Idiosyncratic Risk and Expected Stock Returns: An Empirical Investigation on the GIPS Countries

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Abstract

The thesis aims to provide a framework for understanding how the idiosyncratic risk (IVOL) may affect the returns of individual stocks in the context of the Capital Asset Pricing Model and the Fama-French three factor model. We examine the Greek, Italian, Portuguese and Spanish (GIPS) Equity Markets. The final sample includes 654 stocks over the years 1992-2012. Classical financial theory argues that IVOL has no role in explaining why some securities may have higher returns than others, while alternative theories of behavioral finance predict a positive relationship between idiosyncratic risk and excess stock returns. Recent empirical findings developed by Ang, et al. (2006) indicate a negative relationship (IVOL puzzle). The purpose of this paper is to verify whether the pricing models tested in the U.S. market can find confirmation in the GIPS stock markets. In other words, we would like to test whether the IVOL puzzle should be accepted or rejected in the context of the four countries considered. We demonstrate that a zero-cost investment strategy long in securities with lower IVOL and short in securities with higher IVOL earns an economically positive and statistically significant alpha versus both the CAPM model (1.32%) and the FF-3 one (1.18%), suggesting a negative return towards holding idiosyncratic volatility. In line with the previous studies conducted on IVOL, our findings indicate that the low IVOL strategy is positively related to the value premium. In conclusion, we find a positive relation between idiosyncratic risk and systematic risk (market beta).

Keywords: IVOL, CAPM, Fama-French three factor model, GIPS equity markets

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1. Background

1.1. Introduction

The idiosyncratic risk role in explaining why some stocks may have higher returns than others represents a cornerstone of modern theories of finance. Classical financial theory states that idiosyncratic volatility has no role in setting the price of securities; alternative theories of behavioral finance, instead, predict a positive relationship between IVOL and excess stock returns and demonstrate that investors demand compensation for assuming idiosyncratic risk. Recent empirical findings developed by Ang, et al. (2006 and 2009) indicate a negative relationship between IVOL and expected stock returns; the authors find that stocks with high past exposure to innovations in aggregate market volatility earn low future average returns: the "IVOL puzzle".

The main goal of this thesis is to empirically investigate the effect of idiosyncratic risk on return of securities in the GIPS countries. The phenomenon, well documented in the United States literature, is fairly new and unknown in Europe. More specifically, our purpose is to verify whether the pricing models tested in the U.S. market can also be confirmed in the GIPS stock markets. In other words, we would like to test whether the IVOL puzzle, as defined in the work of Ang, et al., should be accepted or rejected in the context of the four countries considered.

As regards the idiosyncratic risk, little research has been done on the Greek, Spanish and Portuguese equity markets, probably due to their small size. However, regarding the CAPM, at least in Italy, the analysis is a little more extended. For example, Di Caprio (1989) considered a time horizon of about forty years and the results seemed to support the findings on IVOL of the model developed by Sharpe. Up to now, the only study on the Fama-French three factor model is the one developed by Fidanza (2001). His results seem to conflict with the classical model, and the one presented by Knight and Costa (1999) that confirm the validity of the three factor model.

An important contribution to the IVOL behavior has been developed by Morck, Yeung, and Yu (2000). These authors find that securities move together more in low-income economies than in high income ones. In other words they state that, in emerging markets, stock price behaviour predominantly reflect systematic risk while in developed economies security changes are more affected by unpredictable "industry and firm" specific factors. However, they also demonstrate that the only rich countries with notably more market-wide price fluctuations are Italy, Spain and Greece which seem to have an extraordinarily poorly functioning stock market compared to the other developed countries.

Since the academic research on the idiosyncratic volatility is still in its early stages, and considering that the GIPS exchange markets behavior has demonstrated to consistently differ from the one of the other high income economies such as United States, the aim of this thesis is to provide further understanding on the existence of the IVOL anomaly by accepting or rejecting its presence in these four countries. The conclusions of this work could be of interest to academic researchers and scholars in order to better understand the type of risk that investors expect to be paid for. To this end, we first investigate the validity of the CAPM, by considering a time horizon of more than twenty years, from January 1992 to November 2012, secondly observe the behavior of the Fama-French three factor model in the same period and finally investigate the validity of both models.

Unlike the study of Ang, et al. (2006 and 2009), our study includes a CAPM-based approach and further analyzes the relationship between portfolios sorted on IVOL and market systematic risk (beta) for the same time horizon. In other words, our goal is to bridge the gap between the research conducted on the risk-return relationship of idiosyncratic risk and betas. Our approach could be considered as an opportunity to identify any co-movement which could undermine the ability of the past asset pricing models to capture the entire systematic risk.

The paper is organized as follows. In section 1, we describe the main characteristics of idiosyncratic risk. Section 2 documents how the IVOL is priced in the past academic research. Section 3 illustrates the theoretical framework of the research conducted in this thesis. In section 4, we develop the empirical analysis. Section 5 presents and test the validity of our main findings. Section 6 concludes.

1.2. Idiosyncratic Risk

The idiosyncratic risk, or IVOL, can be defined as the risk of variations in a stock price, due to the unique circumstances and characteristics of the specific security. In the past, it was called in different ways: specific risk, unsystematic risk, residual risk, diversifiable risk. It is noteworthy that only particular companies or sectors could be vulnerable to the IVOL which is usually uncorrelated to the overall market return.

In the last few decades, the idiosyncratic risk has been under close scrutiny in the economic and financial literature, and often used in order to explain recent anomalies within the cross section of stock returns - e.g. Ang, et al. (2006), Campbell, et al. (2008), Fu (2009). If the classical asset pricing models (such as the CAPM and Fama-French three factor model) have found no relationship between IVOL and the expected returns, more recent studies, instead, have found positive or even negative pricing impact of idiosyncratic volatility on excess returns[1]. These kinds of studies have become increasingly relevant in the last few years due to the financial crisis. During this period, we have seen that the level of IVOL significantly increased compared to the lower levels reached between January 2003 and the first quarter 2007.

In this section, we will attempt to understand how the idiosyncratic risk has been considered throughout the asset pricing literature. It is noteworthy that past empirical studies relied on different stock samples or different selection criteria in conducting these kinds of analyses[2]. As already mentioned, one of the main hypotheses of the CAPM is that idiosyncratic risk plays no role in explaining why some securities may have higher returns than others. A long series of papers dating back to Merton (1987) have argued, however, that this hypothesis does not stand up to empirical examination. In particular, Merton developed a model of imperfect information that led to a series of market forecasts, including the hypothesis that firms with a higher risk enjoy higher returns.

It is clear that, by investing in several stocks, the diversification of risk (assumed in the CAPM model) can be very costly especially when the information is not completely free, nor available. Moreover, as Fu (2009) stated, there is no arbitrage mechanism able to ensure that the return for bearing idiosyncratic risk will disappear in the long term. As a result, investors hold undiversified portfolios and ask for compensation for the additional portion of risk they are bearing.

Ang, et al. (2009), suggested that the high degree of correlation between the spread in returns of portfolios with high idiosyncratic risk versus those with low idiosyncratic risk reflects many factors that are difficult to diversify[3]. Xu and Malkiel (2003) argued that idiosyncratic risk has become increasingly important over time, as the proportion of institutional investors has grown, and the number of securities listed in indices such as the NASDAQ increased[4]. On the other hand,

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[1] See, among others, Jackwerth and Rubinstein (1996), Bakshi, Cao and Chen (2000), Chernov and Ghysels (2000), Burashi and Jackwerth (2001), Coval and Shumway (2001), Benzoni (2002), Pan (2002), Bakshi and Kapadia (2003), Eraker, Johannes and Polson (2003), Jones (2003), and Carr and Wu (2003).

[2] Many existing papers include all the securities in the CRSP (Center of Research in Security Prices) database or the NYSE-Amex-NASDAQ indices - e.g., Ang, Hodrick, Xing, and Zhang (2006); Bali and Cakici (2008); and Bali, Cakici, and Whitelaw (2011). Other research adopts only common shares - e.g., Jiang, Xu, and Yao (2009); Huang, Liu, Rhee, and Zhang (2010); and Han and Lesmond (2011). Alternative studies apply further restrictions - e.g. Bali and Cakici (2008) adopt stocks with prices above $10, while Jiang, Xu, and Yao (2009), Huang, Liu, Rhee, and Zhang (2010), and Bali, Cakici, and Whitelaw (2011) adopt those with prices above $5 in their empirical analysis. Moreover, Han and Lesmond (2011) limit their study to a sample period from January 1984 to June 2008 excluding the subprime crisis and the failures of Lehman Brothers and Bear Stearns.

[3] The two authors found only partial support regarding the fact that aggregate volatility can explain poor performance of high IVOL securities. In fact, they demonstrated that exposure to aggregate volatility can partially explain the so-called "IVOL puzzle", but only for stocks with very low and negative past loadings to aggregate volatility innovation.

[4] In United States, institutional investors have increased their share from holding 37% of total U.S. equities in the 80' to 51.5% in 2000, up to 61% in 2005 (The Conference Board, 2007).

Fu and Shutte (2009) suggested that the idiosyncratic risk is more highly priced when there is a higher proportion of retail investors who tend to inadequately diversify their portfolios. For stocks predominantly held by institutional investors, there is evidence that idiosyncratic risk has less influence on the price[5].

However, there is still no consensus among economists regarding the pricing of idiosyncratic risk in the market. Analyses on single stocks - e.g. Fu, (2009), Malkiel and Xu (2002) - indicated that diversifiable risk is important. Nevertheless, it is at portfolio level, where hypotheses regarding the usefulness of the idiosyncratic risk are still controversial. For example, Bali and Cakici (2008) argued that there is no reliable link between idiosyncratic risk and portfolio return. In fact, in their analysis they often find relationships that are either positive, negative, neutral or even insignificant.

Although Goyal and Santa-Clara (2003) argued that idiosyncratic risk has a role in the pricing of securities[6]. Bali, Cakici, Yan and Zhang (2005) and Bali and Cakici (2005) suggested that the conclusion of Goyal and Santa-Clara may be the result of a mismatch between the portfolios used in measuring risk and returns, so that the link observed between these two factors is actually spurious. This effect might have been caused by small and illiquid securities in the NASDAQ Index.

Huang, et al. (2010) stated that there is no relationship between idiosyncratic risk and expected returns once the possible existence of short-term negative autocorrelation (e.g. negative momentum over short horizons) in stock returns is allowed[7].

Ang, et al. (2006) pointed out that there is a negative relationship between the idiosyncratic risk and the equity return in the United States, arguing that investors who are not able to diversify risk demand premium for holding stocks with high IVOL[8]. In 2009, the authors demonstrated that the same relationship can be found in 23 countries worldwide. However, Goyal and Santa-

[5] It is noteworthy that institutional investors are more likely to invest in index funds than are retail investors. For example, roughly 10% of the mutual funds owned by individual agents were indexed in 2003 while more than 30% of institutional funds were indexed. As a consequence, the vast majority of investors do not invest in the market portfolio. Empirical evidences demonstrate that about 15% of retail investors only own one stock in their portfolio and each investor, on average, holds three stocks.

[6] The two authors adopted average stock variance - which is a measure of total risk - in order to approximate the idiosyncratic volatility.

[7] Huang, et al. showed that the negative relationship between IVOL and Value-Weighted portfolio returns is driven by short-term return reversals. Specifically, they observed that almost 50% of securities in the portfolio quintiles with the highest IVOL were either winner or loser stocks. The vast majority of winners were large cap stocks and experienced significant return reversals, which, in turns, drove down the Value-Weighted portfolio returns and caused the aforementioned negative relationship. Consequently, in the absence of return reversals, no negative relation is observed between IVOL and stock excess returns.

[8] The Ang, et al. (2006) results, have been subsequently confirmed by Brown and Ferreira (2003); Jiang, Tao and Yao (2005); Huang, et al. (2006); and Zhang (2006).

Clara (2003), Ghysels, Santa-Clara and Valkanov (2005), Fu (2009), Diavatopoulos, Doran and Peterson (2008) and Jiang and Lee (2006) found the exact opposite situation: a positive relation between IVOL and stock market returns.

As pointed out by Fu (2009), the main problem related to the Ang, et al. (2006 and 2009) studies is that investors require compensation for the current, not historical risks, and therefore it does not make any sense to analyze lagged relationship.

The disagreement in the economic literature illustrates the fragility of current conclusions on idiosyncratic risk and its role in explaining the cross-section variation in returns. Table 1 summarizes the empirical results developed by numerous scholars in the past years.

Table 1: Empirical evidence on IVOL

The table below provides an overview of the past empirical literature on the inter-temporal and cross-sectional relationship between stocks expected excess return and IVOL.

Study	Sample Period	Idiosyncratic risk definition	Measure of expected volatility	Result
Panel A: Inter-temporal relationship				
Goyal & Santa Clara (2003)	1926-1999	Total Variance	Lagged	Positive relation
Bali, et al. (2005)	1962-2001	Total Variance	Lagged	No relation
Guo & Savickas (2006)	1963-2002	Total Variance	Lagged	Negative relation
Panel B: Cross-sectional relationship				
Lintner (1965)	1954-1963	CAPM residuals	Lagged	Positive relation
Lehmann (1990)	1931-1983	CAPM residuals	Lagged	Positive relation
Malkiel & Xu (2004)	1975-2000	Total Variance	Lagged	Positive relation
Spiegel & Wang (2005)	1962-2003	FF-3 residuals	EGARCH	Positive relation
Ang, et al. (2006)	1963-2000	FF-3 residuals	Lagged	Negative relation
Eiling (2006)	1959-2005	CAPM residuals	EGARCH	Positive relation
Huang, et al. (2007)	1963-2004	FF-3 residuals	EGARCH	Positive relation
Brockman & Schutte (2007)	1980-2007	FF-3 residuals	EGARCH	Positive relation
Bali & Cakici (2008)	1963-2004	FF-3 residuals	Lagged	No relation
Fu (2009)	1963-2006	FF-3 residuals	EGARCH	Positive relation

1.3. Other volatility anomalies

1.3.1. Low volatility anomaly

In the late '60, Bob Haugen discovered the low volatility anomaly. After having analyzed stock performance by using a sample of data starting in 1926, the author pointed out that securities with lower volatility had obtained a much higher performance than expected by financial analysts while, on the contrary, stocks with higher volatility had obtained a much lower one than expected.

In the following forty years, low-volatility stocks continued to outperform high volatility stocks. This "anomaly" was verified not only in the United States but also in the European, Japanese and Emerging Markets. The phenomenon seems to be due to the investors' behavior since their investment strategies lead to a mismatch between supply and demand. In other words, there is too much demand for securities with high volatility, which pushes up the prices and, therefore, reduces the chance of potential future returns. Why is there an excess demand for high volatility stocks? Simply because investors - retail, institutional or professional managers - often invest in securities supported by the media, securities with a convincing story, easy to propose and that are more likely to be accepted in a portfolio. More specifically, managers and analysts are attracted by these securities because they find it easier to explain and justify their investment decisions. This behavior is one of the main reasons why some securities become more volatile.

In 2011, Baker, et al. contributed to strengthening the "low volatility anomaly" hypothesis, finding that, during the last 40 years, low volatility and low beta stocks substantially outperformed high volatility and high beta stocks. Baker used a sample of the United States equities from a dataset between January 1968 and December 2008. He concluded that the empirical predictions from the theory of efficient markets (where above average returns should only be obtained by taking on above average risk) are weak. When risk is measured as either total volatility or systematic risk, the evidence actually points towards a negative relationship.

Also behavioral economists have tried to provide different explanations to the "low volatility anomaly". One of the main findings is that investors are often overconfident in their judgments and abilities to develop the best investment ideas in the market. In other words, the overconfidence can be seen as a type of bias which makes individuals be overly confident in their own ability and overestimate themselves. For example, a manager who is overconfident in his capabilities might not take the optimal decisions and, on the contrary, will tend to ignore market signals or information that differentiates with his own ideas. As a result of this overconfidence, investors engage in too many trading activities, which, often, lead to suboptimal performance. In theory, although errors related to overconfidence should be corrected over time due to the accumulation of negative events, unfortunately, this does not happen. In fact, faced with a significant loss, investors tend to justify their mistakes as a result of external causes, while, when their decisions turn out to be profitable, they take the credit. How can overconfidence be related to the "low volatility anomaly"? Overconfident investors deliberately choose stocks with the highest volatility since they are sure about their ability to value securities. Therefore, the misalignment between confident investors and market consensus regarding the expected performance of specific stocks will be larger for stocks with higher volatility and this is why the demand for more volatile stocks is higher. Obviously, if these assumptions are verified in the market, the increasing demand for more volatile stocks will lead to higher prices and subsequently lower performance. Given this explanation, why don't institutional investors exploit the overconfidence bias in the market? It seems that managers are more likely to stay close to benchmarks in order to maximize their information, rather than opt for a benchmark-free investment strategy that would maximize their Sharpe-ratio. This behavior discourages institutional investors from exploiting mispricing of volatility and, therefore, provides a possible explanation to why the "low volatility anomaly" persists.

1.3.2. Low beta anomaly

In recent years, further considerations have arisen concerning the quality of the CAPM model. One involves the study of the so-called "low beta anomaly". In a famous paper published in 2010, Frazzini and Pedersen explained the reasons why, in the United States, the security market line is found to be too flat compared to the CAPM forecasts. The two authors, therefore, proposed a theoretical model based on leverage constrained investors. One of the basic principles of the Capital Asset Pricing Model is that all investors tend to invest in stocks with the highest risk-return ratio, and, subsequently, de-lever and lever the portfolio in order to generate their optimal risk profile. According to the Frazzini and Pedersen model, these agents often do not use the leverage to adjust their risk profile. They, instead, tend to invest in riskier stocks, which lead to an increase in demand for high beta securities, thus increasing the price and lowering returns. The leverage constrained investors model, initially focused only on the U.S. equity market, was subsequently applied in the vast majority of global equity markets and through different asset classes such as: treasury bonds, corporate bonds and futures. Once again, low beta stocks seemed to outperform high beta securities, providing a higher risk-adjusted return.

Table 2: High VS Low Vol. Quintiles (All Stocks); US Equities 1968-2009

Indicator	Q1(beta)	Q5(beta)	Q1(Vol)	Q5(Vol)
Excess Return Rp-Rf	4.42%	-2.42%	4.38%	-6.78%
Beta	0.6	1.61	0.75	1.71
Volatility	12.13%	27.77%	13.10%	32.00%
Tracking Error	9.74%	14.52%	6.76%	20.33%
Sharpe Ratio	0.42	0.05	0.39	-0.05
Information Ratio	0.1	-0.18	0.16	-0.29

Table 3: High VS Low Vol. Quintiles (Top 1,000 Stocks); US Equities 1968-2009

Indicator	Q1(beta)	Q5(beta)	Q1(vol)	Q5(vol)
Excess Return Rp-Rf	5.09%	-1.89%	4.12%	-0.82%
Beta	0.63	1.52	0.7	1.54
Volatility	12.40%	25.95%	12.74%	27.13%
Tracking Error	8.83%	13.02%	7.45%	14.95%
Sharpe Ratio	0.46	0.06	0.38	0.11
Information Ratio	0.17	-0.21	0.08	-0.09

2. Academic Research

The estimation of the cost of capital, also known as the expected return for shareholders, represents one of the most debated issues in the theory of finance. The different estimation models have been mainly studied in the Anglo-Saxon financial literature.

