ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΛΟΠΟΝΝΗΣΟΥ
ΣΧΟΛΗ ΕΠΙΣΤΗΜΩΝ ΔΙΟΙΚΗΣΗΣ ΚΑΙ ΟΙΚΟΝΟΜΙΑΣ
ΤΜΗΜΑ ΟΙΚΟΝΟΜΙΚΩΝ ΕΠΙΣΤΗΜΩΝ

Evaluating Market Timing Trading Strategies: Neutral vs. Non-Neutral Approaches with a Comprehensive Application to Exchange Traded Funds

Αξιολόγηση επενδυτικών στρατηγικών βασισμένων στον χρονισμό της αγοράς: μια σύγκριση ουδέτερων και μη-ουδέτερων στρατηγικών με μια ολοκληρωμένη εφαρμογή σε Διαπραγματεύσιμα Αμοιβαία Κεφάλαια

ΠΑΝΑΓΙΩΤΗΣ ΣΧΙΖΑΣ

ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

Τρίπολη, Ιούλιος 2009

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Υπεβλήθη στο Τμήμα Οικονομικών Επιστημών του Πανεπηστιμίου Πελοποννήσου ως μέρος των απαιτήσεων για την απόκτηση Διδακτορικού Διπλώματος.

Η εκπόνηση της διατριβής συνετελέσθη με την καθοδήγηση τριμελούς Συμβουλευτικής επιτροπής υπό την Εποπτεία του καθηγητή κ Θωμάκου Δημήτριου.

ΤΡΙΠΟΛΗ, Ιούλιος 2009

Acknowledgements:

This thesis is the result of a four year of research as a PhD student at the School of Management and Economics at the Department of Economics of the University of Peloponnese. This thesis would not have been written without the encouragement, help and support of numerous people, whom I like to thank here.

First of all, I am very grateful to my supervisor Professor Thomakos Dimitrios at University of Peloponnese. He convinced me and stayed next to my work from the first day until the last days of my research. His support was really precious since his guidance was novel in every aspect that we collaborate and without his continuing support the outcome will not be identical.

I would like to state that the main part of my thesis and concretely the second chapter completed during my stay and collaboration in New York, at the Graduate Center of City University of New York. I am also grateful to Associate Professor Tao Wang at the Department of Economics, Queens College and the Graduate Center, City University of New York (CUNY), for his help, interest, guidance and contribution during my stay in New York. I appreciate our regular meetings in discussing my work. I would also like to express my appreciation to the numerous colleagues of CUNY who took an interest in my work.

I want to help the executive director of Graduate Center of City University of New York, Professor Thom Thurston for providing me with the required facilities in order to accomplish my research.

I would like to also thank Professors Gikas Hardouvelis and Panayiotis Liargovas, the two members of my committee for providing me with helpful comments.

Finally, I would like to thank my family and especially my parents for their virtue support to my effort. They support me and gave me the opportunity to study free of obstacles as they solve any roadblocks all the previous years.

Dedicated:

To my parents

Tables:

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Introduction

My doctoral thesis provides evidence of two different types of trading strategies. The first type is based on market neutral trading strategies under the methodology of pair trading strategies. The second part is on rotation strategies according to sign forecasting specifications and explores the probability of profitable market and volatility timing. The thesis is comprised by three chapters.

The first chapter is dedicated to Exchange Traded Funds, ETFs. I am presenting an extended literature review on the topic. The review tries to capture every aspect of ETFs that is of concern for the academic community. Moreover, I am presenting the mechanism of ETFs and the pros and cons that are inherent in an ETF structure. In addition, I am discussing active ETFs. On the 4th of March 2008, the Securities and Exchange Commission approved the listing and trading of Active Exchange Traded Funds in the US market. This decision opens up a new era on asset management. I am trying to identify the most appealing issues from this new decision. I am analysing the similarities and the differences with passive ETFs and conventional mutual funds and the obstacles that arise from the inception of active ETFs.

