equity	155
BAS GY Equity	43	RNO FP Equity	100	KPN NA Equity	156
BAYN GY Equity	44	SAN FP Equity	101	MT NA Equity	157
BEI GY Equity	45	SEV FP Equity	102	PHIA NA Equity	158
BMW GY Equity	46	SGO FP Equity	103	PNL NA Equity	159
CBK GY Equity	47	STM FP Equity	104	RAND NA Equity	160
DAI GY Equity	48	SU FP Equity	105	RDSA NA Equity	161
DB1 GY Equity	49	UG FP Equity	106	REN NA Equity	162
DBK GY Equity	50	UL FP Equity	107	SBMO NA Equity	163
DPB GY Equity	51	VIE FP Equity	108	TOM2 NA Equity	164
DPW GY Equity	52	VIV FP Equity	109	UL NA Equity	165
DTE GY Equity	53	VK FP Equity	110	UNA NA Equity	166
EOAN GY Equity	54	3465593Q SM Equity	111	USG NA Equity	167

FME GY Equity	55	ABE SM Equity	112	WHA NA Equity	168
HEN3 GY Equity	56	ABG SM Equity	113	WKL NA Equity	169
IFX GY Equity	57				

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