An important contribution was made by Harry Markowitz (1952), the father of the Modern Portfolio Theory, who provided a theoretical framework for the analysis of the risk-return relationship. By arguing that the investors' behavior is, on average, characterized by risk aversion, the author set the foundation for identifying the two key variables for investment decisions: the expected return and variance, or standard deviation of the stocks. Following Markowitz's studies, Sharpe (1964), Lintner (1965) and Mossin (1966) developed the Capital Asset Pricing Model, a model that predicts the expected return of securities as a function of their risk. In other words, by assuming a context characterized by information efficiency, no transaction costs, one-period time horizon, homogeneity of expectations, and presence of risk-free securities (the risk-free rate), the CAPM shows the trade-off between risk and return. In order to develop the model, three variables are taken into account: the rate of return on government bonds (or risk-free rate), the coefficient of systematic risk (beta), and the reward expected for risk. Although some of the underlying assumptions appear far from the truth - e.g. being able to borrow money with no limitations and at a risk-free rate, the absence of taxes, etc. - in the last forty years, the CAPM has been the subject of intense debate in financial studies. The first test of the Capital Asset Pricing Model was carried out by Sharpe (1966) and Jensen (1967) on mutual funds with comforting results. However, the idea of borrowing money without limitations and at the same risk-free rate still appeared far from the truth. To overcome this problem, and to facilitate the analysis, Black (1972) studied a variant of the model known as "zero beta model". This modification involves the replacement of the risk-free with another security which is not correlated with the market.

Black, Jensen and Scholes (1972) found that the results obtained by implementing these alternative models - while not fully reflecting the expectations of the classical version of the CAPM - were in line with the zero beta CAPM model. Fama and MacBeth (1973) proposed similar conclusions.

Over the years, the CAPM was widely criticized and the idea that the beta is not the only factor that can explain the stock returns has increasingly taken shape. In fact, if the first empirical evidence showed the linearity between risk and return, subsequent tests revealed the inability of the beta to fully express this relationship. In light of this, a new framework, the Arbitrage Pricing Theory (APT), was developed by Ross (1976) and Roll (1977). According to the new hypothesis, several different factors can affect the stock prices. While not explicitly indicating these factors, the APT demonstrated that some macroeconomic indicators such as the price of oil, inflation, interest rates, GDP, etc. play a key role in explaining the excess return of securities. The empirical anomalies arising from imperfect linearity in the risk-return relationship made economists suspect the existence of different factors that would probably play a key role in generating stock returns. Banz (1981), for example, detected the presence of a negative relationship between size and performance.

Fama and French (1992) showed that the beta did not predict returns during the 1963-1990 period. The two authors developed the so-called three factor model through which they found that the reward for the risk depends not only on the market risk, as stated by the CAPM, but also on two other factors: the size of the company and the relationship between the book value and market value.

2.1. Capital Asset Pricing Model

As before mentioned, the CAPM can be regarded as a financial model which predicts the equilibrium price of an asset. It tries to establish a relationship between the yield of a security and its risk. This relationship is measured by a single risk factor, called beta (systematic risk). The beta measures how much the value of the stock moves in line with the market.

Beta greater than 1 implies a risk, on average, higher than that of the market as a whole; vice versa, beta less than 1 denotes a lower risk. Therefore, more risky assets will have a higher beta and will be discounted at a higher rate, while less risky assets will have a lower beta and will be discounted at a lower rate. In this sense, the CAPM is consistent with the intuition that an investor would require a higher expected return to hold a more risky security.

In short, the assumptions of the standard CAPM are:

1) Mean Variance Portfolio Selection
Single Period Portfolio Selection
Agent preferences are consistent with the Mean Variance criterion
2) Assets Markets are in equilibrium
Flexible and perfectly liquid markets
Ability to borrow unlimited amounts of money at the risk-free
Assets are divisible into any desired unit
All assets can be bought / sold at the observed market price
Investors are price takers
Same taxes for every investor and every source of income
3) Homogenous Beliefs and absence of information asymmetries

In the classic formulation, the model equation is:

$$r_t - r_f = \alpha_t + \beta_t\left(r_m - r_f\right) + \varepsilon_t$$

That in terms of expected value is equal to:

$$E[r_t] - r_f = \beta_t\left(E[r_m] - r_f\right)$$

The key factor of the model is clearly the β coefficient, which, again, is proportional to the covariance between the security yield and the market trend:

$$\beta_t = \frac{Cov(r_t, r_m)}{Var(r_m)}$$

The parameter α_t is assumed to be zero since the CAPM theory excludes the possibility of obtaining yields systematically different from those of the market. These equations clearly show how the correlation between each stock and the market portfolio influences the performance of the security itself. Moreover, we can divide the variance of the portfolio in two parts:

$$Var(r_t) = \beta_t^2 Var(r_m) + Var(\varepsilon_t)$$

We can see that the risk of a portfolio involves a systematic (undiversifiable) component and a firm-specific, idiosyncratic (diversifiable) one. In the context of the CAPM, the systematic component represents the portion of risk common to all the financial assets traded on the market - in fact, it is defined as the so-called "market risk". The idiosyncratic component is, instead, associated with the characteristics of the individual financial asset and, by its nature, can be reduced through diversification - e.g. it is possible to offset the risk associated with fluctuations in the value of a security by investing in financial alternatives that move in the opposite direction.

Sharpe argued that it would be counterintuitive to expect that an investor receives a return for bearing a diversifiable risk; in other words, it is not rational to expose an investor's wealth to a greater risk than necessary. Consequently, the required return for a given financial asset - the return that compensates the investor for the risk he is bearing - should be closely linked to the risk of the asset itself within the portfolio context - e.g. in terms of the security contribution to the risk of the overall portfolio. In the CAPM, it is stated that this risk is represented solely by a greater or smaller variance in the portfolio performance.

To sum up, the model shows that the excess return of a single stock is, on average, equivalent to the market risk premium multiplied by the beta of the security. The model is not rejected when the alpha coefficient is statistically null and the beta of the stock is significant. The idiosyncratic risk has no role in the stock pricing.

2.2. Size and Value

The empirical anomalies arising from the CAPM and, specifically, from the imperfect linearity in the risk-return relationship, make economists suspect the existence of alternative factors that would probably affect more significantly the equity excess returns. Moreover, in the last decades, doubts have arisen concerning the validity of the market efficiency theory. Banz (1981), for example, was the first to highlight the fact that the size of a company can better describe the risk-return profile of a stock. The author, in particular, noted that smaller firms - measured by the market capitalization - had, on average, a higher risk adjusted return within the selected sample. The size effect was mainly prevalent in micro-cap (very small companies). After having examined the ordinary shares listed on the NYSE during the period 1931-1975, he found a strong negative relationship between size and returns.

Basu (1977) examined 1,400 companies listed on the NYSE in the period 1957-1971, and showed that stocks with a low price-earnings ratio were able to obtain, on average, higher returns than those with a higher P/E and even in excess with respect to their level of systematic risk. The author's aim was twofold: on the one hand, he wanted to test the ability of the Capital Asset Pricing Model to interpret the risk-return relationship, on the other, to identify the presence of alternative factors that could have better illustrated the aforementioned relationship. The results are placed in sharp contrast with the hypothesis of market efficiency outlined by Fama.

2.3. Arbitrage Pricing Theory and Fama-French Three Factor Model

According to the Arbitrage Pricing Theory (APT) model, the performance of a security can be expressed as a function of the returns of a number of risk factors (for example, macroeconomic variables such as, the price of oil, the GDP or the inflation). To be more precise, within the APT framework, the expected return of an asset is expressed as a linear function of a number of factors plus a specific idiosyncratic risk component. The sensitiveness of the expected return with respect to variations in the different risk factors is known as the "factor loading".

In order to apply the model, it is necessary to find a comprehensive list of risk factors that are likely to contribute to the expected return of the asset taken into account, and then attain an estimate of the expected return of each of these factors.

For this purpose, different approaches have been proposed. Chen, Roll and Ross (1993) developed a four factor model which specifies the economic variables generating the returns. These factors affect either the size or the value of future cash flows related to each single security in which an individual has invested:

- the growth rate of industrial production, as it affects alternative investment opportunities and, subsequently, the actual value of cash flows;
- the inflation rate, that has a significant impact on both the discount rate and the value of the future cash flows;
- the interest rates' term structure, expressed as the difference between the long-term rates minus the short-term ones, as it can influences the value of payments depending on the maturity of each investment;
- the risk premium, expressed as the difference between the performance of securities with rating (Aaa) and (Baa), in order to measure the market reaction to risk;

Other authors have suggested including other two explanatory factors: a) the world economy trend in relation to the positive correlation between the share prices in the world stock markets; b) the currency movements in relation to the structure and the currency denomination of listed companies.

A second approach is the use of factor analysis, namely, a series of techniques that make it possible to explain and represent certain relationships made evident by independent variables (factors). This approach consists of extracting a small number of independent factors based on the correlations between the observed variables. One of the most important methods used in this model comes from the analysis of the so-called "principal components".

The most commonly used approaches in academic research are: the Fama-French three factor model (1992) and the Carhart four factor model (1997)[9]. It is noteworthy that the risk factors used in these models cannot be immediately interpreted as macroeconomic indicators. Fama and French (1992) demonstrated that the beta, up to now considered as an explanatory variable for the risk-return relationship, does not fully capture all the different factors of risk. The two authors developed a three factor model, through which they showed that the reward for the risk depends not only on the market, as stated by the CAPM, but also on two other factors: the size of the company and the relationship between the book value and the market value of that firm.

According to the two authors, empirical evidence shows that the three factor system can explain more precisely the returns of equities. This statement is demonstrated by the fact that, for example, companies with a higher book to market equity ratio seem to deliver abnormal high returns and vice versa.

The factors used by Fama and French are:

- the market risk premium;
- the difference between the return of smaller and larger companies (in terms of market capitalization; this factor is known as the size factor, or SML);
- the difference between the return of companies with higher and lower book to market value (the ratio between the book value and market value of the firm's shares; this factor is known as book to market or HML);

Carhart extended this model by adding another factor related to the premium assigned by the market to companies whose securities have benefited from a positive market performance in the past (the so-called momentum factor).

3. Theoretical Framework

3.1. Research Question and Hypotheses

In order to provide an in-depth comprehension of the main purposes and limitations of our analysis, it is essential to define the research questions, the ex-ante hypotheses and conceptual framework of this study. As a matter of fact, the quality of the conclusions substantially depends

[9] The Fama and French and Carhart benchmark factor loadings - SMB, HML and MOM - are constructed from six size / value portfolios and do not consider transaction costs. Rm - the market return - is represented by the value-weighted return on all NYSE, AMEX, and NASDAQ stocks obtained from CRSP. Rf - the risk free rate - is represented by the one-month Treasury bill rate.

on the soundness of the methodology employed, which, in turn, relies on specific economic models and statistical techniques.

The aim of this research paper is to analyze the main characteristics of idiosyncratic risk, by attempting to understand the role it plays in setting the price of a security. Among all the stock and exchange markets that could have been used for the analysis, the focus was on those not sufficiently covered by the current literature. As already mentioned, we decided to include only primary stocks listed in Greece, Italy, Spain and Portugal, approaching the study by means of the two most popular models in the financial world: the CAPM and the Fama-French three factor model. We first reviewed some characteristics of the companies targeted in order to investigate whether they could have been included in our sample. After carefully studying the arbitrage pricing literature, we subsequently developed our ex-ante hypotheses on the expected results. Since the past papers demonstrated contradictory results, it became even more interesting to study the univariate interaction in the sample period considered.

Based on an under-diversification hypothesis developed by Levy (1978), Merton (1987) and Malkiel and Xu (2004) and the vast majority of empirical evidence, we expected to find a non-neutral relationship between idiosyncratic risk and excess returns of the single stocks[10].

H_0: There is a non-neutral cross-sectional relation between IVOL and excess returns. In other words, if we build a zero-cost portfolio strategy with a long position in the sub-portfolio that has the lowest idiosyncratic risk and a short position in the sub-portfolio that has the highest idiosyncratic risk, we will earn statistically significant abnormal returns.

H_1: There is a neutral cross-sectional relation between IVOL and excess returns. In other words, if we build a zero-cost portfolio strategy with a long position in the sub-portfolio that has the lowest idiosyncratic risk and a short position in the sub-portfolio that has the highest idiosyncratic risk, we will not earn statistically significant abnormal returns.

3.2. Disposition

As previously mentioned, the aim of our analysis is to empirically test the role of idiosyncratic risk in pricing the stocks listed in the GIPS countries. The period studied spans

[10] These authors argued that there are many rational and irrational reasons why some investors tend to under-diversify their portfolios. For example, transaction costs and taxes restrict the portfolio holdings of investors, therefore limiting diversification. Employee compensation plans sometimes provide workers with stocks in their companies but limit the possibility to sell these holdings, thereby leading to a concentrated exposure. Private information is another justification for the under-diversification. Barber and Odean (2000) demonstrated that the household's portfolio, on average, includes only 4.3 stocks (worth around $47,000), and the median household invests in 2.6 stocks (worth roughly $16,000). Goetzmann and Kumar (2001) and Polkovnichenko (2001) presented further hypotheses on the lack of diversification. Benartzi (2001) and Benartzi and Thaler (2001) found that investors hold an excessive amount of their pension plans in the securities of the firm they work for. Huberman (2001) argued that agents are more likely to invest in familiar stocks.

over twenty years (January 1992 - November 2012), including the performance of securities in times of crisis, such as: the dot-com bubble (2000), and the most recent financial crisis (2007-2012) that still has not been examined in any economic research.

Our study follows a six-step procedure in order to include all relevant information. We have tried to reduce to a minimum all the ex-post arbitrary decisions in order to avoid any potential problem related to the so-called "selection bias". We now present an overview of the main steps:

Step 1: Collection of daily and monthly data for all the stocks listed within the Greek, Italian, Portuguese and Spanish equity markets between the January 1992 and November 2012. In particular we have downloaded and transferred to Excel three key indicators: the total return index (comprehensive of dividends), the market capitalization of the different listed companies and their book to market value. The databases mainly used are Thomson DataStream and Bloomberg.

Step 2: Identification of a risk-free rate consistent with our analysis. This process has involved extensive use of Internet research on official websites, like the European Central Bank and business periodicals, as well as the use of DataStream.

Step 3: Sample cleaning and preparation, in the attempt to create the basis for the most accurate and consistent analysis. In this phase the study of past academic research has been crucial. It has, however, been necessary to adapt past methodologies to our sample, in order to integrate them with the particular characteristics of our study.

Step 4: Calculation of daily and monthly logarithmic returns and construction of a value-weighted index - based on the universe of securities in our sample - in order to replicate the market portfolio. We have subsequently proceeded to construct the six value-weighted portfolios formed on size and book to market value, as required by Fama and French.

Step 5: OLS time-series regressions have been run in order to derive our alpha, beta and idiosyncratic volatility for each stock presented in the database, on a monthly basis. This has been useful to understand whether, within the sample, the initial hypothesis is accepted or rejected. As previously mentioned, we have used both the CAPM and the Fama-French three factor model.

The analysis concludes with comments regarding the main findings, and by describing what the potential statistical and logical limits of our study could be. The following paragraphs illustrate in detail the various steps mentioned above together with the final results.

3.3. Limitations

An important part of any empirical thesis is to understand not only the strengths but also the potential limitations of the analysis. The limitations of our thesis also reflect the limitations already present in the existing academic literature; and the drawbacks of the statistical and econometric techniques here employed were widely investigated in the last decades.

- Data Mining: According to Hand, et al. (2000), data mining is defined as "the process of seeking interesting or valuable information within large data sets." A problem could arise when a particular relationship within the model is spurious and its presence in the database is due exclusively to chance. As our study has been very restrictive in reducing the size of the dataset in order to satisfy certain conditions, and considering that we are applying a well delineated and established methodology , the possibility of potential problems of data mining are not considered an issue.

- Data Snooping: White (2000) defined data snooping as something that "occurs when a given set of data is used more than once for purposes of inference or model selection." Since our study is conducted on a completely new dataset and the exchange markets have received little attention in this area, we do not think that data snooping could create any sort of distortion or bias in our results.

- Model Mining: The process that involves a series of variations in the model that has to be tested in order to obtain satisfactory and significant results, consistent with our ex-ante hypothesis. As this thesis is based on the model developed by Ang, et al. (2006), it could be considered an out-of-sample analysis on a different dataset, thereby limiting the risk of finding biased patterns.

- Selection bias: It refers to the situation in which observations are chosen that are not independent with respect to the outcome variables, therefore resulting in biased findings. Reducing the sample in accordance with the application of pre-established criteria could lower randomness within the remaining sample. As already mentioned, we have limited our sample to stocks listed on the major stock exchanges of the four GIPS countries. We can justify this selection by arguing that these markets have more stringent listing requirements than those of other European countries, and as such, financial information should be of better quality. In addition, we have chosen to maintain the sample as unadjusted as possible in order to minimize the possibility of selection bias.

- Survivorship Bias: The selected sample starts from January, 1st 1992, and only includes listed securities from that date onwards. The main implication of this approach is that some companies included in the dataset no longer exist as a result of acquisitions, mergers or bankruptcies. This could lead to phenomena of survivorship bias and, in turn, cause some distortion to the returns of the portfolios when companies experience larger IVOL ahead of events. Such bias cannot be excluded, even though we are strongly convinced that such events are so rare that they do not significantly impact on our results.

3.4. The advantage of choosing daily data

In the financial literature, it is possible to consult a broad production of empirical studies aimed at assessing the validity of the CAPM, the Fama-French three factor model and the APT. However, when selecting the sample, the practice of using monthly data has always been widespread. Such a choice is motivated by the investment strategy pursued by institutional investors; in fact, up to a few years ago, fund managers rarely used to update their portfolios more than once a month since it was difficult to find statistical techniques sufficiently sophisticated to easily handle large amounts of data. In addition, many managers - especially small investors – are sometimes reluctant to adopt methods of analysis that are not consolidated, and, due to their conservative approach, spend a long time verifying and analyzing the companies they have chosen to invest in. Finally it should be kept in mind that some managers base their investment decisions on long term horizons, and, therefore, do not require frequent changes in the composition of their portfolios.

These are the reasons why, for a long time, the choice of using monthly returns seemed to be the most logical and straightforward one to implement. However, in the last few years, the evolution of statistical analysis has led to the rapid spread of computers and software capable of implementing advanced calculation. Simultaneously, the progress made in the communication services gave a large number of fund managers the opportunity to access an amount of data significantly broader than in the past.

By virtue of these factors, managers have started to update the composition of their portfolios more frequently that once a month, thus modifying the losing and winning positions in a more proactive way and, at the same time, making possible strategies based on short horizons. We have, therefore, decided to use daily data even if this choice differs from the standard models; in fact, our twofold aim is to monitor the market with a frequency sufficient to capture the unique aspects of the operation and management techniques, and gain control of the portfolio analysis carried out by all investors on a daily basis.

4. Empirical Analysis

4.1. Data Gathering

The first step of the analysis included collecting the relevant data. We downloaded the original dataset from Thomson DataStream and Bloomberg; it encompasses the data of 893 stocks listed within the GIPS stocks exchanges: Borsa Italiana - London Stock Exchange Group (356 companies in total); Bolsa de Madrid (199 companies); Lisbon Stock Exchange (64 companies) and Athens Stock Exchange (274 companies). The acronym GIPS groups together some European countries: Greece, Italy, Portugal and Spain, which are now experiencing precarious conditions in their public finance. Due to their lack of economic competitiveness in the global markets, they are finding it extremely difficult to repay their accumulated debt.

The GIPS have several macroeconomic indicators in common including:

a) public debt, in relation to GDP;
b) public deficit, in relation to GDP;
c) government bond yields;
d) balance of foreign accounts and foreign debt;
e) level of productivity;

First of all, the GIPS show a very high debt to GDP ratio. Moreover, since 2008, they have generally recorded a large deficit. In 2010, the IMF emphasized that, in the past, these countries have had negative economic growth rates which were among the lowest in the world.