The second chapter is dedicated to pair trading strategies. Gatev, Goetzmann and Rouwenhourt (2006) applied a trading algorithm based on the concept of mean reverting returns. Prices of two assets that move together in the long run and diverge in the short term will revert to their equilibrium. An alternative definition for the pair trading strategies is that of a relative value statistical arbitrage methodology. Engleberg, Gao and Jagannathan (2009) examined pair trading methodology and tried to explain the factors behind the profitability. The contribution of my work is the implementation of a modification of pair trading investment strategy and the examination of the profitability and the motives that create the profitability in the contest of ETFs. I implement different estimations for each separate step of the formulation of the strategies in order to examine and find an "optimal" algorithm. I then conduct different tests to check the robustness of my methodology. In the next step, I check the pattern of profitability based on several tests based on the segmentations according to market capitalization, emerging and developed markets. The second part involves the empirical evidence of pair trading portfolios according to risk profile. I incorporated Fama and French risk factors to explain for potential patterns behind the profits. The estimations included national and international risk factors on profitability. The most important part is the decomposition of the traded pairs and the examination one by one according to its own risk characteristics. My dataset is constructed by international ETFs which is the tradable version of country indices. In that concept, I research in each separate pair its own variables and I test the factors that affect profitability. Among the extended research all over pair trading strategies, this research provides the following contributions. 1. It is the first time that ETFs are used in pairs trading. 2. International evidence on pair trading with easily accessible instruments. 3. Pair trading profitability outperforms S&P500. 4. The US and international Fama and French risk factors are insufficient to explain pair trading international profitability.

The third chapter is dedicated to volatility and market timing strategies. I examined a new methodology that assesses the economic and statistical significance of market and volatility timing according to a novel forecasting specification. My methodology combines the dynamics of time-varying expected returns and volatility timing and several thresholds derived by expected returns and variability. The specification is incorporating forecasting sign ability. The forecast estimations are incorporated to create trading rules and the formation of portfolios. The trading rules, then, are incorporated to the allocation decision. In every decision, we allocate the total wealth to one asset. In every transaction, we rotate between the two assets. The methodology is based on a pairwise asset evaluation. I test for the patterns behind volatility timing, and for the day of the week effect. The results indicate that under specific assumptions market and volatility timing can lead to profitable trading strategies. The selection of the specification appear to be sensitive between past returns and volatility which confirms the initial conception of the cross interaction between time varying expected returns and variation. Comparing the performance of the rotation portfolios based on forecasts using different model selection criteria, the rotation trading is performing the highest final wealth, when there is not a clear domination between expected return and variation. Applying the methodology under different days of the week, I can differentiate from the literature in means of the performance with rotation trading to exhibits the most statically and economic significant excess returns on Monday. The next test examines if different levels of volatility generate correct sign predictions. The empirical analysis shows that there is not clear dependence between returns and level of volatility.

Empirical evidence appear to be sensitive about the selection of trading specification which confirms the motivation of the research of cross interactions between time varying expected returns and variation. Rotation trading outperformed the market in means of final performance and risk levels as represented by the maximum drawn down indicator.

My thesis makes a distinct contribution in the area of active asset management and asset allocation methods. It explores in depth two different trading strategies in the context of a relatively new financial tool, the Exchange Traded Fund (ETF), and is to the best of my knowledge one of the few existing works that address the issue of ETF profitability in a relatively thourough manner, always in the context of active trading.

Chapter 1. A Brief Exploration and Overview on Exchange Traded Funds - ETFs

Introduction

ETFs or Exchange Traded Funds represents the outstanding experience of an evolution in asset management. The start of the new millennium uncovers many investors to invest in "hedge funds", however a financial product that accomplishes a great expansion is ETFs. To testify the aforementioned argument, a concrete investment objective of this asset "International ETFs" had the biggest contributor to asset growth with 59% growth on 2007.

ETFs originated with Index Participation Shares (IPS), a proxy for the S&P500 Index traded on the American stock exchange and the Cash Index Participation (CIP) that was traded on Philadelphia Stock Exchange in 1989. Due to their complicated characteristics were considered to be closer to future contracts as they were traded similar to futures contracts, and simultaneously were treated (margined and collaterized) as stocks. According to complex properties, Chicago Mercantile Exchange and Commodity Futures Trading commission asserted those investment products as futures tools and should be traded only to futures exchanges. Chicago federal court accepted the lawsuit of CME and obliged the owners to liquidate their shares.