The downloaded sample consists of 21 years (January 1, 1992 - November 30, 2012) of data with daily stock total return indices, market capitalization and market to book value. We have excluded securities that did not respect specific requirements such as stocks with negative book values, not available information, secondary listing (when the primary listing is included) and preference stocks, leading to a final sample of 654 stocks listed at the end of the period. The number of securities with available information in January 1992 amounted to 132, and the average number of included stocks throughout the overall period was 412 (Table 15). In 251 months of observations, we collected 2,253,102 daily records and 103,042 monthly ones. We have decided to limit the time period to two decades in order to take into account, at least, two business cycles while still having a sufficient number of observations to achieve consistent results within the five different, ranked, portfolios as will be subsequently discussed. The currency used for this study is the EURO since we have performed the analysis on four European countries on an aggregated level.

The second step has consisted in identifying a proxy for the risk-free rate. At first glance, the Euro OverNight Index Average (EONIA) - namely, the overnight interest rate computed as a weighted average of all unsecured lending transactions within the interbank market - seemed to match with our purposes and our time horizon. Unfortunately, the EONIA started to be active in January, 1999 while our analysis begins 7 years before. We have decided, therefore, to replicate the EONIA rates between January, 1992 and December, 1998.

How was this done? We have taken into account a weighted average of the 1 month interbank offered rates of the 6 largest countries that would soon form the Euro Area: France, Germany, Greece, Italy, Portugal and Spain. The 1 month interbank rate seems to be the shortest yield available that could be considered risk-free. As the latter is a monthly rate, while the EONIA is a daily rate computed with the formula act/360, we had to adjust them so that they would follow a common path, consistent with the rest of the study.

As an official GIPS total return index does not exist, we have generated a market cap weighted index from the companies included within our sample as a proxy for the market portfolio. Ideally, at first glance, a researcher could prefer to study countries individually rather than on aggregated level, in order to formulate conclusions for specific markets, such as the Italian equity one. However, in order to obtain an adequate sample size to allow for valid statistical inference, we have chosen to include more countries in our dataset.

Deciding to take into accounts four different markets, rather than limiting our analysis to only Italy, tripled our total sample size. A fair alternative would have been to consider all equities in the world in order to have the perspective of a global investor. However, this would have been far beyond the scope of our analysis. The decision to consider not only Italy within our sample has also been the result of the studies of French and Poterba in 1992. These two scholars introduced the so-called home bias: the tendency of investors to invest predominantly in their home countries with not always positive performance. Since the portfolios are concentrated in a single domestic market, they are not well diversified from a geographical perspective and clash with the modern portfolio theory which demonstrates the efficiency of portfolios diversified at an international level.

In summary, we think that considering the aforementioned characteristics of the GIPS countries our portfolio of stocks offer a good trade-off between sample size and market relevance.

4.2. Characteristics of the Sample

The average market capitalization of the companies being considered in the sample is roughly €1.3bn, while the median is ca. €103mln. More than four fifth of the sample refers to firms below €1bn and ca. 74% below €500mln. We should also note that, given the differences in the average market value of the listed companies in the sample, Spanish firms have, on average, the highest market capitalization (€2.6bn) while Greek companies have the lowest one (€242mln). The average market to book value is 2.7X (median 1.4X) with less than one fifth of the companies above 3X and less than 10% above 4X (growth stocks).

For the sake of comparison, the average market to book value for Italian companies ranges between 2.1 and 2.3X, for Spanish companies between 3 and 3.3X, for Portuguese companies between 1.6 and 1.8X while for Greek ones between 2.8 and 3.2X.

4.3. Methodology

The methodology adapted in order to see how the idiosyncratic risk may affect the return of single stocks is inspired by previous analyses, mainly the one developed by Ang, et al. (2006).

4.3.1. CAPM Time Series Regression Analysis

When we run a CAPM regression, we need a proxy for the risk-free rate, the return of each single security within our portfolio and the excess return of the market (also known as market premium). The risk-free rate is the return that an investor obtains with a systematic (market) risk - measured as the beta - equal to zero. In this case, the specific security offers remuneration only for the so-called "default risk" (the risk of a credit transaction in which the debtor cannot fulfill his obligations of repayment of principal and interest to his creditor). Unfortunately, even government bond yields can bear a risk. This is the reason why they cannot be considered completely as risk-free rates: in fact, the yield is not certain and depends, to a small extent, on changes in the stock market. The risk-free rate, therefore, can be defined as the expected return for a risk averse investor. When an individual decides to invest in a specific company, he should add to the risk-free rate, the market risk premium and the specific risk of the company in which he is willing to invest (beta). As mentioned before, in our case, in order to minimize the beta, we have chosen as risk-free rate, an interest rate with the same maturity as the stocks being considered. We have used, therefore, the European OverNight Index Average (EONIA).

The market risk premium is represented by the excess return of the stock market with respect to an investment in risk-free debt. Since being a shareholder is riskier than being a bondholder, we also expect a higher return on investments in equity. How can the market risk premium be calculated? We proceed by observing a sufficiently long time series of stock market returns and EONIA interest rates. Usually and incorrectly, in order to replicate the market portfolio, researchers used to consider stocks worldwide and an investor could decide where to invest without special restrictions or additional costs. In practice, it seems more correct to replicate a market portfolio using stocks listed where investors really invest. This is the reason why we create a value-weighted index (market cap weighting) based on the universe of securities in our sample. We construct the market cap weighted GIPS Total Return Index by backtracking the total returns (including dividends) of the stocks in the sample, which is used as the proxy of the market return.

$$EMR_t = \sum_{i=1}^{n} w_{i,t-1} \left[\frac{Div_{i,t}+(P_{i,t}-P_{i,t-1})}{P_{i,t-1}} - rf_t\right]$$

For t = 1, …, T

Where:

$EMR_t = \text{the market risk premium of the portfolio in day } t$

$w_{i,t-1} = \text{the market cap of each stock, divided by the total market cap at closing of } t\text{–}1$

$Div_{i,t} = \text{dividend proceeds of each security at time } t$

$P_{i,t} = \text{the price of each security at time } t$

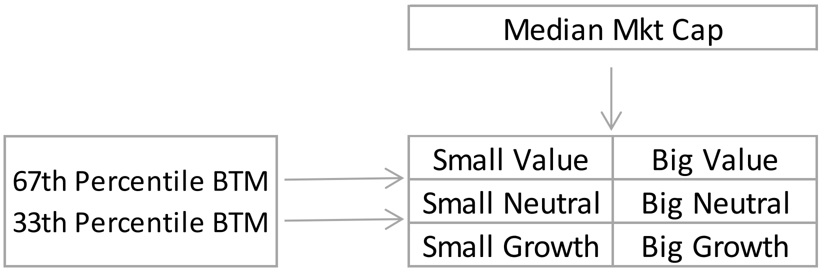
$rf_t = \text{the risk} - \text{free rate at time } t$

One last thought is dedicated to the beta coefficient. As already mentioned, it measures the risk specific to each single company; in other words, it represents the amount of risk that investors bear when investing in a particular company rather than in the stock market as a whole. The beta is the expression of the systematic risk, thus not diversifiable. It indicates how, on average, the returns of a security will vary depending on variation in the market returns.

4.3.2. FF-3 Time Series Regression Analysis

The Fama and French factors are constructed by using six value-weighted portfolios based on size and book to market value. In other words, stocks are sorted into six different groups depending on their size and book to market value. How is this done? We divide our sample of data into two equal portions according to their market capitalization: small group and big group. The two groups are subsequently split into three further groups respectively, with an equal number of securities depending on their book to market value.

Figure 1: FF-3 six value-weighted portfolios, methodology description



SMB (Small minus Big) represents the average return on the three small portfolios minus the average return on the three big ones:

$$SMB = \frac{1}{3}[SM + SH + SL] - \frac{1}{3}[BM + BH + BL]$$

HML (High minus Low) is the average return on the two value portfolios minus the average return on the two growth ones:

$$HML = \frac{1}{2}[SH + BH] - \frac{1}{2}[SL + BL]$$

Since we have daily returns and are interested in dynamics on a monthly basis, we also rebalance the 2x3 size/book to market portfolios on a monthly basis. It is noteworthy that this approach represents a slight deviation from the classical Fama-French three factor model which does rebalances the portfolio on a yearly basis. We are strongly convinced that our methodology is more compatible with this particular study, even though we must point out that such a deviation can slightly affect the final results.

4.3.3. Idiosyncratic Risk Estimation

Recent studies have employed different methodologies in order to estimate the idiosyncratic volatility. For example, papers focused on inter-temporal relationship have tended to use the total variance as a proxy for the IVOL. Instead, cross-sectional studies have used the CAPM residuals or Fama-French three factor model ones. Recently, the most common way to derive a proxy for the IVOL has involved the Fama and French model.

We should also pay attention on how to estimate the expected idiosyncratic risk: for example, Ang, et al. (2006) used the lagged one-month volatility of excess returns relative to the Fama-French three factor model. This one-month volatility was computed as the standard deviation of the portion of daily returns not explained by the model itself. Another methodology to estimate the IVOL was introduced by Fu (2009) who showed that, since the idiosyncratic risk is time varying, the one-month lagged estimate may not be considered an accurate proxy for the IVOL of the following month. Fu demonstrated that in the time interval between July 1963 and December 2006, the average first order autocorrelation of each single security IVOL was approximately 0.33. Dickey-Fuller's empirical tests showed that for more than 90% of the stocks, their IVOL did not follow a random walk process. Fu suggested using an autoregressive conditional heteroskedasticity process (ARCH) in order to capture the time varying feature of idiosyncratic volatility. Moreover, Bali and Cakici (2008) made a comparison between the conditional idiosyncratic risk estimates GARCH (1, 1) and EGARCH (1, 1) models with different data frequencies. They argued that the IVOL based on past monthly returns provided a more appropriate forecast of conditional IVOL than the one based on daily returns.

In our specific case, in order to estimate the idiosyncratic volatility, we first had to calculate the daily and monthly excess log return of the securities included in our sample, according to the following equation:

$$r_t^i = ln\left(\frac{p_t^i + d_t^i}{p_{t-1}^i}\right) - r_t^f$$

Where r_t^i represents the excess return of the individual stock i at time t, p_t^i is the price of stock i at time t, and r_t^f is the risk-free rate at time t. In order to estimate the realised monthly IVOL between January 1992 and November 2012, factor models were used to run monthly linear OSL on the daily excess return of each stock:

Relative to the CAPM:

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \varepsilon_t^i$$

And to the Fama-French three factor model:

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i$$

Where MKT_t represents the market risk premium, SMB_t is the excess return of the small portfolio relative to the big portfolio, and HML_t is the excess return of the high book to market stocks relative to the low book to market stocks, at time t.

The beta (β) represents the estimated "factor loading" in the time series regression (systematic risk). The residual ε_t^i is the portion of the stock return, in t, that remains unexplained by the factor model, and can be considered as the idiosyncratic part of the return. In other words, the unsystematic portion of the return of security i during t. We performed these time series regressions for each single stock for the entire sample period of 20 years and 11 months (therefore 20x12+11 = 251 months).

In conclusion, the idiosyncratic risk can be defined as the standard deviation of the residual ε_t^i derived through both the CAPM and the Fama-French three factor model. In order to minimize the impact of sporadic trading on IVOL estimates, we decided to only consider stocks with a minimum of 10 trading days in a month for which DataStream reports not only a daily return but also a non-zero trading volume[11]. Moreover, we transformed the daily idiosyncratic volatility to the correspondent monthly one by multiplying the daily standard error of residuals by the square root of the number of trading days in each single month[12].

We will now proceed to organize and rank each security within quintiles according to their estimated idiosyncratic volatility in t-1.

- The quintiles form five sorted portfolios that we will call P1, P2, P3, P4 and P5. P1 will include the stocks with the lowest estimated idiosyncratic risk in the previous month, while P5 will include stocks with the highest estimated IVOL.

- Each of the five portfolios will be held for one month during t (the month after the regression has been performed and the IVOL estimated).

- We subsequently calculate the market value-weighted monthly excess return of the sorted portfolios, and repeat the procedure for the entire periods (20x12+11-1=250 months, since the first month - January 1992 - can be only used to perform the first regression and estimate the first IVOL).

- Finally, as already mentioned in our ex-ante hypotheses, we construct a zero-cost portfolio strategy long in stocks with the lowest IVOL and short in securities with the highest IVOL in order to measure whether the idiosyncratic risk affects the excess return of single stocks.

Lo and MacKinlay (1990) analyzed the potential consequences of sorting securities within specific portfolios. Among the main advantages of this process we can mention the minimization of measurement error and, usually, a greater quality of the empirical test. However, since the

[11] In our sample, the trading days per month range between 20 and 23 days with a median and a mean of 22 days.

[12] The same procedure was used by French, Schwert, and Stambaugh (1987), and Schwert (1989).

criteria for sorting are often not random but based on some predefined characteristics, there might be the possibility of incurring in a selection bias.

Moreover, Berk (2000) argued that, by dividing the sample, the reliability of a model will diminish. In other words, the increase in the number of portfolios (by dividing the sample depending on several different conditions) could likely result in analysis with significant bias. This is the principal reason why we have decided to sort our stocks into quintiles, therefore limiting the number of sub-portfolios to five. In each quintile the observations will range between 75 and 128.

In order to estimate the systematic portion of the risk (market risk, size and value premium), we need to assess the performance of the sorted portfolios by estimating and examining the CAPM and Fama-French three factors model alphas. The regression methodologies are the same as the ones previously discussed. However, although so far we have used daily data in order to perform monthly regressions to estimate the single stocks' idiosyncratic volatility, we will now use monthly data in order to examine the returns generated by the IVOL sorted portfolios P1 to P5.

5. Results and Analysis

In our sample, the market risk premium over the risk-free rate is around 0.5% per month. The study shows a large value premium mainly due to the fact that, within the 21 years taken into consideration, the high book to market significantly outperformed the low book to market by 0.75% per month. As regards the size premium, we cannot confirm the presence of any size effect since the difference between the small caps and big ones does not statistically differ from zero (Table 17 in the Appendix).

Figure 2 shows an inverse relation between idiosyncratic risk (measured by the CAPM and the FF-3 models) and the regression alphas. This counter intuitive finding will be the focus of the following section.

Figure 2: Alphas of IVOL sorted portfolio quintiles

The chart presents the Fama-French and CAPM regression alphas of portfolios P1 to P5 ranked on idiosyncratic volatility with IVOL measured through the Fama-French and CAPM models. Since we implement two distinct methodologies in order to estimate the IVOL and have two different factor models to evaluate the portfolio performances, we will, finally, generate four sets of alphas. In the notation below, the first word illustrates the methodology that has been used to measure the IVOL; the second denotes what is sorted, while the third describes the model applied to calculate the alphas. For example, "CAPM IVOL FF-3" means that portfolios are IVOL sorted and that the idiosyncratic risk is measured through the CAPM while the alphas are computed against the FF-3.

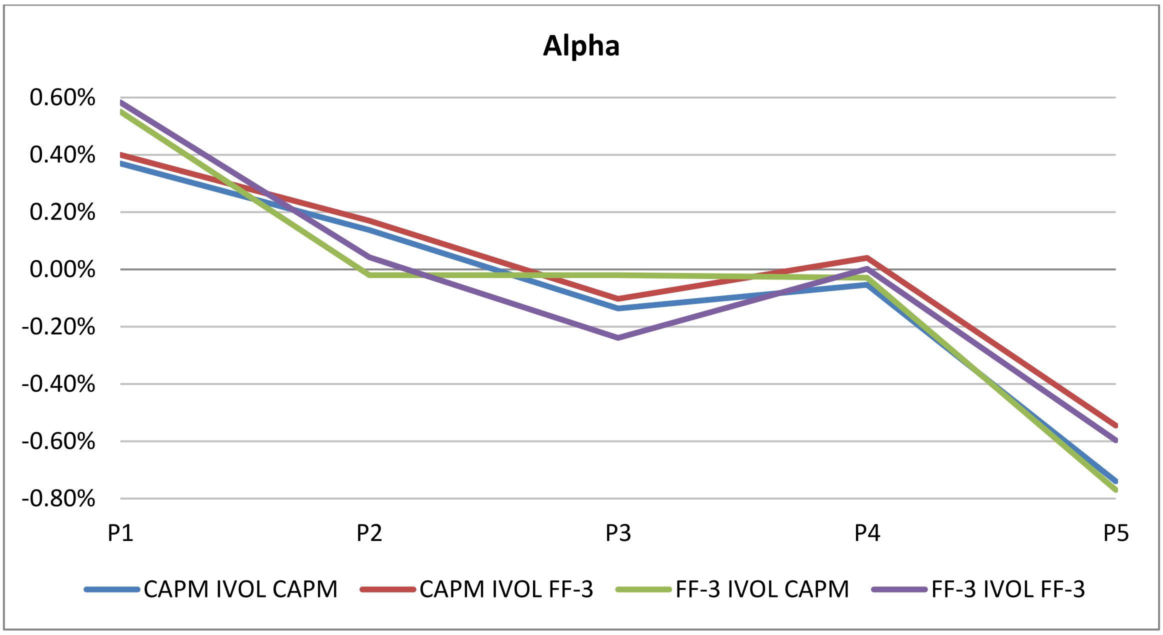


Table 4: Properties of portfolio quintiles sorted by IVOL relative to the CAPM

This table presents summary statistics and regression results of the IVOL sorted portfolio quintiles P_C1 to P_C5. The idiosyncratic volatility has been measured through the CAPM. P_C1 represents the portfolio quintile with the lowest idiosyncratic risk while P_C5 is the one characterized by the highest IVOL. The P_C1-P_C5 portfolio provides the excess return of a zero-cost investment strategy long in P_C1 and short in P_C5. The arithmetic and geometric means are computed as the average monthly returns in excess of the portfolios. Volatility is measured as the monthly standard deviation. Alphas and factor loadings are estimated and reported along with Newey-West (1987) t-statistics (in square brackets)[13].

	Low	Ranking on IVOL relative to CAPM			High	
	P_C1	**P_C2**	**P_C3**	**P_C4**	**P_C5**	**P_C1-P_C5**
Arithmetic Mean	0.39%	0.17%	-0.11%	-0.02%	-0.71%	1.10%
Geometric Mean	0.25%	-0.03%	-0.34%	-0.32%	-1.18%	1.43%
Median	0.62%	0.53%	0.39%	0.47%	-0.39%	1.22%
Skewness	-0.46	-0.52	-0.72	-0.02	0.16	-0.44
Kurtosis	1.11	1.83	1.24	1.24	1.37	1.79
Volatility	5.31%	6.19%	6.72%	7.75%	9.67%	7.63%
CAPM						
Alpha	0.37%	0.14%	-0.14%	-0.05%	-0.74%	1.11%
	[2.68]	[0.79]	-[0.67]	-[0.20]	-[1.64]	[2.35]
Mkt	0.87	1.00	1.06	1.16	1.17	-0.30
	[35.17]	[31.96]	[28.72]	[23.66]	[14.35]	-[3.52]
FF-3						
Alpha	0.40%	0.17%	-0.10%	0.04%	-0.55%	0.95%
	[2.87]	[0.96]	-[0.50]	[0.15]	-[1.19]	[1.98]
Mkt	0.87	0.99	1.05	1.13	1.18	-0.32
	[34.06]	[30.94]	[27.73]	[22.92]	[14.19]	-[3.63]
SMB	0.06	0.05	0.07	0.22	0.14	-0.08
	[1.76]	[1.20]	[1.40]	[3.27]	[1.23]	-[0.66]
HML	0.02	0.01	0.03	0.10	-0.12	0.14
	[0.60]	[0.25]	[0.58]	[1.47]	-[1.11]	[1.24]

[13] The Newey-West robust standard error is more reliable than the OLS one since it try to correct the t-statistics for the autocorrelation and heteroskedasticity in the residuals.

Table 5: Properties of portfolio quintiles sorted by IVOL relative to the FF-3

This table presents summary statistics and regression results of the IVOL sorted portfolio quintiles $P_{FF\text{-}3}1$ to $P_{FF\text{-}3}5$. The idiosyncratic volatility has been measured through the FF-3. $P_{FF\text{-}3}1$ represents the portfolio quintile with the lowest idiosyncratic risk while $P_{FF\text{-}3}5$ is the one characterized by the highest IVOL.
The $P_{FF\text{-}3}1$-$P_{FF\text{-}3}5$ portfolio provides the excess return of a zero-cost investment strategy long in $P_{FF\text{-}3}1$ and short in $P_{FF\text{-}3}5$. The arithmetic and geometric means are computed as the average monthly returns in excess of the portfolios. Volatility is measured as the monthly standard deviation. Alphas and factor loadings are estimated and reported along with Newey-West (1987) t-statistics (in square brackets).

	Low	**Ranking on IVOL relative to FF-3**			High	
	$P_{FF\text{-}3}1$	**$P_{FF\text{-}3}2$**	**$P_{FF\text{-}3}3$**	**$P_{FF\text{-}3}4$**	**$P_{FF\text{-}3}5$**	**$P_{FF\text{-}3}1$-$P_{FF\text{-}3}5$**
Arithmetic Mean	0.58%	0.01%	0.01%	0.01%	-0.74%	1.32%
Geometric Mean	0.43%	-0.18%	-0.23%	-0.26%	-1.13%	1.56%
Median	0.74%	0.31%	0.50%	0.49%	-0.74%	1.51%
Skewness	-0.34	-0.77	-0.56	-0.25	0.13	-0.45
Kurtosis	1.02	2.03	1.53	1.38	1.18	1.83
Volatility	5.44%	6.08%	6.83%	7.22%	8.79%	6.52%
CAPM						
Alpha	0.55%	-0.02%	-0.02%	-0.03%	-0.77%	1.32%
	[4.03]	-[0.11]	-[0.12]	-[0.08]	-[2.00]	[3.27]
Mkt	0.90	0.99	1.08	1.09	1.14	-0.25
	[36.23]	[33.60]	[29.35]	[24.20]	[16.50]	-[3.38]
FF-3						
Alpha	0.58%	0.04%	-0.24%	0.00%	-0.60%	1.18%
	[4.18]	[0.26]	-[0.12]	[0.01]	-[1.54]	[2.88]
Mkt	0.89	0.99	1.07	1.06	1.14	-0.25
	[35.10]	[32.80]	[28.20]	[23.20]	[16.20]	-[3.39]
SMB	0.05	0.07	0.05	0.14	0.16	-0.10
	[1.56]	[1.66]	[0.99]	[2.23]	[1.66]	-[1.04]
HML	0.02	-0.01	0.05	0.11	-0.07	0.09
	[0.49]	-[0.32]	[1.05]	[1.85]	-[0.75]	[0.88]

At first glance, we can see that the IVOL sorted portfolios - measured by the CAPM (Table 4) - produce very similar results compared to the correspondent portfolios measured by the Fama-French three factor model (Table 5). We can see that the two different asset pricing models lead to similar distribution of returns, alphas and factor loadings. The correlation between the returns of each monthly IVOL sorted portfolio calculated through the FF-3 and the corresponding counterpart when the idiosyncratic risk is calculated using the CAPM is above 96% for all the five alternative pairs of portfolios. This analysis is in line with the studies conducted by Ang, et al. (2006) who computed a correlation higher than 99% between the corresponding IVOL sorted portfolios. Our view is that the lower correlation in our sample is predominantly due to the fact that Ang, et al. (2006) used a larger sample in their analysis, which reduces the noise within the portfolios. However, as our correlations are much higher than 95% and the alphas calculated using both the CAPM and the FF-3 are not significantly different, we can consider these results as equivalent.

Therefore, the following analysis will mainly consider the findings related to the idiosyncratic risk measured by the Fama-French three factor model[14]. Obviously, the same conclusions can be made when using the IVOL generated by the CAPM.

The descriptive statistics in Table 4 and Table 5 show how the arithmetic mean of the portfolio returns decreases as we move from P1 to P5. Instead, as regards the geometric mean of portfolio returns, we can note how it tends to decrease in a more than proportional way compared to the arithmetic mean. Such a decreasing trend seems to be mainly due to the increase in volatility that characterizes the passage from P1 to P5 and the consequent decrease of the log returns. Moreover, the regression results summarized in Table 4 and Table 5, show how the zero-cost portfolio created assuming a long position in securities with the lowest IVOL (P1) and a short position in securities with the highest one (P5), achieves an economically large positive CAPM alpha of 1.32% and FF-3 alpha of 1.18%.

These alphas have a high robust t-statistics of about 3.27 (CAPM) and 2.88 (FF-3), which allows us to reject the null hypothesis that the zero-cost portfolio does not earn significant abnormal returns at the 1% significance level. We can also demonstrate how, moving from P1 to P5, the CAPM and the FF-3 alphas follow a downward trend, meaning that as the IVOL increases, the portfolios produce increasingly lower abnormal returns. As shown in Table 4 and Table 5, by studying the alphas of the different IVOL sorted portfolios, we can note that P5 - characterized by stocks with the highest idiosyncratic risk in the previous month - generates the most negative alpha (-0.77% CAPM and -0.60% FF-3) that are still statistically significant in both the CAPM (t-statistics of 2.00) and FF-3 (t-statistics of 1.54). Considering that on the opposite side, P1 has a largely positive alpha (0.55% CAPM and 0.58% FF-3) we can conclude that both portfolios contribute in a consistent manner to the abnormal return generated by our zero-cost portfolio strategy.

It therefore seems clear that the mispricing of idiosyncratic risk in our sample is guided by a low demand for securities with the lowest idiosyncratic volatility (higher returns) and a high

[14] Since the difference between P5 and P1 alphas relative to the CAPM is very similar to the difference in the FF-3 alphas, we decided to consider the Fama and French alphas as they control for the standard set of systematic factors.

demand for securities with the highest idiosyncratic volatility (lower returns). We also note that our findings on the alpha behavior of the P1-P5 zero-cost portfolio strategy, are predominantly due to the performance of the short side of the portfolio (-0.77%). The strong impact of the short side on the performance of a portfolio strategy is a common phenomenon in the financial literature above all when researchers find a mispricing in idiosyncratic risk - e.g. Finn, et al. (1999). Shorting rules and limitations are often regarded as one of the main reasons why some mispricing of securities cannot be fully exploited - Lamont and Thaler (2003).

As regards the factor loadings (MKT beta, SMB, HML), we can note a consistent positive trend in the market beta and SMB values when we move from P1 to P5, and the P1-P5 portfolio strategy has, therefore, negative loadings. From the reported HML, we can see that the P5 has a significant positive (0.7) loading, which, combined with the large and consistent value premium that characterizes our analysis, help us to understand why the FF-3 alphas of the P1-P5 portfolio strategy are slightly lower (1.18%) compared to the corresponding CAPM strategy (1.32%).

Figure 3: Market betas of IVOL sorted portfolio quintiles

The chart presents the Fama-French and CAPM estimates for the market betas of portfolio quintiles P1 to P5 ranked on idiosyncratic volatility with IVOL measured through the Fama-French and CAPM models. Since we implement two distinct methodologies in order to estimate the IVOL and have two different factor models for evaluating the portfolios performances, we will finally generate four sets of market betas. In the notation below, the first word illustrates the methodology that has been used for measuring the IVOL; the second denotes what is ranked, while the third describes the model applied to calculate the market betas. For example, "CAPM IVOL FF-3" means that portfolios are IVOL ranked and the idiosyncratic risk is measured through the CAPM while the market betas are computed against the FF-3.

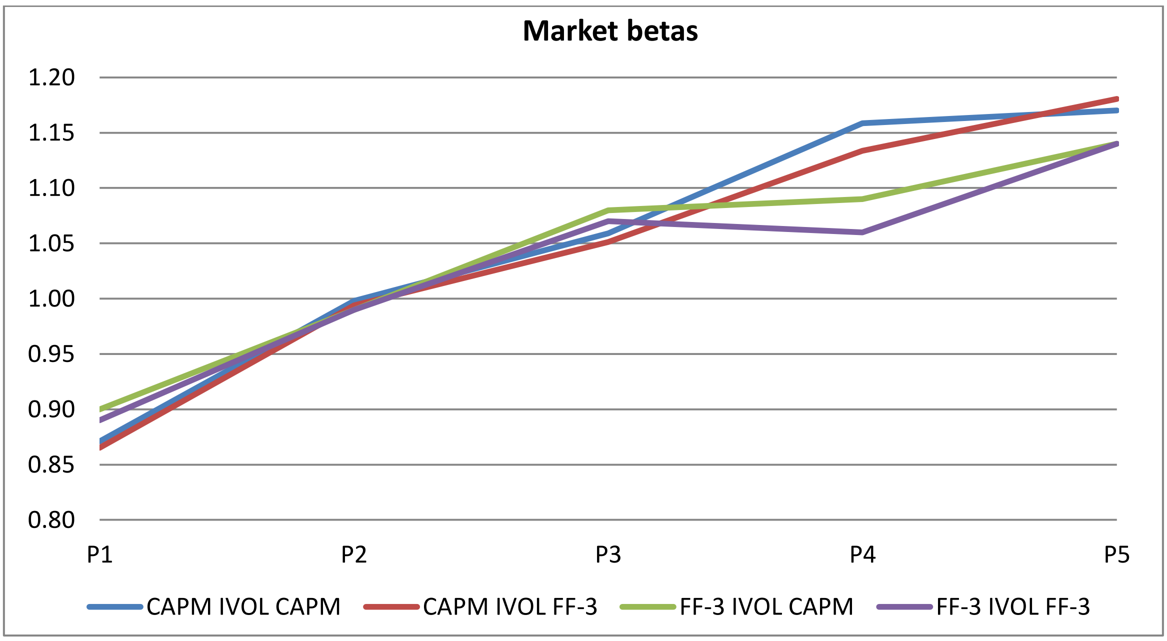


Figure 3 underlines how the systematic risk increases in the IVOL sorted portfolios as we move from P1 to P5, meaning that the idiosyncratic volatility has a positive relationship with the market beta. The main issue here is that, if the market risk is mispriced - e.g. when the idiosyncratic risk mispricing is caused by an irrational demand for market beta - our analysis would suffer from a bias due to the spurious relationship between alpha and IVOL. In order to test the quality and robustness of our model, we will try to see if by ranking portfolios on systematic risk would also lead to mispricing phenomenon. We will apply a portfolio ranking procedure similar to the one previously implemented for the IVOL sorted portfolios. However, instead of sorting according to the previous month idiosyncratic volatility, we will now rank on market beta estimated through the CAPM model, and compare the new ranked portfolios against the CAPM and Fama-French three factor model.

Table 6: Properties of market beta sorted portfolio quintiles

This table presents summary statistics and regression results of the market beta ranked portfolio quintiles $P_\beta 1$ to $P_\beta 5$. The systematic beta risk has been measured through the CAPM. $P_\beta 1$ represents the portfolio quintile with the lowest systematic risk while $P_\beta 5$ is the one characterized by the highest beta. The $P_\beta 1$-$P_\beta 5$ portfolio provides the excess return of a zero-cost investment strategy long in $P_\beta 1$ and short in $P_\beta 5$.

	Low		**Ranking on beta**		High	
	$P_\beta 1$	**$P_\beta 2$**	**$P_\beta 3$**	**$P_\beta 4$**	**$P_\beta 5$**	**$P_\beta 1$-$P_\beta 5$**
Arithmetic Mean	0.27%	0.18%	0.19%	0.50%	0.08%	0.19%
Geometric Mean	0.13%	0.05%	0.05%	0.35%	-0.21%	0.34%
Median	0.51%	0.36%	0.61%	0.83%	0.92%	0.26%
Skewness	-0.01	0.11	-0.63	-0.12	-0.23	-0.20
Kurtosis	2.48	3.75	1.53	0.40	1.66	1.84
Volatility	5.19%	5.24%	5.27%	5.53%	7.58%	6.32%
CAPM						
Alpha	0.25%	0.16%	0.17%	0.48%	0.05%	0.20%
	[1.05]	[0.76]	[1.03]	[3.04]	[0.23]	[0.58]
Mkt	0.64	0.70	0.82	0.89	1.21	-0.57
	[14.91]	[18.61]	[27.56]	[31.38]	[30.36]	-[9.07]
FF-3						
Alpha	0.30%	0.16%	0.19%	0.51%	0.06%	0.24%
	[1.22]	[0.75]	[1.14]	[3.16]	[0.27]	[0.67]
Mkt	0.65	0.69	0.82	0.89	1.20	-0.55
	[14.65]	[17.71]	[26.62]	[30.66]	[29.25]	-[8.55]
SMB	0.01	0.09	0.05	0.00	0.06	-0.05
	[0.15]	[1.77]	[1.11]	-[0.01]	[1.04]	-[0.56]
HML	-0.05	0.10	0.02	-0.04	0.05	-0.10
	-[0.91]	[1.87]	[0.41]	-[0.98]	[0.86]	-[1.17]

Even in this case, the arithmetic mean of the returns generated by the beta sorted portfolios follow a decreasing pattern as we move from P1 to P5.

The zero-cost portfolio strategy P1-P5, in the interval of time considered, seems to achieve a performance of about 0.19%. The geometric mean decreases from P1 to P5 with the increase of the previous month estimated market beta. As the alpha on the P1-P5 computed through the CAPM is positive but not statistically significant (t-statistics of 0.58) we cannot conclude that the CAPM fails to price the market risk in our sample. The same findings are generated when we implement a FF-3 regression model on the same market beta sorted portfolio (t-statistics of 0.67). Again, looking at the factor loadings, we can notice a consistent increase in the value of the market beta, the SMB and the HML as we move from P1 to P5.

Since we can state that the systematic risk is not mispriced - the market beta sorted P1-P5 zero-cost strategy has not significant alpha versus both the CAPM and the FF-3 models - one of our main concerns (that mispricing in market risk would lead to an inconsistent analysis and a spurious relationship between alpha and IVOL) disappears.

However, we decided to take a closer look at the relationship between idiosyncratic volatility and market beta. We proceeded by implementing a double ranking methodology on both the idiosyncratic volatility and the beta. Each month, we split the stocks in our sample within three terciles depending on their market betas estimated through the CAPM model. Subsequently, having three beta sorted portfolios, in each tercile we constructed five IVOL sorted portfolios depending, again, on the idiosyncratic volatility of the previous month. Thus we will have, in total, 15 different portfolios sorted depending on the previous month systematic risk and idiosyncratic volatility. By implementing this approach, it seems possible to further analyze and eventually determine whether our findings concerning the market beta and the idiosyncratic volatility are consistent and robust.

Table 7: Properties of IVOL sorted portfolio quintiles in beta sorted terciles

This table presents regression results of the IVOL ranked portfolio quintiles $P_{DR}1$ to $P_{DR}5$ within the market beta ranked portfolio terciles CAPM BETA LOW to CAPM BETA HIGH. Both the idiosyncratic volatility and the systematic beta risk have been measured through the CAPM. $P_{DR}1$ represents the portfolio quintile with the lowest idiosyncratic risk while $P_{DR}5$ is the one characterized by the highest IVOL. CAPM BETA LOW represents the portfolio tercile with the lowest systematic beta risk while CAPM BETA HIGH is the one characterized by the highest beta. The $P_{DR}1$-$P_{DR}5$ double ranked portfolio provides the excess return of a zero-cost investment strategy long in $P_{DR}1$ and short in $P_{DR}5$. Alphas and factor loadings are estimated and reported along with Newey-West (1987) t-statistics (in square brackets).

	Low	**Ranking on beta and IVOL**			High	
	$P_{DR}1$	**$P_{DR}2$**	**$P_{DR}3$**	**$P_{DR}4$**	**$P_{DR}5$**	**$P_{DR}1$-$P_{DR}5$**
CAPM BETA LOW FF-3						
Alpha	0.50%	0.15%	-0.25%	-0.28%	-0.33%	0.83%
	[2.38]	[0.51]	-[0.72]	-[0.75]	-[0.62]	[1.46]
Mkt	0.52	0.66	0.76	0.83	0.81	-0.29
	[13.71]	[11.89]	[12.09]	[11.98]	[8.27]	-[2.79]
CAPM BETA MID FF-3						
Alpha	0.56%	0.10%	0.08%	-0.32%	-1.00%	1.56%
	[2.89]	[0.40]	[0.30]	-[0.89]	-[1.80]	[2.62]
Mkt	0.71	0.80	0.89	1.07	1.07	-0.36
	[20.36]	[17.25]	[19.05]	[16.05]	[10.58]	-[3.33]
CAPM BETA HIGH FF-3						
Alpha	0.29%	0.01%	-0.22%	0.10%	-0.67%	0.95%
	[1.25]	[0.03]	-[0.82]	[0.29]	-[1.19]	[1.63]
Mkt	0.99	1.07	1.17	1.23	1.31	-0.32
	[23.60]	[24.60]	[23.92]	[20.32]	[12.79]	-[2.98]

Comparing the findings in Table 7 with the values generated through the Fama-French three factor model in Table 5 - with the idiosyncratic volatility measured by the CAPM in both regressions - we can advance understanding on the potential mispricing phenomenon related to the asset pricing approaches used so far.

It is clear that the FF-3 alphas of the double sorted portfolio P1-P5 decrease for the low beta tercile and remain equal for the high beta tercile compared to the alphas generated by the IVOL sorted zero-cost strategy P1-P5 measured through the FF-3 model (0.95%). Moreover, the statistical significance of the new alphas tends to decrease and finally disappears. As regards the mid beta sub-portfolio, we can highlight how both the economic value of the alpha (1.56%

compared to 0.95%) and the t-statistics (2.62 compared to 1.98) tend to increase, implying that the statistical significance of the abnormal returns is higher. In other words, this means that the abnormal returns are highest among mid beta securities.

However, it should be mentioned that the mispricing of the idiosyncratic volatility still remains economically significant in all the three alternative beta sub-portfolios, with monthly alphas moving from 0.83% of the low beta subgroup, through 1.56% of the mid beta subgroup, to 0.95% of the high beta subgroup. Furthermore, it is noteworthy that, since the low and high beta terciles are statistically insignificant, the interpretation of our new findings is strongly limited by the significant reduction in the number of stocks included within each sub-portfolio. Obviously, when we decide to reduce the size of a portfolio we need to take into account the fact that this approach is likely to result in greater noise and higher potential biases. Therefore, the model could lose the ability to provide any statistical significance, leading to less accurate results in our reduced total sample[15].

[15] Berk (2000) demonstrated that the consistency and statistical significance of a model is always smaller within a subgroup rather than in the overall sample. By selecting a sufficient number of groups to sort into, an analyst can reduce and destroy the within-group explanatory power of even an economically and statistically correct asset pricing model.

Table 8: Properties of total realised volatility sorted portfolio quintiles

This table presents summary statistics and regression results of the volatility ranked portfolio quintiles P_v1 to P_v5. The volatility has been measured as the aggregate of systematic and idiosyncratic risks. P_v1 represents the portfolio quintile with the lowest volatility while P_v5 is the one characterized by the highest volatility. The P_v1-P_v5 portfolio provides the excess return of a zero-cost investment strategy long in P_v1 and short in P_v5. The arithmetic and geometric means are computed as the average monthly returns in excess of the portfolios. Volatility is measured as the monthly standard deviation. Alphas and factor loadings are estimated and reported along with Newey-West (1987) t-statistics (in square brackets).