However, the idea of those instruments appeal to be interesting in the financial world and few months later, in 1989, in Canada was launched the first ETF (called TIPS Toronto Index Participations), which tracked the shares of 35 of the largest companies listed on the Toronto Stock Exchange. After many unsuccessful attempts in the US, the first ETF has been launched in 1993 (second globally after the TIPS), on the American Stock Exchange, under the name SPDRs - Standard & Poor's Depository Receipts or "Spiders"- tracking the S&P 500 index. Afterwards, the tremendous success of SPDR, many investment companies launched their own ETFs with the most numerous to be based on MSCI Indices and NASDAQ 100 index.

Due to the particular properties specialized investment companies launched to managed only ETFs where the dominant peer groups are presented below.[1] The originated group was launched under the name SPRDs which incepted a whole range of ETFs tracking Standard and Poor's several broad and sector stock indices. The most popular ETF among Spiders (S&P500) Gastineau (2001) reported that attracted 70% to 90% of the total inflows that directed to S&P500 portfolios (the second most attractive investment tool was Vanguard 500 index fund). At the end of 1998, there were created select sector SPRDs are they called under the objective to track basic sectors on American Stock Exchange. SPDRs are organized and registered as unit trust, unlike the portfolios of the most US unit trusts[2], and can be changed as the index changes.

The second peer of ETFs is known as WEBS (World Equity Benchmark Shares) tracking several domestic and foreign security indices and the majority of the indices was launched on March 1996 parallel on NYSE and the AMEX. Foreign securities have been considered as country specialized range of securities that track the price

[1] The ETF generation tree is as: SPRDS, WEBS, DIA, QUBES - NASDAQ 100 and sector SPRDS.

[2] We refer to the legal structure extensively on the next section.

and the yield performance of MSCI country indices. This grouping is also known as International ETFs. The success consists in the opportunity of an investor to invest on emerging markets and especially in a period, before the turn of the century, where local stock exchanges have many obstacles. WEBS has been sponsored by the biggest ETF investment company Barclays Global investors under the name of Ishares.

WEBs launched have been followed DIA or Diamond trust tracking the Dow Jones Industrial Index. The respective ETF has been launched on January 1998 on AMEX. The sponsor is the State Street Bank investment company.

On March 1999, has been launched, Cubes (QQQQ), tracking the NASQAD 100 Stock Index on AMEX. QQQQ consists the second largest ETF in US[3] market (after SPRD 500).

Another popular group of ETFs are VIPERs Vanguard Index Participation Receipts tracking several indices among them the well known MSCI indices. The first Viper has been launched on December 2001.

A different group to the traditional definition of ETF are Holdrs, Holding Company Depository Receipts consist a basket of stocks, instead of index tracking, and follow a specific strategy which is predefined by Merrill Lynch - the sponsor. In that concept, represents a passive portfolio of securities which do not track a specific index or market and especially can not be considered as index linked ETFs. The very first ETF, Tele Brasil-Telebras Hldrs (TBH), formed in mid-1998. The majority of Holdrs were launched on 2000 and afterwards.

Apart from the major peers and singles numerous ETFs, they has been a great expansion on ETFs industry and by the end of the first quarter of 2008, were traded

[3] Based on September 2006 assets under management

1.280 ETFs with 2.165 listings having under management $760 billions, managed by 79 managers which listed on 42 exchanges throughout the world.[4] [5]

An EXCHANGE TRADED FUND (ETF) can be defined as a fund that duplicate a stock index or a basket of stocks of one or more sectors and can be treated - bought or sold- as a unit. A more broaden definition for ETFs could be whatever tracks a specific index of a specific basket of stocks and is available to sell as a unit stock belongs to ETF industry. As a financial product, ETFs have many distinctive properties which are the best alibi of the tremendous explosion of the last decade providing exposure to the whole range of asset allocation map, including equity sectors, fixed income, commodities, currencies and alternative assets. Within the asset classes ETFs, cover a broad spectrum of investment solutions, including market capitalization, investment styles, sectors and countries. The investment options are unlimited with ETFs tracking private equity indices, infrastructure indices, real estate indices, dividend indices and recently they are Shariah ETFs[6]. The recent years they have been launched ETFs based their investment objective directly on futures and option contracts and ETFs with their investment objective of "shorting" major indices of the spot market.

Investing at ETFs could capture an exposure to futures markets with more than 300 options and 13 futures listed on the markets on US, Canada and Europe.[7] The history of ETFs in futures markets incepted with the first ETF option on the MidCap SPDR on November, 1998 on US. ETFs options like stocks options, which settle stocks, settle ETFs shares and they have all the advantages of a conventional futures

[4] The information is by Morgan Stanley ETF Q1 2008 Global Industry Review

[5] Only in the US by the end of 2007 only in the US, ETFs had under management $608B assets, with 58 billions average daily volumes

[6] Shariah etfs have been built with respect to Islamic Law

[7] According to Morgan Stanley in the Us there are 288 options, which means that 47% of US listed ETFs have options

product like e-mini futures contract[8]. Although there are some distinguish appealing properties which consider them more attractive than traditional derivatives. ETFs are traded on their start up ratio which the majority of ETFs to be a fraction of the underlying index. The most indicative example is SPDR 500 option which is traded on the $1/10^{th}$ of the index S&P500 index, consequently the strike price for the aforementioned ETF is lower than the conventional S&P500 index options. In addition, the QQQQ option expires at the end of the day while the NASDAQ regular index option expires at the open. Derivatives on ETFs are not a counterpart to equity futures product but exhibits prevailing advantages on delivering not only single stocks but entire trading strategies. However, through ETFs an investor could have access on derivative markets where an individual investor could not have access as many emerging markets.

ETFs appear a remarkable expansion under short interest.[9] Similar to equities and contrary to conventional mutual funds, ETFs provide an opportunity of short exposure to investors. The option, is known, to be extremely crucial allowing an investor for hedging and building long/short strategies on the spot markets, covering a broad range of indices and generally investment strategies like building strategies. A representative example names allocation on emerging markets. As it is known several emerging markets have restrictions on foreign direct investments, immature futures and frictionless stock loan markets. Though short ETFs we can overcome those obstacles. The latest transitions by SEC which has abounded the up tick rule for short selling helped the concrete product while the outstanding number of shorted ETFs is significant higher than ordinary stocks.

[8] E-mini contracts correspond to 1/5 of the regular contracts

[9] At the 1Q SPDR S&P500, Ishares Russell 2000 and Financial Select Sector SPDR has been the most active shorted ETFs, showing the crucial role of shorted etfs on the banking solvency crisis

So far, we concentrated on the advantages of equity ETFs and the multiple merits that encompass relative to many investment competitors (like index linked mutual funds), on the contrary a particular attend needed to be shown on Fixed-Income ETFs. This specific asset class under an ETF structure faces many obstacles which arise from the spotty price reporting and the relatively wide spreads of different bond types apart from Treasury securities. Briefly, there are not so widely known indices to be based on like on equities. ETF fixed income structure is growing both in the cash and in the futures markets relatively to equity ETFs slowly.

2. Literature Review on Exchange Traded Funds and Fundamental Properties

Due to the properties ETFs and especially on the trading behaviour as equity the majority of the research that has conducted to empirical evaluate the properties of stocks have been transferred on Exchange Traded Funds Industry. On the context of the recent expansion of ETFs, the vast majority of the research dated back to the last 6 years. Specific and distinctive characteristics of ETFs structure have fragmented the research into 3 major fields: Fluctuations between trading prices and NAVs, the ability of the ETFs to replicate the index and lastly, the tax efficiency that an ETF usually achieves mainly versus the conventional mutual funds. In the next we are referring to the literature that extends and covers a wide range of empirical evidence.

This field of research is based on the relationship between trading price and NAV. The fluctuations between the prices and the NAVs are a vital field of ETF research since premiums or discounts emerge trading strategies and riskless profits.