	Low	**Ranking on volatility**			High	
	P_v1	**P_v2**	**P_v3**	**P_v4**	**P_v5**	**P_v1-P_v5**
Arithmetic Mean	0.25%	0.22%	0.30%	0.47%	0.09%	0.17%
Geometric Mean	0.13%	0.09%	0.16%	0.32%	-0.21%	0.34%
Median	0.42%	0.47%	0.62%	0.82%	0.91%	0.25%
Skewness	-0.30	0.10	-0.53	-0.12	-0.22	-0.22
Kurtosis	2.10	3.68	1.45	0.39	1.64	1.54
Volatility	4.98%	5.11%	5.23%	5.52%	7.62%	6.21%
CAPM						
Alpha	0.24%	0.20%	0.28%	0.45%	0.05%	0.18%
	[1.06]	[0.97]	[1.68]	[2.88]	[0.24]	[0.54]
Mkt	0.64	0.72	0.82	0.89	1.21	-0.58
	[15.90]	[19.78]	[27.43]	[31.59]	[30.10]	-[9.51]
FF-3						
Alpha	0.25%	0.19%	0.29%	0.49%	0.06%	0.19%
	[1.12]	[0.96]	[1.73]	[3.07]	[0.28]	[0.55]
Mkt	0.64	0.70	0.81	0.89	1.20	-0.56
	[15.46]	[18.85]	[26.50]	[30.92]	[28.99]	-[9.03]
SMB	0.01	0.09	0.03	0.01	0.06	-0.05
	[0.14]	[1.86]	[0.69]	[0.27]	[1.13]	-[0.66]
HML	-0.02	0.10	0.01	-0.04	0.05	-0.07
	-[0.31]	[1.98]	[0.28]	-[1.07]	[0.94]	-[0.83]

The last step in comparing the pricing of the alternative risk factors involves the construction of portfolios based on the past month total volatility, which could be seen as the sum of systematic and idiosyncratic risk. Our main findings, shown in Table 8, clearly demonstrate the poor risk-return relationship within the sample considered. The monthly arithmetic mean decreases from 0.25% for the portfolio with the lowest volatility (P1) to 0.09% for the portfolio with the highest realised volatility (P5). Similarly, the geometric mean significantly decreases as we move from P1 to P5 (from 0.13% to -0.21%). As regards the alphas, they are neither economically large nor statistically significant versus both the Fama-French three factor model and the CAPM. As the idiosyncratic volatility and the systematic risk have been argued to be positively correlated, while the former is considered mispriced and the latter not mispriced versus the CAPM and the Fama-French three factor model, the finding that the total realised volatility is not mispriced can be seen as a logical consequence of the fact that the market beta has a greater impact on the overall model than the IVOL.

We have also reported descriptive statistics of the factor loadings in order to understand their behavior over time and through different portfolios. As already mentioned, our studies show a significant value premium and an irrelevant size premium effect. We can notice how the HML loading follows a different path between high idiosyncratic volatility securities (negative value) and stocks with high market beta and total realised volatility (positive value). One of the main reasons of this finding could be that high IVOL and high beta stocks are driven by different factors. In fact, securities with high idiosyncratic risk are often financially distressed and more sensitive to firm-specific and short-term news, while stocks with higher beta and higher total volatility are usually growth stocks more sensitive to macroeconomic drivers.

The success of the systematic risk factors used in our thesis in order to price the different sorted portfolios is perfectly in line with the market efficiency theory and the risk aversion hypotheses, where higher returns are, on average, obtained only when an investor takes additional undiversifiable risk. Moreover, the fact that we have a positive market risk premium of roughly 0.50% suggests that agents, on average, are risk averse when pursuing an investment strategy which, in turn, explains why there is a poor risk-return relationship within the different portfolios constructed in our sample.

Instead, as regards the unsystematic, idiosyncratic risk, there is still no consensus in the market efficiency theories on why agents are willing to accept lower returns for investments in securities with high idiosyncratic volatility. One of the best available explanations for this finding is provided by behavioral finance. As already mentioned, for example, Baker, et al. (2011) argued that overconfident investors deliberately choose to invest in securities with the highest volatility and therefore, cause a reduction in performance of these stocks. In order to further support this theory, it should be pointed out that the mispricing of the idiosyncratic volatility predominantly comes from an excess demand for the higher IVOL securities and is largest for stocks with mid beta and, to a less extent, high beta.

So far, we have focused our analysis on idiosyncratic risk and market beta concluding that the IVOL is mispriced versus both the CAPM and the FF-3 models while the systematic portion of the risk and the total realised volatility seem to be in line with the efficient market hypotheses. We also decided not to study whether the mispricing could create a potential arbitrage opportunity. The main reason is that we have not explicitly worked out the potential limits to arbitrage, such as shorting constrains, transaction costs and liquidity issues. Moreover, as reported in Table 16 and Figure 8 and 9 in the Appendix, the stocks moved significantly from one quintile to another during all the months considered.

Our result is that, on average, only the 40% of securities did not move from their quintiles while the remaining 60% should have been rebalanced each month in order to implement arbitrage strategies. In demonstrating the high implied costs of an active trading strategy based on a long-short, zero-cost portfolio, we need to introduce a simplified version of the analysis developed by Barber and Odean (2000). The authors argued that trading costs should include: the bid-ask spread and the market impact cost - the additional cost an investor has to pay over the initial price due to the so-called "market slippage" that is caused by the fact that the transaction itself could have changed the price of the security. Clearly, these kinds of costs are considered higher for illiquid and smaller companies rather than for very liquid and larger ones.

In their paper, Barber and Odean (2000) disregarded the differentiation between small-big and liquid-illiquid stocks and developed a proxy of a round trip transaction cost (including a complete buy and sell order) that was set around 4%[16]. Nowadays, this estimate could be considered too high especially if we think that technological innovation in the last 12 years - from the Barber and Odean (2000) paper - made it possible to significantly reduce costs related to trading transactions. However, if we consider that roughly 60% of our P1-P5 zero-cost portfolio should have been bought and sold, this could have led to a 2.4% rebalancing cost on a monthly basis. Thus, implementing this trading strategy could be very costly. We decided not to further examine the possibility of exploiting potential arbitrage opportunities using the IVOL sorted portfolios as this is far beyond the main purpose of our thesis.

[16] Specifically, the average trade involves a round-trip transaction cost of about 1% for the bid-ask spread and roughly 3% in further commissions. At aggregate level, round-trip trades cost 1% for the bid-ask spread and roughly 1.4% in further commissions. In order to develop more consistent descriptive statistics on percentage commissions, the authors decided to exclude trades of less than $1,000. If these small trades were included, the round-trip commission cost would have been, on average, of 5% (2.1% for purchases and 3.1% for sales).

Table 9: Summary statistics of the various ranking methodologies

This table presents summary statistics and regression results of the zero-cost portfolio P1-P5 sorted by idiosyncratic volatility, systematic beta risk and total realised volatility.

Summary of P1 - P5 portfolios

				beta sorted IVOL			
	CAPM IVOL	**FF-3 IVOL**	**BETA**	**LOW**	**MID**	**HIGH**	**VOL**
Arithmetic Mean	1.10%	1.32%	0.19%	0.93%	1.72%	1.00%	0.17%
Geometric Mean	1.43%	1.56%	0.34%	1.26%	2.15%	1.45%	0.34%
Median	1.22%	1.51%	0.26%	1.52%	1.59%	1.15%	0.25%
Skewness	-0.44	-0.45	-0.20	-0.59	-0.10	-0.09	-0.22
Kurtosis	1.79	1.83	1.84	1.47	2.28	1.91	1.54
Volatility	7.63%	6.52%	6.32%	8.98%	9.45%	9.24%	6.21%
CAPM							
Alpha	1.11%	1.32%	0.20%	0.93%	1.72%	1.01%	0.18%
	[2.35]	[3.27]	[0.58]	[1.66]	[2.93]	[1.76]	[0.54]
Mkt	-0.30	-0.25	-0.57	-0.24	-0.32	-0.32	-0.58
	-[3.52]	-[3.38]	-[9.07]	-[2.40]	-[2.97]	-[3.11]	-[9.51]
FF-3							
Alpha	0.95%	1.18%	0.24%	0.83%	1.56%	0.96%	0.19%
	[1.98]	[2.88]	[0.67]	[1.46]	[2.62]	[1.63]	[0.55]
Mkt	-0.32	-0.25	-0.55	-0.29	-0.36	-0.32	-0.56
	-[3.63]	-[3.39]	-[8.55]	-[2.79]	-[3.33]	-[2.98]	-[9.03]
SMB	-0.08	-0.10	-0.05	0.13	0.06	-0.06	-0.05
	-[0.66]	-[1.04]	-[0.56]	[0.95]	[0.42]	-[0.45]	-[0.66]
HML	0.14	0.09	-0.10	0.27	0.29	0.00	-0.07
	[1.24]	[0.88]	-[1.17]	[1.99]	[2.00]	[0.02]	-[0.83]

5.1 IVOL behaviour in the pre and post financial crisis

In table 10 and 11 we examine the IVOL behaviour during the pre and post financial crisis. In order to understand how the IVOL has affected the return of individual stocks depending on different market conditions, we perform the same tests as the ones implemented in the previous section, analyzing two reduced samples: from Jan 1992 to Jun 2007 (pre-financial crisis) and from Jul 2007 to Nov 2012 (financial crisis). For what concerns such samples, we can highlight the fact that the alpha generated during the pre-financial crisis period is nor economically positive neither statistically significant (weak t-statistics). On the contrary, a zero-cost investment strategy held during the financial crisis - long in low IVOL stocks and short in high

IVOL ones - earns an economically positive and statistically significant abnormal return versus both the CAPM model and the FF-3 one.

Table 10: IVOL sorted portfolio quintiles (vs CAPM) pre and post financial crisis

This table presents summary statistics and regression results of the IVOL sorted portfolio quintiles P1 to P5. The idiosyncratic volatility has been measured through the CAPM. P1 represents the portfolio quintile with the lowest idiosyncratic risk while P5 is the one characterized by the highest IVOL. The P1-P5 portfolio provides the excess return of a zero-cost investment strategy long in P1 and short in P5. In the notation below, the first word illustrates the methodology that has been used to measure the IVOL; the second denotes what is sorted, while the third describes the model applied to calculate the alphas. For example, "CAPM IVOL FF-3" means that portfolios are IVOL sorted and that the idiosyncratic risk is measured through the CAPM while the alphas are computed against the FF-3.

	Low	Ranking on IVOL relative to CAPM			High	
	Pre-Crisis (Jan 1992 - Jun 2007)					
	P1	**P2**	**P3**	**P4**	**P5**	**P1-P5**
CAPM IVOL CAPM						
Alpha	0.34%	0.14%	0.00%	0.36%	-0.06%	0.40%
	[2.22]	[0.68]	[0.02]	[1.11]	-[0.12]	[0.71]
Mkt	0.88	1.02	1.08	1.12	1.08	-0.2
	[29.32]	[26.12]	[23.76]	[17.89]	[10.45]	-[1.79]
CAPM IVOL FF-3						
Alpha	0.56%	0.09%	0.00%	0.33%	-0.06%	0.63%
	[3.65]	[0.48]	-[0.02]	[1.23]	-[0.14]	[1.28]
Mkt	0.90	1.00	1.13	1.01	1.11	-0.21
	[29.78]	[28.39]	[23.78]	[19.31]	[12.52]	-[2.17]
	Post-Crisis (Jul 2007 - Nov 2012)					
	P1	**P2**	**P3**	**P4**	**P5**	
CAPM IVOL CAPM						
Alpha	0.42%	0.04%	-0.64%	-1.15%	-2.42%	2.85%
	[1.36]	[0.10]	-[1.45]	-[2.26]	-[2.77]	[3.53]
Mkt	0.86	0.95	1.01	1.18	1.25	-0.39
	[18.28]	[17.60]	[15.13]	[15.33]	[9.49]	-[3.22]
CAPM IVOL FF-3						
Alpha	0.51%	-0.38%	-0.26%	-0.79%	-2.76%	3.27%
	[1.68]	-[1.00]	-[0.66]	-[1.36]	-[3.92]	[4.92]
Mkt	0.89	0.96	1.00	1.18	1.12	-0.23
	[19.26]	[16.82]	[16.97]	[13.43]	[10.54]	-[2.27]

Table 11: IVOL sorted portfolio quintiles (vs FF-3) pre and post financial crisis

This table presents summary statistics and regression results of the IVOL sorted portfolio quintiles P1 to P5. The idiosyncratic volatility has been measured through the FF-3. P1 represents the portfolio quintile with the lowest idiosyncratic risk while P5 is the one characterized by the highest IVOL. The P1-P5 portfolio provides the excess return of a zero-cost investment strategy long in P1 and short in P5. In the notation below, the first word illustrates the methodology that has been used to measure the IVOL; the second denotes what is sorted, while the third describes the model applied to calculate the alphas. For example, "CAPM IVOL FF-3" means that portfolios are IVOL sorted and that the idiosyncratic risk is measured through the CAPM while the alphas are computed against the FF-3.

	Low		**Ranking on IVOL relative to FF-3**		High	
			Pre-Crisis (Jan 1992 - Jun 2007)			
	P1	**P2**	**P3**	**P4**	**P5**	**P1-P5**
FF-3 IVOL CAPM						
Alpha	0.38%	0.17%	-0.01%	0.43%	0.34%	0.04%
	[2.42]	[0.80]	-[0.40]	[1.31]	[0.66]	[0.06]
Mkt	0.88	1.02	1.07	1.1	1.16	-0.28
	[28.14]	[24.96]	[22.51]	[17.01]	[11.16]	-[2.51]
FF-3 IVOL FF-3						
Alpha	0.59%	0.15%	-0.02%	0.32%	0.24%	0.35%
	[3.73]	[0.84]	-[0.08]	[1.16]	[0.53]	[0.71]
Mkt	0.90	1.00	1.12	1.00	1.15	-0.26
	[28.45]	[27.49]	[22.55]	[18.23]	[12.82]	-[2.64]
			Post-Crisis (Jul 2007 - Nov 2012)			
	P1	**P2**	**P3**	**P4**	**P5**	
FF-3 IVOL CAPM						
Alpha	0.53%	0.15%	-0.45%	-0.77%	-1.65%	2.16%
	[1.61]	[0.40]	-[0.97]	-[1.47]	-[1.87]	[2.67]
Mkt	0.86	0.95	1.01	1.17	1.23	-0.37
	[18.10]	[17.39]	[15.31]	[15.54]	[9.93]	-[3.22]
FF-3 IVOL FF-3						
Alpha	0.62%	-0.29%	-0.15%	-0.24%	-2.26%	2.89%
	[1.91]	-[0.71]	-[0.36]	-[0.41]	-[3.12]	[4.16]
Mkt	0.89	0.96	1.00	1.17	1.10	-0.22
	[19.03]	[16.61]	[16.71]	[13.93]	[10.65]	-[2.18]

It therefore seems clear that the mispricing of idiosyncratic risk in our study is predominantly guided by the performance of the short side of our portfolio during the Jul 2007 - Nov 2012 period.

6. Conclusion

We have analyzed the pricing of the idiosyncratic risk - which is relatively new for the GIPS markets - in its main characteristics, behavior and consequences. The main findings include both evidence of continuity and interesting divergences from the results of academic research. Our thesis aims to promote more understanding in the studies of low volatility anomalies by examining not only the role of the IVOL within the financial markets but also how it is related to the systematic market beta and the total realised volatility. We exhibit a weak relationship between the average performances among the sub-portfolios sorted on the previous month idiosyncratic volatility. Moreover, we find that a zero-cost investment strategy, where an investor goes long in low IVOL securities and short in high IVOL ones, earns economically positive and statistically significant alpha when evaluated against both the CAPM and the Fama-French three factor model. This suggests that we can accept our null hypothesis which states that there is a non-neutral relationship between IVOL and excess returns. We can also argue that the IVOL mispricing is largest in high IVOL securities, which confirms the behavioral finance research on overconfidence to explain why low volatility stocks often outperform high volatility ones.

We have also highlighted the fact that the idiosyncratic risk is positively related with the market beta, and concluded that portfolios ranked on systematic risk are not mispriced, consistent with market efficiency theories. In other words, since the market beta is not mispriced, no spurious relationship between IVOL and alpha emerges. We can therefore state that the mispricing of the IVOL sorted sub-portfolios is completely due to the irrational investors' demand for idiosyncratic volatility. Moreover, our results point toward an inverted risk-return relationship in the GIPS equity markets. Indeed, if we consider the difference between the returns of portfolio sorted on past IVOL, market beta and total realised volatility we can see a decreasing trend in the arithmetic mean as we move from portfolios with lower risk to portfolios with higher risk. In other words, sub-portfolios with lower IVOL, beta and total realised volatility obtain, on average, statistically larger performance. The weak risk-return relationship is clarified in our empirical analysis where the CAPM and the FF-3 fail to price IVOL sorted portfolios and succeed in pricing beta and total volatility sorted ones.

The presented results make it possible to implement the different investment strategies depending on the investor's risk aversion and the agent's typology of risk-reward preferences. For example, for investors supporting the mean variance portfolio theory, our findings would suggest investing in low market beta stocks and low total realised volatility securities in order to improve their utility function as these portfolios have demonstrated to generate a better risk-return relationship. Agents who are willing to invest in value securities (high book to market stocks) are advised to go long on low IVOL securities. Conversely, agents who dislike exposing their portfolios to value securities could buy high IVOL stocks while avoiding low IVOL investments. In other words, our empirical analysis tells us that if an investor is willing to create a hedge against value stocks exposure, he should go long on securities with higher idiosyncratic volatility and short on low IVOL stocks.

In conclusion, we think that an interesting issue for future studies would be to further analyze the potential arbitrage opportunities that investors could exploit when the idiosyncratic volatility is mispriced. As already mentioned, our research demonstrates that, in the period considered, a trading strategy involving a long position in low IVOL and a short position in high IVOL implies an overly high turnover in order to be economically profitable. The next logical step in such an analysis would therefore be to test whether a similar investment strategy, but with a longer holding period, would produce different results and investors would be able to realise a profit after trading costs. Moreover, we would suggest conducting analyses on how specific trading ideas implying positions in low IVOL securities could be reconciled with value stocks investing. For a long time, economists and researchers have been studying high book to market stocks as they used to generate economically large and statistically significant performances not explained by the Capital Asset Pricing Model. At the same time, low IVOL stocks have become increasingly attractive, not only among scholars but also among investors because of their peculiar feature of earning above-average performances without the need to bear above-average risk. We would, therefore, encourage evaluating how the low volatility anomaly could be exploited in order to further enhance the performance on value investment positions.

Finally, an interesting topic for practitioners would be to closely examine the role of investor sentiment in reconciling the relation between excess return of securities and idiosyncratic risk. For example, Hou and Loh (2001) argue that investors' lottery preferences, short-term return reversal, and earnings shocks can explain roughly the 60-80% of the negative idiosyncratic volatility-return relationship. In other words, we would suggest testing the idiosyncratic volatility behavior during time of high investor sentiment compared to low sentiment periods. We are convinced that, particularly in the cultures of the GIPS countries, the market sentiment can play a crucial role in explaining the IVOL puzzle.

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Data sources:

Bloomberg

DataStream

Thomson One

World Bank database (http://data.worldbank.org/)

8. Appendix

Figure 4: Selection of macroeconomic indicators for the GIPS markets

Data are rebased to 100 at 1992 level.