When ETF is trading on a discount (premium) we can buy (sell) the constituents of the underlying index directly by the exchange create units and achieve riskless profits in means that fluctuations are temporary. On that context, the existence of futures products pressures the temporary fluctuations onto equilibrium. The majority of the existing literature provides evidence that price deviations from NAV are short lived and tend to converge to zero.

Cherry (2004) analyzed the relationship between prices and NAVs, and argued that there is a one to one correspondence, indicating that ETF prices reflect all NAV information. Efficiency of these assets shows that Ishares prices contribute significantly to the price discovery process along with the NAVs.

Delcoure and Zhong (2007) provided evidence that Ishares is trading at an economically significant premium which ranges between 10% to 50% with the proper adjustments to the transaction costs and time zone measurement errors. On the evaluation of the risk price returns reveals to present a more volatile behaviour relative to the respective NAV returns.

Simon et al (2004) examined if there is any relationship between 3 European ETFs (Ishares Germany, UK and French) and US market after the trading session of European markets. They provided evidence of a leading relationship between US market and European ETFs. The link can lead to substantial profitable strategies since the information generated from US is embodied on the price of European ETFs the next business day.

Engle et al (2002) compared domestic against international ETFs in means of premiums/discounts, into 4 separate horizons, during a day, end of the day, minute by minute and intraday. In the relative comparison between domestic and international ETFs, argued that international ETFs reveals lower and shorter fluctuations in means of NAV and the causality factor names the higher creating and redemption costs. The standard deviations of the premiums/discounts is substantially smaller than bid-ask spread, but the most dramatic finding insists that fluctuations in international ETFs remain for several days which arise arbitrary opportunities and winning strategies.

According to their structure ETFs fluctuations are temporary. Moreover, several ETFs are dual listing and are accompanied by futures contracts. In that context, the question which emerges can be summed up to: Which market has the swiftest disclosure of the ETFs price? ETFs have futures contracts and options which help someone to create trading strategies and achieving an efficient price disclosure with respect to the most efficient market trading either physical or electronically. Tse et al (2006) compared the DJIA Index and its three derivative products, DIAMONDS,[10] the floor traded regular futures and the electronically traded mini futures and they confirmed the hypothesis that an investor of a multi market trading ensures greater pricing efficiency. Their results indicate that price disclosure is dominated by the future contracts which are traded on alternative platforms and especially to archipelagos (ECN) followed by DIAMOND ETF. However DJIA index and its regular futures contribute least to price discovery.

The existence of fluctuations reflects a level of volatility. Tse et al (2007) analyzed the level of price volatility incorporating international Ishares. The findings exhibit that prices are mainly motivated by information disclosure during each local market's trading session. On the segmentation of the regions, Asian and European ETFs exhibit lower variance during the day, while their results are reverting on the examination of American ETFs, and provide significant higher volatility during the day trading session instead of overnight. To the extent of the empirical evidence they

[10] DIAMONDS are ETFs that track the Dow Jones Industrial Index. The sponsor is State Street Bank.

argued that international ETFs exhibit higher variation in prices than NAVs across the regions, suggesting an advanced noise trading in the ETF markets than in the underlying local markets.

The second major empirical field applies the probability for an ETF to mimic the underlying index efficiently, not only in the allocation of the underlying constituents but also on the terminal performance. As we referred to previous section, tracking errors are created by the structure that an ETF operates. Elton et al (2002) identify for the most actives ETFs, Standard and Poor's Depository Receipts, the treatment of dividends is an important factor explaining their underperformance relative to the S&P 500 and to the S&P500 index funds. On the extend to their research, Elton et al (2004) identified that even S&P 500 Index funds allocation map hold virtually both the same stocks in the same weights, a significant distinction exists in the final performance and management fees.

Blume and Edelen (2004) evaluate the difficulties faced by index managers around index reconstitution dates, finding that index fund managers would benefit from executing less rigid replication strategies surrounding index revisions.

Frino et al (2005) in means of optimality proved that index-oriented funds exercising greater flexibility in index replication.