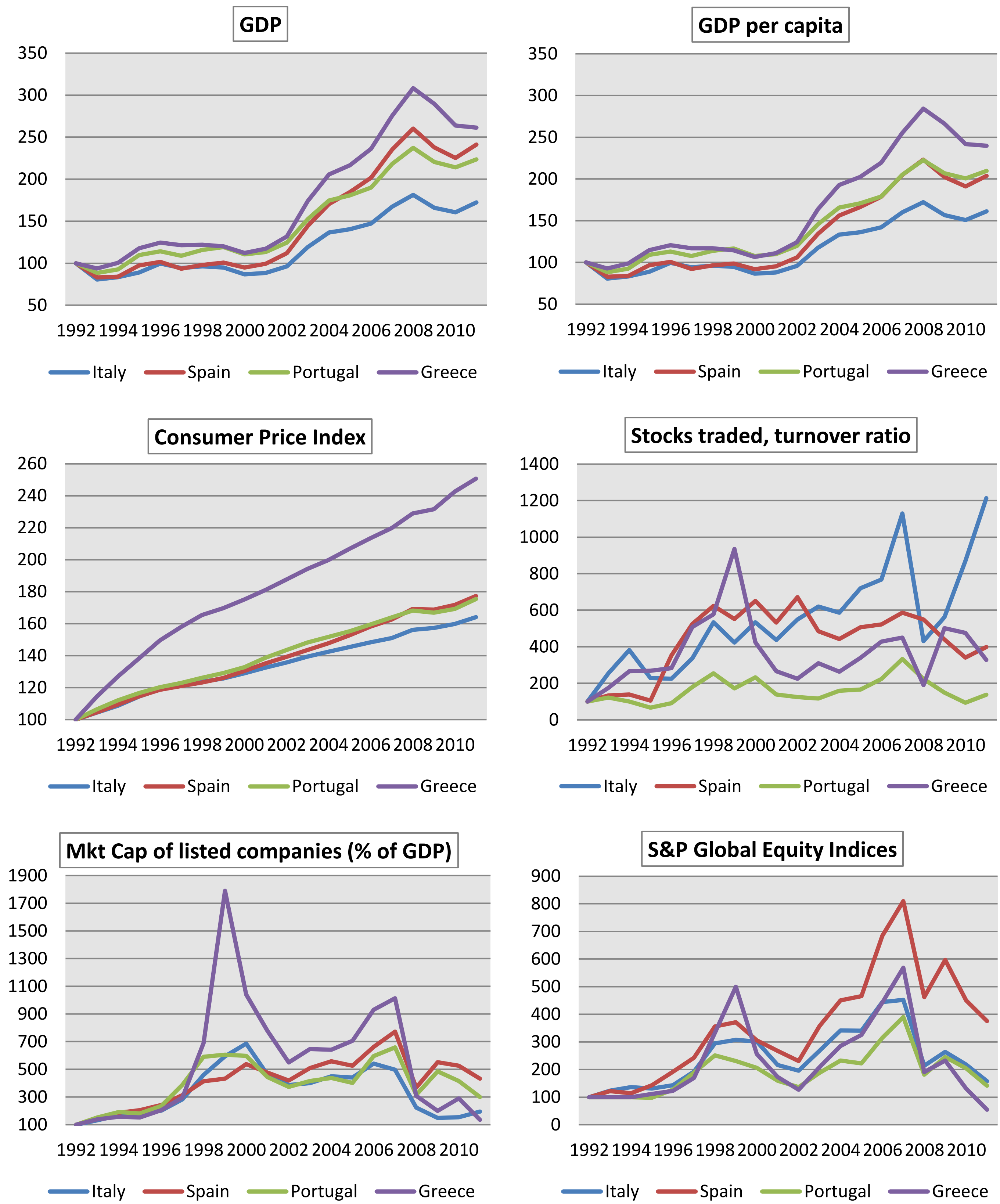


Figure 5: Presentation of the GIPS Total Return Index

The chart presents the development of the GIPS Index Gross TR and the GIPS Index Excess TR.

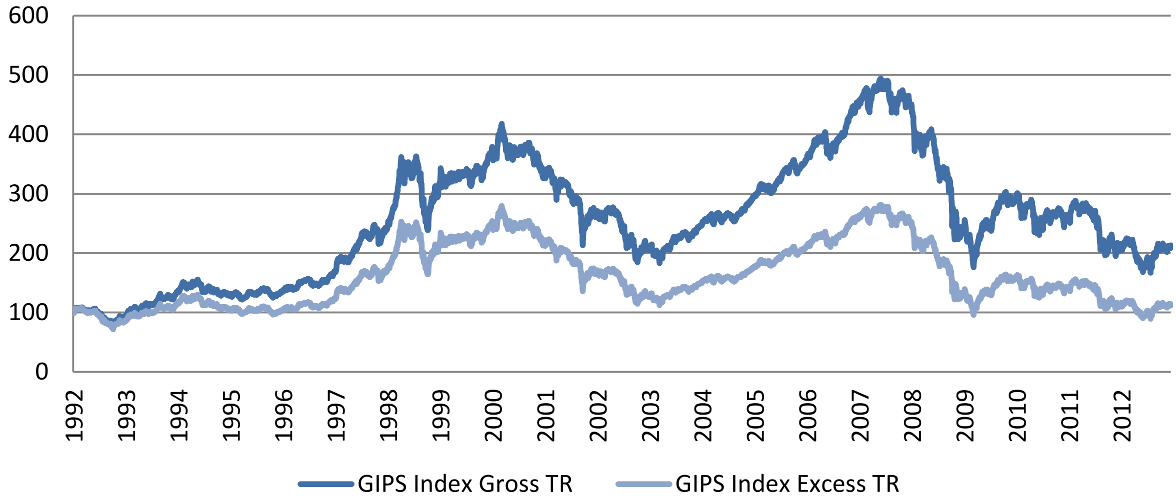


Figure 6: Equal and Value-Weighted portfolio IVOL relative to the CAPM

The two charts below plot the idiosyncratic volatility against the CAPM for equal and value-weighted portfolio for the period January 1992 to November 2012.

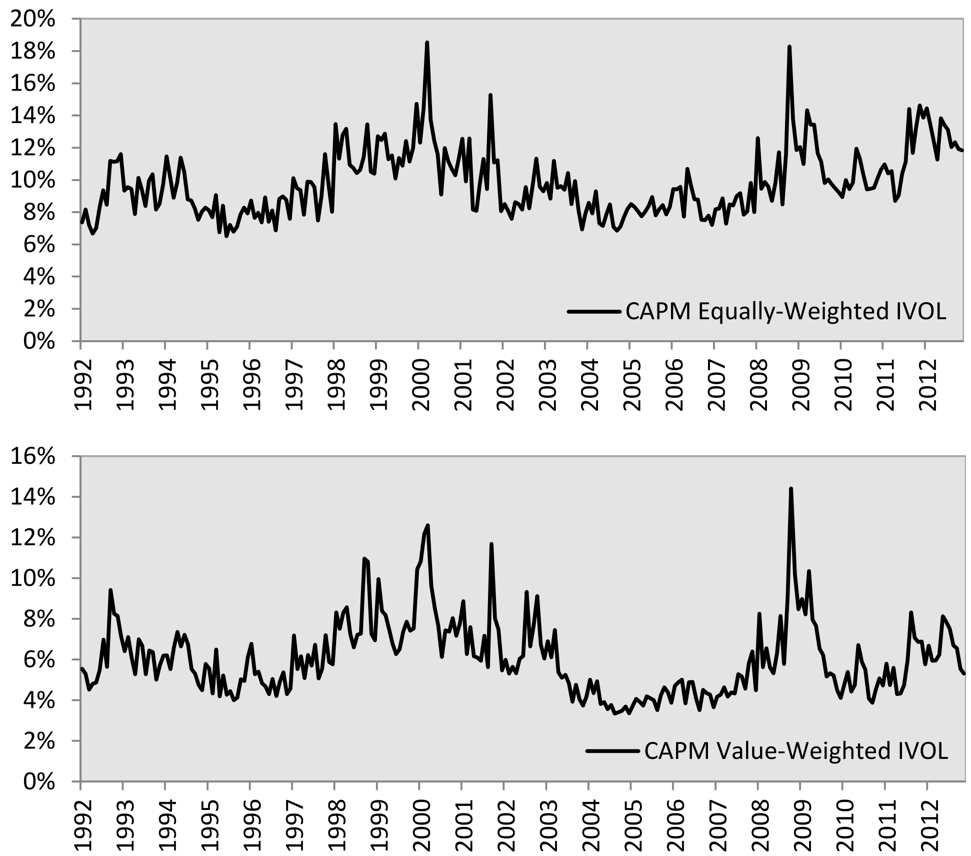
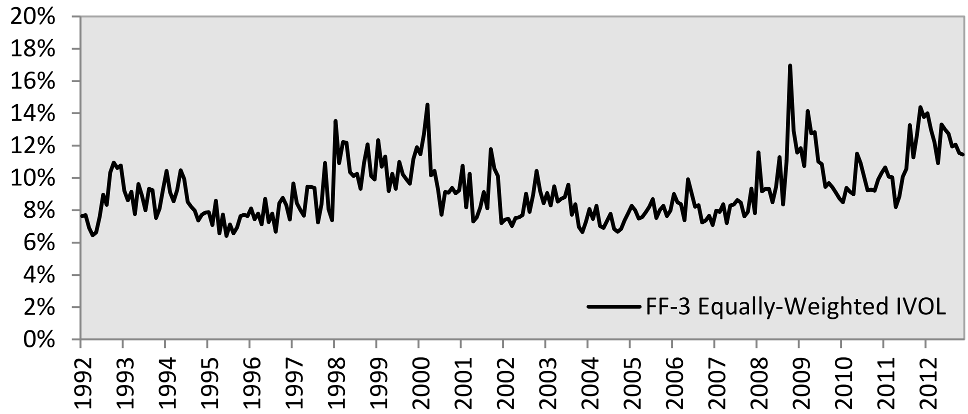


Figure 7: Equal and Value-Weighted portfolio IVOL relative to the FF-3

The two charts below plot the idiosyncratic volatility against the FF-3 for equal and value-weighted portfolio for the period January 1992 to November 2012.



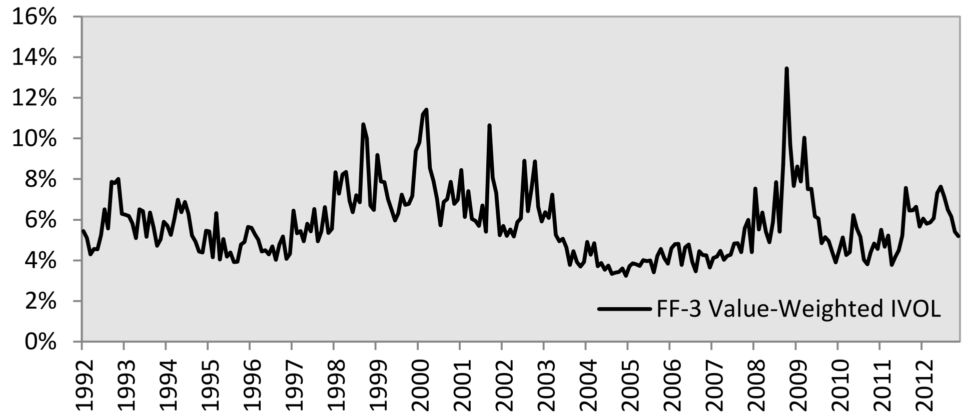


Table 12: Descriptive statistics for the various IVOL estimates

	Summary Statistics of Idiosyncratic Volatility			
	CAPM EW IVOL	CAPM VW IVOL	FF-3 EW IVOL	FF-3 VW IVOL
Arithmetic Mean	9.86%	6.05%	9.22%	5.76%
Median	9.50%	5.71%	8.95%	5.43%
Std Dev	2.07%	1.83%	1.83%	1.67%
Skew	0.99	1.22	1.01	1.20
Kurt	1.34	2.22	0.99	2.09
1st Quartile	8.24%	4.72%	7.80%	4.46%
3rd Quartile	11.19%	7.13%	10.26%	6.57%
	Correlation Matrix			
	CAPM EW IVOL	CAPM VW IVOL	FF-3 EW IVOL	FF-3 VW IVOL
CAPM EW IVOL	1.00			
CAPM VW IVOL	0.81	1.00		
FF-3 EW IVOL	0.96	0.74	1.00	
FF-3 VW IVOL	0.81	0.99	0.75	1.00

Table 13: List of Italian companies included in the sample

Italian Companies			
A2A	CARRARO	GEOX	PIQUADRO
ACEA	CATTOLICA ASSICURAZIONI	GIOVANNI CRESPI	PIRELLI
ACEGAS-APS	CDC	GRANDI VIAGGI	PMS
ACOTEL GROUP	CEMBRE	GRUPPO CERAMICHE RICCHET	POLIGRAFICA S F
ACQUE POTABILI	CEMENTIR HOLDING	GRUPPO EDIT.L'ESPRESSO	POLIGRAFICI EDITORIALE
ACSM-AGAM	CENTRALE DEL LATTE DI TRO.	GRUPPO MUTUIONLINE	POLIGRAFICI PRINTING
AEDES LIGURE LOMBARDA	CENTRO HL DISTRIBUZIONE	HERA	POLTRONA FRAU
AEFFE	CIA	IKF	PRELIOS
AEROPORTO DI FIRENZE	CIR CIE.INDI.RIUN.	IL SOLE 24 ORE	PREMAFIN FINANZ.HOLDING
ALERION CLEAN POWER	CLASS EDITORI	IMA INDUA.MACCHINE	PREMUDA
AMBROMOBILIARE	COBRA AUTOMOTIVE TECHS.	IMMOBILIARE GRANDE DISTRIB.	PRIMA INDUSTRIE
AMPLIFON	COFIDE GRUPPO DE BENEDET	IMMSI	PRYSMIAN
ANSALDO STS	COMPAGNIA ASSICURAZIONE	IMPREGILO	RAFFAELE CARUSO
ARNOLDO MONDADORI EDI.	COMPAGNIA DELLA RUOTA	INDESIT COMPANY	RATTI
ASCOPIAVE	CONAFI PRESTITO	INDUSTRIA E INNOVAZIONE	RCF GROUP
ASSICURAZIONI GENERALI	CREDITO BERGAMASCO	INTEK GROUP	RECORDATI INDUA.CHIMICA
ASTALDI	CREDITO EMILIANO	INTERPUMP GROUP	RENO DE MEDICI
ATLANTIA	CSP INTERNATIONAL	INTESA SANPAOLO	REPLY
AUTOGRILL	DADA	INVESTIMENTI E SVILUPPO	RETI TELEMATICHE ITALIAN
AUTOSTRADA TORINO-MILANO	DAMIANI	IRCE	RIZZOLI CORRIERE DELLA SERA
AUTOSTRADE MERIDIONALI	DANIELI	IREN	ROSSS
AZIMUT HOLDING	DATALOGIC	ISAGRO	SABAF
B&C SPEAKERS	DAVIDE CAMPARI MILANO	IT WAY	SADI SERVIZI INDUSTRIALI
BANCA CARIGE	DE LONGHI	ITAL TBS TELEMATIC &. BIOMED.	SAES GETTERS
BANCA FINNAT EURAMERICA	DEA CAPITAL	ITALCEMENTI FABBRICHE RIUNITE	SAFILO GROUP
BANCA GENERALI	DELCLIMA	ITALMOBILIARE	SAIPEM
BANCA IFIS	DIASORIN	K R ENERGY	SALVATORE FERRAGAMO
BANCA INTERMOBILIARE	DIGITAL BROS	LA DORIA	SARAS
BANCA MONTE DEI PASCHI	DMAIL GROUP	LANDI RENZO	SAVE-AEP.DI VNZ.MRC.POLO
BANCA POPOLARE DI MILANO	EEMS ITALIA	LE BUONE SOCIETA	SCREEN SER.BCAST.TEC.
BANCA PPO.DI SONDRIO	EI TOWERS	LOTTOMATICA GROUP	SERVIZI ITALIA
BANCA PPO.DI SPOLETO	EL EN	LUXOTTICA	SIAS
BANCA PPO.EMILIA ROMAGNA	ELICA	M & C	SNAI
BANCA PPO.ETRURIA LAZIO	EMAK	MADE IN ITALY	SNAM
BANCA PROFILO	ENEL	MAIRE TECNIMONT	SO.AEREOPORTO TOSCANO
BANCO DI SARDEGNA RSP	ENEL GREEN POWER	MARCOLIN	SOGEFI
BANCO POPOLARE	ENERVIT	MARR	SOL
BASICNET	ENGR.INGEGNERIA INFORMA	MEDIACONTECH	SORIN
BASTOGI	ENI	MEDIASET	SS LAZIO
BCA.PICCOLO CDT.VALTELL	ERG	MEDIOBANCA BC.FIN	TAMBURI INV.PARTNERS
BEE TEAM	ERGYCAPITAL	MEDIOLANUM	TELECOM ITALIA
BEGHELLI	ESPRINET	MERIDIE	TELECOM ITALIA MEDIA
BENI STABILI	EUROTECH	METHORIOS	TERNA RETE ELETTRICA NAZ
BEST UNION	EXOR PREF.	MID INDUSTRY CAPITAL	TERNIENERGIA
BIALETTI INDUSTRIE	EXPRIVIA	MITTEL	TESMEC
BIANCAMANO	FALCK RENEWABLES	MOLMED	TOD'S
BIESSE	FEDON (PAR)	MONDO TV	TREVI FIN INDUSTRIALE
BNC.DI DESIO E DELB.	FIAT	MONRIF	TXT E-SOLUTION
BOERO BARTOLOMEO	FIAT INDUSTRIAL	MONTEFIBRE	UNICREDIT
BOLZONI	FIDIA	NEUROSOFT	UNIONE ALBERGHI ITALIANI
BONIFICHE FERRARESI	FIERA MILANO	NEWRON PHARMACEUTICALS	UNIONE DI BANCHE ITALIAN
BORGOSESIA RSP	FINMECCANICA	NICE	UNIPOL GRUPPO FINANZIARI
BRIOSCHI SVILUPPO IMMBL	FINTEL ENERGIA GROUP	NOEMALIFE	VALSOIA
BRUNELLO CUCINELLI	FIRST CAPITAL	NOVA RE	VIANINI INDR.
BUZZI UNICEM VINCOLI	FNM	OLIDATA	VIANINI LAVORI
CAD IT	FONDIARIA-SAI	PANARIA GP.INDUSTR.CRMH.	VINCENZO ZUCCHI
CAIRO COMMUNICATION	FRENDY ENERGY	PARMALAT	VITA SOCIETA EDITORIALE
CALEFFI	FRENI BREMBO	PIAGGIO	VITTORIA ASSICURAZIONI
CALTAGIRONE	GAS PLUS	PIERREL	YOOX
CALTAGIRONE EDITORE	GEFRAN	PININFARINA	ZIGNAGO VETRO
CAM-FIN	GEMINA		