ETFs are often promoted as being more "tax efficient" than traditional equity mutual funds. Investors have the opportunity to entry ETF industry by purchasing individual shares on the open market, and in this procedure the fund does not involved in any transaction. In the contrary, when an investor sale his mutual funds shares the trustee has to react by liquidating a portion of its portfolio holdings. This procedure is considers as taxable efficient and under specific circumstances may create profitable opportunities which then distributed to the remaining investors.

Poterba et al (2002) for the horizon between 1994 and 2000 compared ETFs with traditional mutual funds and argued that ETFs realized smaller distributions of taxable capital gains. In the relative comparison between the pre- and post-tax returns of SPDR S&P500 and the Vanguard Index 500, the largest equity index fund, provided evidence of no significant difference between pre and after-tax returns. The distinction consists in the after-tax and the pre-tax returns on the fund were minor higher in comparison with ETF suggesting an apparent benefit for taxable investors.

2.1. Existing ETF Review Capturing Special Dynamics

The extent to the literature of the fundamentals emerge from the structure many other aspects of ETFs have been explored. A basic property is the differences between ETF and closed end funds in the disclosure of NAV. Harper et al (2006) compared return, risk performance and the risk adjusted returns between ETFs and Closed End Funds. They argued that ETFs attribute higher means returns and higher risk, which in risk adjusted basis, conclude to higher Sharpe ratios. Higher returns reveal the result of lower expenses, on the contrary higher risk reveal the flexibility of closed end funds managers to a rational diversification benefit according to the conditions of the market. On the absolute comparison, the majority of 29 closed end funds exhibits negative Jensen alpha's over the same period.

To that concept, Hughen et al (2007) confirmed the hypothesis of higher trader costs of closed end funds than ETFs due to the frequency of the trading. In addition, closed end funds represent higher trading costs, due to the ability of ETFs shares to exhibit lower fluctuations between share prices and NAV. Finally, to both products, prices are affected negatively to announce of the NAV and affected positive to stocks market returns.

Pennathur (2002) compared the performance of international ETFs with closed end funds of the objective country in means of diversification benefit. To understand the scope of their examination better, international ETFs are determined in the US and country Funds in their home country. His evidence argued that the two prices are affected by different risk exposures.[11] Applying weekly estimations ETF returns proved to higher than closed end funds. In the relative comparison, international ETFs provides a merely diversification benefit, since they exhibit a positive correlation with the US market.

Ascioglu et al (2006) examined the intraday behaviour between ETFs and common stocks in means of bid-ask spreads. Their findings suggesting that ETFs spreads are lower than those of common stocks during the trading hours, supporting that ETFs have lower information asymmetry versus to common stocks. They argued that narrow spreads is the main causality of lower transaction costs of ETFs and conclude to less information asymmetry issues.

A popular field of research is the behaviour and the relationship between spot and futures ETFs. Blancard et al (2007) examined the effect of the inception of S&P500 (Spider) options on the traditional S&P500 index options market. Their evidence revealed that Spider options to the S&P500 call options to tightens and put options to widen. The second evidence proved that average daily volume of S&P500 put options increased while average daily volume of the call decreased with the implied volatility to decline slightly.

[11] Ishares organized as a fund under the investment company act of 1940, and they don't have the obligation to mimic the index but just a proxy of it. Ishares choose the constituents using the portfolio-sampling technique based on specific criteria such as capitalization, industry, and other fundamental. Keep in mind that MSCI world has circa 2000 constituents

Chou et al (2004) examined the effect of decimalization between ETFs and index futures in means of trading costs, informed trading and speed of information disclosure. They proved that trading activity increased, as well as spreads tightening due to lower trading costs and that informed trader's switch their trades from the cash market to the future market. Moreover, they proved that there is an increased adverse selection for the components of the ETFs, however the index futures decreases.

Hausbrouck (2001) examined in means of efficiency of price disclosure S&P500 index, Nasdaq100 and S&P400 index versus their respective future contracts and ETFs. For SP500 and Nasdaq 100, futures contract and especially e-mini contracts revealed to be the most efficient market to invest in. For the S&P400, the ellipse of e-mini futures contract accomplishes ETF as the most efficient solution. On the second part of the same publication, Hausbrouck examined the ability to replicate S&P500 index using sector ETFs of the index. He argued that the replication of the index requires an advanced expense ratio (S&P500 ETF has 0.12% expense ratio and sector ETFs 0.28%) and the findings can not confirmed his hypothesis.

Yu (2005) incorporated ETFs as a proxy of basket securities in order to investigate the behaviour of past returns and trade innovations in the price formation under a multi-asset variance decomposition methodology. The results indicate that ETFs return innovations helps to efficient price variance of the underlying stocks, comparable to the stocks own return innovations, but the reversal do not exist. ETF trades do not contain any information about the price formation of component stocks.

Guedj et al (2008) investigate the probability if ETFs can substitute index mutual funds and argued that conventional index funds provides a cross-subsidization relation between the investors by sharing the transaction costs. On the contrary, ETFs are a more efficient solution in the environments of high market volatility and liquidity shocks and when the underlying indexes are high risk or less liquid.

Boney et al (2006) under the perspective of liquidity examined the inflows of SPDR S&P500 ETF, Vanguard S&P500 index fund and 33 other index funds with investment objective to mimic S&P500 index. They asserted that ETFs have greater average inflows than traditional index funds and higher volatility. Furthermore, argued that the inception of ETF on S&P500 switched flows from traditional index funds to ETFs.

Hedge et al (2000) investigate market liquidity effect of the introduction of two numerous ETFs, Diamonds and Nasdaq 100. Their asserted that over the first 50days of the trading, DIA and QQQ[12] revealed higher liquidity than the corresponding stocks of the underlying indices. For the same period, market liquidity of their underlying stocks improved due to a decline in the adverse cost selection. Overall, the inception of ETFs increases the volume and the interest of DJIA and NASDAQ 100 index future contracts.

On the same concept, Boehmer et al (2003) examined the fragmentation on competition, liquidity, trading volume and price discovery as a result of the entry, three of the biggest ETFs QQQ, SPY and DIA by their listing on April 6, 2001. The entry increased liquidity and help to the decrease of the trading costs. Although the listing provided several benefits basically on liquidity and trading volume, in price discovery do not exhibit any significant affect.

On 2004, one of the numerous ETFs that is tracking NASDAQ 100 index known QQQQ switched its trading from AMEX to NASDAQ exchange. Broom et al (2007) examined the switching between two stock exchanges and they asserted that

[12] Before the inception of trading on NYSE NASDAQ ETF has a QQQ quote, but by the inception the quote changed to QQQQ

the transfer increased overall volume of the objective ETF, minimized the costs and simultaneously raised the issue of different trading venues. The decline in the costs is affected by the different cost charges made by market makers and specialists in Nasdaq.

Hendershott et al (2005) examined the effect of the foreclose of Island (ECN) one of the most popular and active alternatives platforms. On September of 2002, SEC deals with Island, the electronic communications network to trade some of the most active ETFs. Simultaneously, Island management decided to close the automated limit book to any market participant. As a direct effect was liquidity to increase but at the same point price disclosure become less efficient and island lost his dominance among electronic communication platforms.

Hendershott et al (2005) on a different publication examined the direct affect of that legislation of SEC to the trade though rule for the three most active traded ETFs, allowing markets to execute trades at prices up to three cents than those posted at other venues. The change in regulation does not exhibit any significant realized impact on the spreads, but ETF prices appear to be more efficient.

Kimberly (2004) examined herding behaviour in ETFs in periods of market instability and high volatility. Using 9 sector ETFs, he argued that there is no evidence of herding behaviour to investor in period of high volatility, on the contrary investor's behaviour is unshaped since they are moving away from the consensus. Moreover, he argued that there is a weak evidence of herding behaviour only at small stocks, and not at large stocks, due to lack of public information that small companies delectate.

Alexander et al (2007) provided an empirical comparison of the out of sample hedging performance from the naïve and minimum variance hedge ratios for the four largest US index ETFs. Efficient hedging is important to offset long and short positions on market makers accounts, and especially to cover imbalances in net creation or redemption demands around the time of dividend payments. Their model includes three different performance criteria, including aversion to negative skewness, excess kurtosis and reduction in variance. They argued that hedging is less efficient near the time of dividend payments, however, the relative comparison of three regimes GARCH, OLS and EWMA hedging ratios, does not arise any significant role in the results.