Table 14: List of Spanish companies included in the sample

Spanish Companies			
ABENGOA	CIA GEN.DE INVERS.SICAV	GRIFOLS	NICOLAS CORREA
ABERTIS INFRAESTRUCTURAS	CIA LOG.DE HICRS.CLH	GRINO ECOLOGIC	OBRASCON HUARTE LAIN
ACCIONA	CIA.VINICOLA DEL NORTE DE ESP.	GRUPO CATALANA OCCIDENTE	PAPELES Y CARTONES DE EUROPA
ACERINOX 'R'	CIE AUTOMOTIVE	GRUPO NOSTRUM RNL SA	PESCANOVA
ACS ACTIV.CONSTR.Y SERV.	CLEOP	GRUPO TAVEX	PRIM
ADOLFO DOMINGUEZ	CLINICA BAVIERA	HULLERA VASCO LEONESA LTD.DATA	PROMOTORA DE INFIC.
ADVEO GROUP INTERNACIONA	CODERE SA	IBERDROLA	PROSEGUR
AHORRO FAMILIAR LIMITED DATA	CONST Y AUXILIAR DE FERR	IBERPAPEL GESTION	QUABIT INMOBILIARIA
ALMIRALL	CORPN.DERMOESTETICA	IMAGINARIUM	REALIA BUSINESS
ALZA REAL ESTATE	CORPORACION FINCA.ALBA	INDITEX	RED ELECTRICA CORPN.
AMADEUS IT HOLDING	DAMM	INDRA SISTEMAS	RENTA 4 SERV.DE INVN.
AMPER	DEOLEO	INMOBILIARIA DEL SUR LIMITED	REPSOL YPF
ANTENA 3 DE TELEVISION	DINAMIA CAPITAL PRIVADO	INMOFIBAN	SACYR VALLEHERMOSO
ANTEVENIO	DISTRIBUIDORA INTNAC.DE ALIM.	INMOLEVANTE LIMITED DATA	SECUOYA GPO.DE COMCIOS.
AYCO GRUPO INMOBILIARIO	DOGI INTL.FABRICS	INVERFIATC	SOLARIA ENERGIA
AZKOYEN	DURO FELGUERA	INVERS.MOBILIARI BARCINO LIMITED	SOTOGRANDE
BANCO DE SABADELL	EBRO FOODS	INYPSA INFORMES Y PROYECTOS	TECNICAS REUNIDAS
BANCO ESPANOL DE CREDITO	EDP RENOVAVEIS	LBOS.FARMACEUTICOS ROVI	TECNOCOM TC.Y ENERGIA
BANCO POPULAR ESPANOL	ELECNOR	LETS GOWEX	TELEFONICA
BANCO SANTANDER	ENAGAS	LINGOTES ESPECIALES	TUBACEX
BANKIA	ENCE ENERGIA Y CELULOSA	LIWE ESPANOLA LIMITED DATA	TUBOS REUNIDOS
BANKINTER 'R'	ENDESA	LUMAR NATURAL SEAFOOD	UNION CATALANA DVL.
BARON DE LEY	EUROESPES	MAPFRE	UNION EUROPEA DE INVERS
BBV.ARGENTARIA	FAES FARMA	MEDCOMTECH SA	URALITA
BIONATURIS	FERROVIAL	MELIA HOTELS INTL.	URBAR INGENIEROS LTD DATA
BIOSEARCH	FERSA ENERGIAS RNVBL.	METROVACESA	URBAS GUADAHERMOSA
BODEGAS BILBAINAS	FIN.INMUEBLES CISNEROS	MINERSA	VERTICE TRSTA.GRADOS
BODEGAS RIOJANAS	FLUIDRA	MIQUEL Y COSTAS	VIDRALA
BOLSAS Y MERCADOS ESPANOLES	FOMENTO CONSTR.Y CNTR.	MONTEBALITO	VISCOFAN
CAIXABANK	FUNESPANA	MSET.ESP.COMUNICACION	VOCENTO
CAMPOFRIO FOOD GROUP	GAMESA CORPN.TEGC.	NATRA	VUELING AIRLINES
CEMENTOS MOLINS	GAS NATURAL SDG	NATRACEUTICAL	ZARDOYA OTIS
CEMENTOS PORT.VALDERR.	GEN. DE ALQUILER DE MAQUINARIA	NEURON BIOPHARMA	ZELTIA
CEVASA	GPO.EMPRESARIAL SAN JOSE	NH HOTELES (EX-COFIR)	ZINKIA ENTERTAINMENT

Table 15: List of Portuguese companies included in the sample

Poruguese Companies			
ALTRI SGPS	F RAMADA INVESTIMENTOS	MOTA ENGIL SGPS	SOARES DA COSTA
BANCO BPI	FENALU LIMITED DATA	NOVABASE	SOCIETY AGUAS DA CURIA LIM.
BANCO COMR.PORTUGUES 'R'	GALP ENERGIA SGPS	OLIVEIRA AND IRMAO LIMITED DATA	SONAE CAPITAL
BANCO ESPIRITO SANTO	GI.GLB.INTEL.TECHS.SGPS	OREY ANTUNES	SONAE COM LIMITED DATA
BANIF-SGPS	IBERSOL - SGPS	PORTUCEL EMPRESA	SONAE INDUSTRIA SGPS
BRISA-AUTSDS.DE PORTUGAL	IMMOBL.CON.GRAO-PARA	PORTUGAL TELECOM SGPS	SONAE SGPS
CIMENTOS DE PORTL.SGPS	IMPRESA SGPS	PROGADO LIMITED DATA	SONAGI LIMITED DATA
CIPAN LIMITED DATA	INAPA	RACOES PROGADO LIMITED DATA	SOPRAGOL LIMITED DATA
CONDURIL ENGENHARIA LIM	JERONIMO MARTINS	REDITUS	SUMOL COMPAL
COPAM LIMITED DATA	LITHO FORMAS PORTUGUESA LIM.	REN	TEIXEIRA DUARTE
CORTICEIRA AMORIM	MARTIFER	SAG GEST	TOYOTA CAETANO
EDP ENERGIAS DE PORTUGAL	MEDIA CAPITAL	SEMAPA	ZON MULTIMEDIA
ESTORIL SOL 'B'			

Table 16: List of Greek companies included in the sample

Greek Companies			
AEGEAN AIRLINES CR	ELASTRON	INTERWOOD-XYLEMBORIA	PEGASUS PUBLISHING
AEGEK CR	ELBISCO HOLDING	INTRACOM CONSTRUCTIONS	PERSEUS SPECIALTY FOODS
AEOLIAN INVESTMENT FUND	ELEFTHERI TILEORASI	INTRACOM HOLDINGS	PETROS PETROPOULOS
AGRI.BANK OF GREECE	ELFICO	INTRALOT INTGRTD.SYSV.	PG NIKAS
AKRITAS	ELGEKA CR	IONIAN HOTEL	PHILIPPOS NAKAS
ALCO HELLAS	ELINOIL	J & P AVAX	PIPE WORKS CR
ALP.GIS.PWR.&.ENCR.SYS.	ELLAKTOR	JUMBO	PIRAEUS PORT AUTH.CR
ALPHA ASTIKA AKINITA	ELTON CR	KARATZIS	PLAISIO COMPUTERS
ALPHA BANK	ELTRAK PROPERTY	KARELIA TOBACCO	PRAXITELIO HOSPITAL CR
ALPHA TRUST INV.SERVICES	ELVAL-HELLENIC ALUM.IND.	KARMOLEGOS	PROFILE SYS.&.SOFTWARE
ALPHA TST.ANDROMEDA IT.	ELVE	KATHIMERINI	PROODEFTIKH TCHN.CO.
ALSINCO	ELVIEMEK LNDV.LOGIST.PK.	KEKROPS	PROTON BANK
ALUMIL ALUMINIUM IND.	ENTERSOFT	KIRIACOULIS SHIPPING	PUBLIC POWER
ANEK LINES CR	EPSILON NET	KLEEMAN HELLAS	QUALITY & RELIABILITY
AS COMPANY	ETEM	KLOUKINAS LAPPAS	QUEST HOLDINGS CR
ASTIR PCE.VOULIAGMENI	EUROBANK PROPS.REIT.	KORDELLOS CH BROS	REAL ESTATE MAN.&.HLDG.
ATH.WT.SUPPLY & SEWAGE	EUROCONSULTANTS	KORRES NTRL.PRDS.	REVOIL
ATHENA	EURODRIP	KREKA	RILKEN
ATHENS MEDICAL CENTRE	EUROLINE INVESTMENT CR	KRETA FARM	S&B INDUSTRIAL MRLS.
ATLANTIC SUPERMARKET	EUROMEDICA	KRI KRI CR	SANYO HELLAS HOLDING
ATTI-KAT	EUROPEAN REL.GEN.INS.CR	KRITON ARTOS	SCIENS INTL.INVS.&HDG.
ATTICA BANK	EVROFARMA	KTIMA KOSTAS LAZARIDIS	SELECTED TEXTILE
ATTICA HOLDINGS	FASHION BOX CR	LAMDA DEVELOPMENT	SELONDA AQUACULTURE
ATTICA PUBLICATIONS	FG EUROPE	LAMPSA HOTEL	SFAKIANAKIS CB
AUDIO VISUAL ENTS.	FHL H KRKD.MRBL.GRANITE	LANAKAM CB	SHEET STEEL
AUTOHELLAS	FIERATEX	LAVIPHARM CR	SHELMAN PROPERTY
AVENIR LEIS.& ENTM.INTC.	FINTEXPORT	LIVANI PUBLISHING ORG	SIDENOR
BABIS VOVOS INTL.TCHN.	FLEXOPACK	LOGISMOS INFO.SYSTEMS	SIDMA
BALKAN REAL ESTATE	FLOUR MILLS KEPENOS	LOULIS MILLS	SPACE HELLAS
BANK OF GREECE	FOODLINK	MARITIME CO.OF LESVOS	SPIDER
BIOKARPET	FORTHNET	MATHIOS	SPRIDER STORES
BIOMED.& ROBOTICS TECH.	FOURLIS HOLDING	MEDICON HELLAS	STEALTH GAS
BIOTER	FRIGOGLASS	MEDITERRA	STELIOS KANAKIS
BITROS HOLDING CR	G E DIMITRIOU	METKA	T BANK
BYTE COMPUTER	GALAXIDI FISH FARMING	MEVACO METALLURGICAL	TECHNICAL OLYMPIC
C CDSL.&.SONS CARDICO	GEK TERNA HLDG.RLST.CON.	MICHANIKI CR	TECHNICAL PUBS.
CARS MCYCLES.MAR.ENN.	GEKE	MIG REAL ESTATE R E I C	TELETYPOS
CENTRIC HOLDINGS	GENERAL BANK OF GREECE	MINERVA KNITWEAR	TERNA ENERGY
CHATZIKRANIOTIS MILLS	GENERAL COML.& INDL.	MINOAN LINES	TEXAPRET
COCA-COLA HLC.BT.	GR SARANTIS	MLS MULTIMEDIA	THE HSE.OF AGRIC.SPIROY
CORINTH PIPE WORKS	HAIDEMENOS	MOCHLOS	THESSALONIKI PORT AUTH.
CPI COMPUTER	HALCOR	MOTOR OIL	THESSALONIKI WATER SUPP.
CRETE PLASTICS	HATZIOANNOU CR	MYTILINEOS HOLDINGS	THRACE PLASTICS
CYCLON HELLAS	HELLENIC CABLES	N LEVENTERIS CR	TITAN CEMENT CR
DAIOS PLASTICS	HELLENIC EXCHANGES HDG.	N VARVERIS-MODA BAGNO	TRASTOR REAL ESTATE
DIAGNOS & THERAPY CAH.	HELLENIC FABRICS	NAFPAKTOS TEX.INDS.	TRIA ALPHA CR
DIAS AQUA CULTURE	HELLENIC FISH FARMING	NEORION HOLDINGS	UNIBIOS HOLDINGS
DIONIC	HELLENIC PETROLEUM	NEWSPHONE HELLAS	VARANGIS
DOMIKI KRITIS	HELLENIC SUGAR IND.	NEXANS HELLAS	VARVARESSOS EUR SPNMILS.
DOPPLER	HELLENIC TELECOM.ORG.	NIREFS	VIDAVO HEALTH TELEMATICS
DROMEAS OFFICE FURNITURE IND.	HERACLES GEN.CEMENT	OLYMPIC CATERING	VIOHALCO CB
DRUCKFARBEN HELLAS	IASO	OPAP	VIS-CONTAINER CR
DUROS	IKTINOS HELLAS	OPTRONICS TECHNOLOGIES	VOGIATZOGLOU SYSTEMS
DUTY FREE SHOPS	ILYDA CR	PAPERPACK-TSOUKARIDIS	XK TEGOPOULOS EDTS.
E PAIRIS	INFORM P LYKOS	PARNASSOS ENTERPRISES	YALCO-CONSTANTINOU
EKTER	INTERINVEST	PASAL REAL ESTATE DEV.	ZAMPA
EL D MOUZAKIS	INTERTECH	PC SYSTEMS	

Table 17: Summary of the number of monthly observations per year

The table summaries the number of stocks with available total return index, market capitalization and book to market value for each month and year of the sample. The average number of securities included in the sample is 412. We collected 2,253,102 daily records and 103,042 monthly ones.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
1992	132	142	142	144	144	144	144	144	145	145	147	147	1992
1993	146	150	154	154	154	155	155	155	155	156	156	157	1993
1994	156	160	160	160	162	162	163	166	168	168	170	172	1994
1995	173	174	174	174	174	174	176	177	180	180	181	184	1995
1996	185	218	218	219	221	221	222	225	225	226	228	229	1996
1997	226	231	232	234	236	236	238	242	244	245	246	249	1997
1998	251	258	258	260	260	262	268	272	276	276	277	278	1998
1999	281	302	303	303	304	305	307	314	316	316	319	325	1999
2000	329	355	359	363	367	368	377	388	395	398	406	411	2000
2001	414	427	428	430	432	435	438	443	445	446	446	448	2001
2002	452	457	460	461	461	461	465	466	466	466	466	467	2002
2003	467	470	470	470	470	470	472	472	473	473	474	475	2003
2004	473	481	484	486	487	487	490	491	491	491	491	493	2004
2005	493	503	504	505	506	507	510	512	512	512	514	517	2005
2006	518	523	523	525	526	532	536	540	540	540	541	545	2006
2007	550	552	553	554	559	561	569	576	576	576	580	584	2007
2008	581	587	589	591	592	594	596	599	600	601	601	601	2008
2009	603	609	610	610	610	613	613	616	617	617	617	617	2009
2010	620	622	622	627	628	628	629	632	633	633	634	636	2010
2011	638	640	641	641	641	641	643	648	648	648	648	648	2011
2012	650	651	651	651	652	652	653	654	654	654	654		2012

Table 18: Yearly movements of securities between IVOL sorted portfolio quintiles

The idiosyncratic volatility is measured through the FF-3 model. The values describe the aggregate number of monthly movements per year.

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	
Remains	546	637	744	736	930	1029	1082	1417	1492	1769	2013	2218	2377	2569	2607	2613	2526	2848	3284	3488	3307	Remains
% of total	*39%*	*35%*	*39%*	*35%*	*37%*	*37%*	*35%*	*40%*	*35%*	*34%*	*37%*	*39%*	*41%*	*43%*	*41%*	*39%*	*36%*	*39%*	*44%*	*45%*	*46%*	*% of total*
Moves 1	521	675	685	803	968	1017	1147	1450	1548	1920	1984	2170	2236	2273	2451	2566	2636	2728	2810	2839	2690	Moves 1
% of total	*37%*	*37%*	*36%*	*39%*	*38%*	*36%*	*37%*	*40%*	*36%*	*37%*	*36%*	*39%*	*39%*	*38%*	*39%*	*38%*	*37%*	*37%*	*38%*	*37%*	*38%*	*% of total*
Moves 2	226	315	297	353	400	499	566	497	832	939	1013	886	873	838	899	1077	1282	1187	1038	1000	803	Moves 2
% of total	*16%*	*17%*	*16%*	*17%*	*16%*	*18%*	*18%*	*14%*	*19%*	*18%*	*18%*	*16%*	*15%*	*14%*	*14%*	*16%*	*18%*	*16%*	*14%*	*13%*	*11%*	*% of total*
Moves 3	82	138	147	121	149	174	240	171	352	405	358	266	238	267	274	345	495	418	247	243	225	Moves 3
% of total	*6%*	*8%*	*8%*	*6%*	*6%*	*6%*	*8%*	*5%*	*8%*	*8%*	*7%*	*5%*	*4%*	*4%*	*4%*	*5%*	*7%*	*6%*	*3%*	*3%*	*3%*	*% of total*
Moves 4	32	38	41	61	75	73	77	49	98	97	119	76	61	77	80	89	127	115	108	106	117	Moves 4
% of total	*2%*	*2%*	*2%*	*3%*	*3%*	*3%*	*2%*	*1%*	*2%*	*2%*	*2%*	*1%*	*1%*	*1%*	*1%*	*1%*	*2%*	*2%*	*1%*	*1%*	*2%*	*% of total*
Total	1407	1803	1914	2074	2522	2792	3112	3584	4322	5130	5487	5616	5785	6024	6311	6690	7066	7296	7487	7676	7142	Total

Figure 8: Monthly movements between portfolios

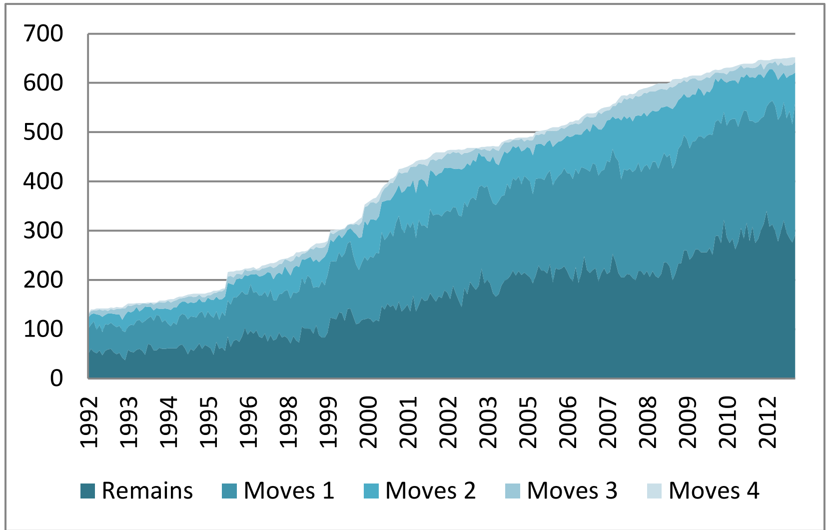


Figure 9: Distribution of the monthly movements

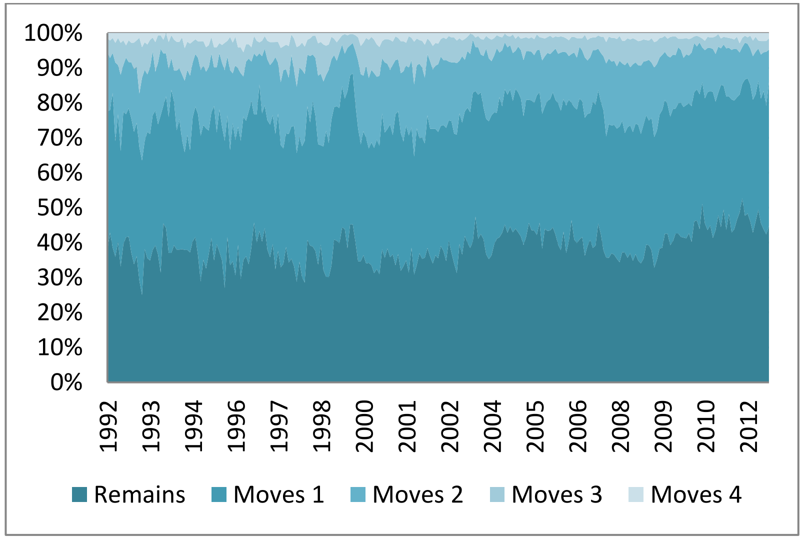


Table 19: Descriptive statistics of "factor loadings": beta MKT, SMB and HML

This table provides descriptive statistics for the value-weighted GIPS Total Return Index (Market) and the FF-3 zero-cost portfolios SMB and HML.

	Market	SMB	HML
Arithmetic Mean	0.50%	-0.07%	0.75%
Median	0.60%	-0.06%	0.63%
1st Quartile	-3.13%	-3.66%	-1.88%
3rd Quartile	3.71%	1.72%	2.71%
Volatility	5.57%	4.77%	4.87%
Kurtosis	1.14	1.51	3.35
Skewness	-0.54	0.30	0.25
Year			
1992	-1.31%	-1.86%	-0.03%
1993	2.53%	-0.04%	0.78%
1994	-0.82%	-0.37%	2.08%
1995	-0.06%	-0.60%	-0.77%
1996	1.47%	-2.50%	1.30%
1997	2.73%	-1.26%	1.84%
1998	1.93%	1.08%	-0.40%
1999	1.29%	4.57%	-3.83%
2000	-1.35%	-5.02%	7.17%
2001	-2.06%	0.59%	1.82%
2002	-2.42%	-2.04%	1.69%
2003	1.41%	-0.28%	2.10%
2004	1.39%	-2.93%	1.06%
2005	1.44%	0.03%	0.89%
2006	1.77%	-0.63%	1.07%
2007	-0.24%	-0.77%	0.30%
2008	-5.43%	0.00%	-0.89%
2009	1.59%	-1.10%	1.76%
2010	-1.15%	-1.89%	-0.22%
2011	-1.71%	-1.00%	-1.93%
2012	0.02%	-0.25%	-0.04%
Month			
January	1.76%	0.02%	0.65%
February	0.07%	-1.40%	3.05%
March	-0.57%	-0.30%	1.93%
April	2.04%	1.17%	-0.51%
May	-0.63%	-1.67%	0.84%
June	-1.31%	1.54%	0.14%
July	-0.35%	-0.03%	0.71%
August	-1.13%	-1.59%	-1.40%
September	-2.20%	-1.38%	-0.55%
October	0.42%	-1.86%	-0.07%
November	0.80%	-2.40%	0.53%
December	1.78%	-1.47%	3.87%

Table 20: Descriptive statistics of double sorted portfolio quintiles

This table presents descriptive statistics of the IVOL ranked portfolio quintiles $P_{DR}1$ to $P_{DR}5$ within the market beta ranked portfolio terciles CAPM BETA LOW to CAPM BETA HIGH. Both the idiosyncratic volatility and the systematic beta risk have been measured through the CAPM. $P_{DR}1$ represents the portfolio quintile with the lowest idiosyncratic risk while $P_{DR}5$ is the one characterized by the highest IVOL. CAPM BETA LOW represents the portfolio tercile with the lowest systematic beta risk while CAPM BETA HIGH is the one characterized by the highest beta. The $P_{DR}1$-$P_{DR}5$ double ranked portfolio provides the excess return of a zero-cost investment strategy long in $P_{DR}1$ and short in $P_{DR}5$. The arithmetic and geometric means are computed as the average monthly returns in excess of the portfolios. Volatility is measured as the monthly standard deviation. Alphas and factor loadings are estimated and reported along with Newey-West (1987) t-statistics (in square brackets).

	Low		**Ranking on beta and IVOL**		High	
	$P_{DR}1$	**$P_{DR}2$**	**$P_{DR}3$**	**$P_{DR}4$**	**$P_{DR}5$**	**$P_{DR}1$-$P_{DR}5$**
CAPM BETA LOW FF-3						
Arithmetic Mean	0.47%	0.24%	-0.15%	-0.29%	-0.46%	0.93%
Geometric Mean	0.37%	0.06%	-0.39%	-0.57%	-0.89%	1.26%
Median	0.76%	0.94%	0.24%	-0.43%	-1.34%	1.52%
Skewness	-0.10	-1.19	-0.46	-0.05	0.58	-0.59
Kurtosis	5.82	5.20	2.71	1.49	1.08	1.47
Volatility	4.45%	5.96%	6.91%	7.41%	9.44%	8.98%
CAPM BETA MID FF-3						
Arithmetic Mean	0.56%	0.14%	0.10%	-0.40%	-1.15%	1.72%
Geometric Mean	0.44%	-0.05%	-0.11%	-0.75%	-1.71%	2.15%
Median	0.88%	0.62%	0.57%	-0.04%	-1.02%	1.59%
Skewness	-0.18	-0.70	-0.61	-0.39	0.13	-0.10
Kurtosis	1.14	3.14	1.66	3.32	2.33	2.28
Volatility	5.01%	6.05%	6.40%	8.24%	10.45%	9.45%
CAPM BETA HIGH FF-3						
Arithmetic Mean	0.24%	-0.02%	-0.27%	0.01%	-0.76%	1.00%
Geometric Mean	0.02%	-0.27%	-0.59%	-0.37%	-1.43%	1.45%
Median	0.59%	0.62%	0.31%	0.48%	-0.63%	1.15%
Skewness	-0.30	-0.37	-0.62	0.16	-0.04	-0.09
Kurtosis	1.75	1.47	0.94	1.02	1.33	1.91
Volatility	6.54%	7.03%	7.72%	8.83%	11.34%	9.24%

Table 21: Summary of the CAPM regressions on all ranking methodologies

The table presents an overview of the CAPM regression results for all the different ranking methodologies applied in this paper. In the notation below, the first word illustrates the method that has been used for measuring the IVOL, the beta and the volatility; the second denotes what is ranked, while the third describes the approach used for calculating the alphas and market betas. For example, "CAPM IVOL FF-3" means that portfolios are IVOL ranked and the idiosyncratic risk is measured through the CAPM while the alphas and market betas are computed against the FF-3. Alphas and factor loadings are estimated and reported along with Newey-West (1987) t-statistics (in square brackets).

	Low		**Alpha**		High	
	P1	**P2**	**P3**	**P4**	**P5**	**P1-P5**
CAPM IVOL CAPM	0.37%	0.14%	-0.14%	-0.05%	-0.74%	1.11%
	[2.68]	[0.79]	-[0.67]	-[0.20]	-[1.64]	[2.35]
FF-3 IVOL CAPM	0.55%	-0.02%	-0.02%	-0.03%	-0.77%	1.32%
	[4.03]	-[0.11]	-[0.12]	-[0.08]	-[2.00]	[3.27]
CAPM BETA CAPM	0.25%	0.16%	0.17%	0.48%	0.05%	0.20%
	[1.05]	[0.76]	[1.03]	[3.04]	[0.23]	[0.58]
CAPM BETA LOW CAPM	0.45%	0.23%	-0.17%	-0.32%	-0.48%	0.93%
	[2.18]	[0.76]	-[0.49]	-[85.00]	-[90.00]	[1.66]
CAPM BETA MID CAPM	0.54%	0.12%	0.07%	-0.43%	-1.18%	1.72%
	[2.87]	[0.47]	[0.29]	-[1.19]	-[2.14]	[2.93]
CAPM BETA HIGH CAPM	0.21%	-0.05%	-0.31%	-0.02%	-0.80%	1.01%
	[0.92]	-[0.20]	-[1.16]	-[0.06]	-[1.45]	[1.76]
CAPM VOL CAPM	0.24%	0.20%	0.28%	0.45%	0.05%	0.18%
	[1.06]	[0.97]	[1.68]	[2.88]	[0.24]	[0.54]
	Low		**MKT**		High	
	P1	**P2**	**P3**	**P4**	**P5**	**P1-P5**
CAPM IVOL CAPM	0.87	1.00	1.06	1.16	1.17	-0.30
	[35.17]	[31.96]	[28.72]	[23.66]	[14.35]	-[3.52]
FF-3 IVOL CAPM	0.90	0.99	1.08	1.09	1.14	-0.25
	[36.23]	[33.60]	[29.35]	[24.20]	[16.50]	-[3.38]
CAPM BETA CAPM	0.64	0.70	0.82	0.89	1.21	-0.57
	[14.91]	[18.61]	[27.56]	[31.38]	[30.36]	-[9.07]
CAPM BETA LOW CAPM	0.54	0.66	0.78	0.81	0.78	-0.24
	[14.46]	[12.33]	[12.76]	[12.14]	[8.21]	-[2.40]
CAPM BETA MID CAPM	0.72	0.82	0.90	1.07	1.04	-0.32
	[21.21]	[18.06]	[19.91]	[16.56]	[10.47]	-[2.99]
CAPM BETA HIGH CAPM	0.98	1.07	1.17	1.27	1.30	-0.32
	[23.95]	[25.31]	[24.51]	[21.03]	[13.10]	-[3.11]
CAPM VOL CAPM	0.64	0.72	0.82	0.89	1.21	-0.58
	[15.90]	[19.78]	[27.43]	[31.59]	[30.10]	-[9.51]

Table 22: Summary of the FF-3 regressions on all ranking methodologies

	Low P1	P2	Alpha P3	P4	High P5	P1-P5
CAPM IVOL FF-3	0.40%	0.17%	-0.10%	0.04%	-0.55%	0.95%
	[2.87]	[0.96]	-[0.50]	[0.15]	-[1.19]	[1.98]
FF-3 IVOL FF-3	0.58%	0.04%	-0.24%	0.00%	-0.60%	1.18%
	[4.18]	[0.26]	-[0.12]	[0.01]	-[1.54]	[2.88]
CAPM BETA FF-3	0.30%	0.16%	0.19%	0.51%	0.06%	0.24%
	[1.22]	[0.75]	[1.14]	[3.16]	[0.27]	[0.67]
CAPM BETA LOW FF-3	0.50%	0.15%	-0.25%	-0.28%	-0.33%	0.83%
	[2.38]	[0.51]	-[0.72]	-[0.75]	-[0.62]	[1.46]
CAPM BETA MID FF-3	0.56%	0.10%	0.08%	-0.32%	-1.00%	1.56%
	[2.89]	[0.40]	[0.30]	-[0.89]	-[1.80]	[2.62]
CAPM BETA HIGH FF-3	0.29%	0.01%	-0.22%	0.10%	-0.67%	0.96%
	[1.25]	[0.03]	-[0.82]	[0.29]	-[1.19]	[1.63]
CAPM VOL FF-3	0.25%	0.19%	0.29%	0.49%	0.06%	0.19%
	[1.12]	[0.96]	[1.73]	[3.07]	[0.28]	[0.55]
	Low P1	**P2**	**MKT P3**	**P4**	**High P5**	**P1-P5**
CAPM IVOL FF-3	0.87	0.99	1.05	1.13	1.18	-0.32
	[34.06]	[30.94]	[27.73]	[22.92]	[14.19]	-[3.63]
FF-3 IVOL FF-3	0.89	0.99	1.07	1.06	1.14	-0.25
	[35.10]	[32.80]	[28.20]	[23.20]	[16.20]	-[3.39]
CAPM BETA FF-3	0.65	0.69	0.82	0.89	1.20	-0.55
	[14.65]	[17.71]	[26.62]	[30.66]	[29.25]	-[8.55]
CAPM BETA LOW FF-3	0.52	0.66	0.76	0.83	0.81	-0.29
	[13.71]	[11.89]	[12.09]	[11.98]	[8.27]	-[2.79]
CAPM BETA MID FF-3	0.71	0.80	0.89	1.07	1.07	-0.36
	[20.36]	[17.25]	[19.05]	[16.05]	[10.58]	-[3.33]
CAPM BETA HIGH FF-3	0.99	1.07	1.17	1.23	1.31	-0.32
	[23.60]	[24.60]	[23.92]	[20.32]	[12.79]	-[2.98]
CAPM VOL FF-3	0.64	0.70	0.81	0.89	1.20	-0.56
	[15.46]	[18.85]	[26.50]	[30.92]	[28.99]	-[9.03]
	Low P1	**P2**	**SMB P3**	**P4**	**High P5**	**P1-P5**
CAPM IVOL FF-3	0.06	0.05	0.07	0.22	0.14	-0.08
	[1.76]	[1.20]	[1.40]	[3.27]	[1.23]	-[0.66]
FF-3 IVOL FF-3	0.05	0.07	0.05	0.14	0.16	-0.10
	[1.56]	[1.66]	[0.99]	[2.23]	[1.66]	-[1.04]
CAPM BETA FF-3	0.01	0.09	0.05	0.00	0.06	-0.05
	[0.15]	[1.77]	[1.11]	-[0.01]	[1.04]	-[0.56]
CAPM BETA LOW FF-3	0.14	-0.04	0.03	-0.03	0.01	0.13
	[2.77]	-[0.60]	[0.41]	-[0.38]	[0.07]	-[0.95]
CAPM BETA MID FF-3	0.06	0.06	0.08	0.13	0.00	0.06
	[1.25]	[0.94]	[1.26]	[1.46]	-[0.01]	[0.42]
CAPM BETA HIGH FF-3	0.03	0.05	0.08	0.29	0.10	-0.06
	[0.59]	[0.87]	[1.27]	[3.64]	[0.72]	-[0.45]
CAPM VOL FF-3	0.01	0.09	0.03	0.01	0.06	-0.05
	[0.14]	[1.86]	[0.69]	[0.27]	[1.13]	-[0.66]
	Low P1	**P2**	**HML P3**	**P4**	**High P5**	**P1-P5**
CAPM IVOL FF-3	0.02	0.01	0.03	0.10	-0.12	0.14
	[0.60]	[0.25]	[0.58]	[1.47]	-[1.11]	[1.24]
FF-3 IVOL FF-3	0.02	-0.01	0.05	0.11	-0.07	0.09
	[0.49]	-[0.32]	[1.05]	[1.85]	-[0.75]	[0.88]
CAPM BETA FF-3	-0.05	0.10	0.02	-0.04	0.05	-0.10
	-[0.91]	[1.87]	[0.41]	-[0.98]	[0.86]	-[1.17]
CAPM BETA LOW FF-3	0.09	0.05	0.15	-0.08	-0.19	0.27
	[1.74]	[0.70]	[1.75]	-[0.91]	-[1.43]	[1.99]
CAPM BETA MID FF-3	0.04	0.08	0.07	0.00	-0.24	0.29
	[0.92]	[1.32]	[1.19]	-[0.05]	-[1.81]	[2.00]
CAPM BETA HIGH FF-3	-0.07	-0.02	-0.03	0.15	-0.08	0.00
	-[1.32]	-[0.32]	-[0.47]	[1.85]	-[0.56]	[0.02]
CAPM VOL FF-3	-0.02	0.10	0.01	-0.04	0.05	-0.07
	-[0.31]	[1.98]	[0.28]	-[1.07]	[0.94]	-[0.83]

Figure 10: Actual vs. Expected CAPM Return of P1 and P5 portfolio quintiles

The chart presents actual returns against the CAPM expected returns relative to the P1 and P5 portfolio quintiles sorted through all the alternative ranking methodologies.

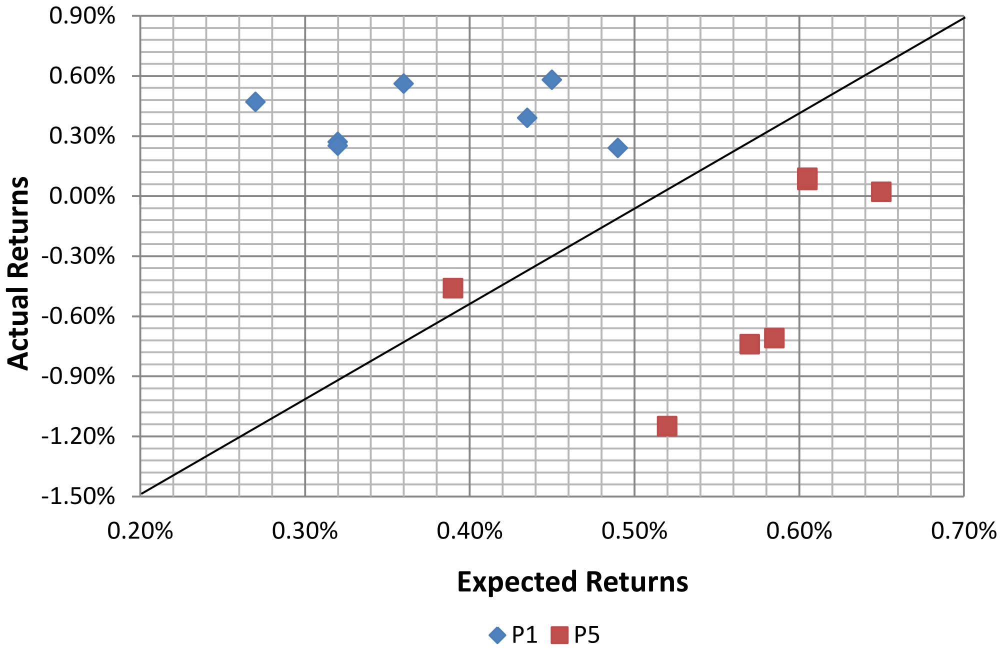


Figure 11: Actual vs. Expected FF-3 Return of P1 and P5 portfolio quintiles

The chart presents actual returns against the FF-3 expected returns relative to the P1 and P5 portfolio quintiles sorted through all the alternative ranking methodologies.

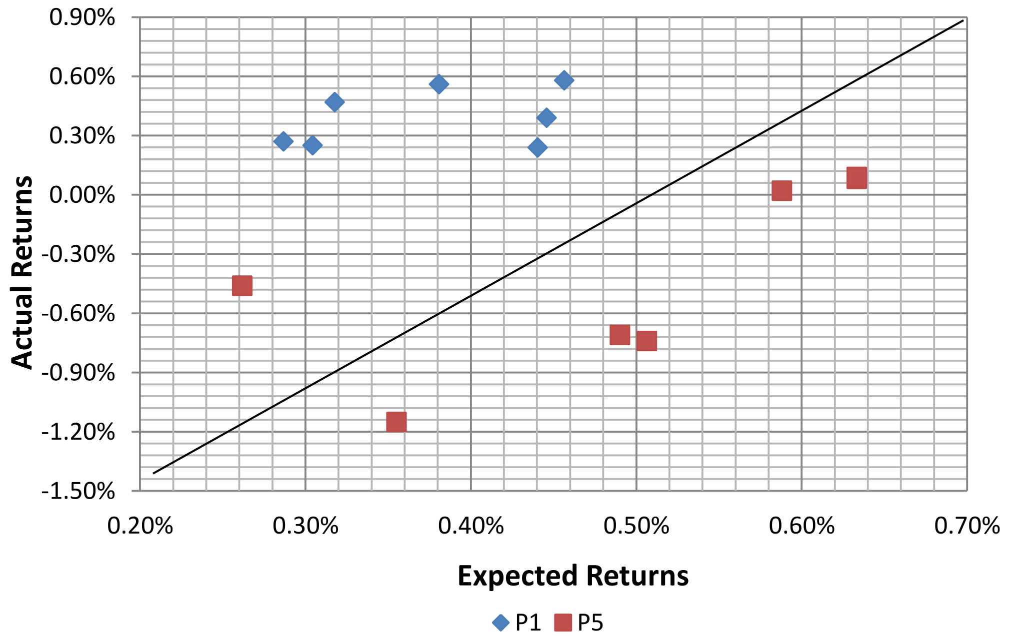


Figure 12: Alphas of IVOL sorted portfolio quintiles vs. the market beta

The chart presents the estimated alphas of IVOL sorted portfolio quintiles versus the systematic beta risk. The idiosyncratic risk has been measured according to both the CAPM and the FF-3 models. In the notation below, the first word illustrates the methodology that has been used to measure the IVOL; the second denotes what is sorted, while the third describes the model applied to calculate the alphas. For example, "CAPM IVOL FF-3" means that portfolios are IVOL sorted and that the idiosyncratic risk is measured through the CAPM while the alphas are computed against the FF-3.

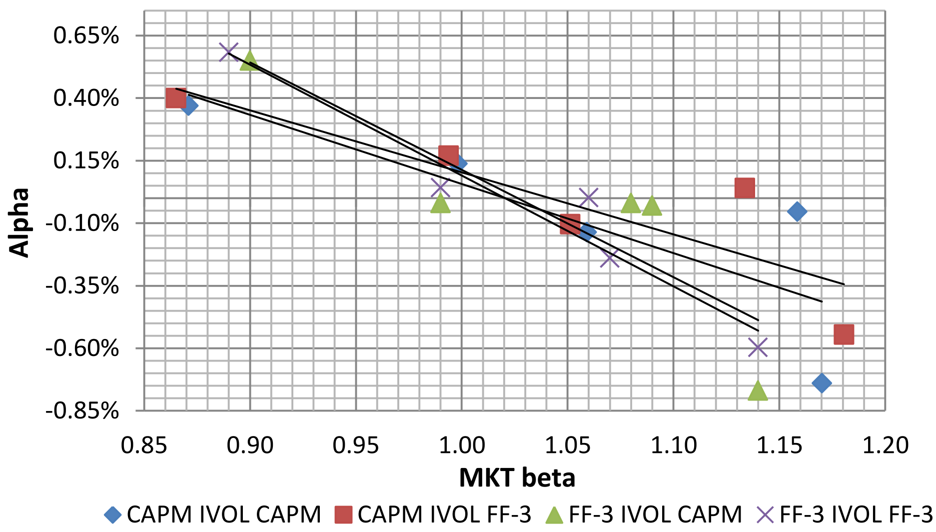


Figure 13: Alphas of beta sorted portfolio quintiles vs. the market beta

The chart presents the estimated alphas of beta sorted portfolio quintiles versus the systematic beta risk.