Wang et al (2006) examined the effects of monetary policy surprises (changes of fed funds rate and changes in direction of the Federal Reserve monetary policy) on returns, volatilities, trading volumes and bid-ask spreads. To their estimations, they incorporated two of the largest ETFs, S&P500 and S&P400 MDY. Their results indicates that an announcement of an 25bps cut in the federal funds rate, for the first 45 minutes, leads to an increase of 1.2 and 1.6 percent of SPY and MDY respectively. Moreover, they argued that an expected decline of 25bps in the four quarter ahead Eurodollar Futures rate concludes to an increase of 0.71 and 0.40 percent for the respective ETFs. The most dramatic results arise from the market reaction to the announcements of the future monetary policy during monetary tightening periods, however, the degree of impact depends on the sizes.

Cabrera et al (2007) examined out of sample return predictability of 8 ETFs using three specifications AR, GARCH and neural networks. Their main aim was to uncover if there are any nonlinearities in ETFs series and the second contribution a comparison of the prediction ability of the three methods. Their evidence indicates that linear models and combined forecasts of linear models have the best performance.

3. Exchange Traded Funds Structure and Evolution

Exchange-traded funds (ETFs) are called also "hybrid" mutual funds as they are capturing the dynamics of index-tracking unit trusts with the merits and tradability of listed investment companies. Its structure surpasses the major demerits of the aforementioned two vehicles given lower operating expenses, trading liquidity, and more efficient tax structures than the conventional index-tracking mutual funds and we define and analyze one-by-one those distinctive virtues.

ETF structure requires three participants in order to be launched on the open market. The most important factor is the ETF sponsor which usually is an investment company, bank or a financial institution. Then, the financial institution searches for an authorized participant (AP), which is the well known specialists or market makers who have as major task the procedure to create or redeem ETF shares. The third participant is the trust company which holds the stocks that underlie ETF. In order to create an ETF, the sponsor submits the file with the plan to the SEC and asks to create a new ETF. In the envelope-plan should clearly define the ETFs investment objective, the constituents of the ETF in other words which securities will be included and the initial amount of the retail ETF shares that will be created by the inception.

After the approval of the plan the sponsor deals with an AP to create the approved number of ETF shares and simultaneously delivers the stocks to the Depositary Trust Company (DTC). Then, the AP receives by the sponsor the appropriate number of ETF shares in large bundles known as creation units. The AP split and sells them as individual ETF shares to investors to the open market. Then, the sponsor provides for a manager to monitor and handle the portfolio of underlying stocks.

When a sponsor submits the file with a new ETF defines the "Start up Ratio" which is the initiative relationship between the ETF and the underlying index. This relationship should be followed during the lifetime of the ETF. By the legislation the stock exchanges are obliged to publish the INAV - indicative net asset value- every 5 seconds in order the market maker to be informed about the ratio between the ETF and the underlying index. For the index linked ETFs, the legislation restricts an ETF to fluctuate more than 3% (including taxes) from the underlying index.

On their legal structure now, ETFs can be divided into 3 categories. The first structure is identical to a conventional open-end index mutual fund where an ETF is registered under the SEC Investment Company Act of 1940. The most popular ETFs on this category are Select Sector SPDRs and Ishares. By this legal structure dividends are reinvested in the fund and contributed quarterly in cash to the shareholders where are permitted to incorporate derivatives and loaning securities. The majority of ETFs are organized as regulated investment companies (RIC) similar to mutual funds and closed-end funds. Under the Investment Company Act of 1940 (ICA), RICS become pass through vehicles for tax purposes, and thus paid no taxes relating to the buying holding, or selling of securities.

The second legal structure is Exchange-traded unit investment trust and is registered under the SEC investment company of 1940 "the 40 Act" under the obligation of fully mimic the underlying index. The 40 act separate the funds into diversified funds and non-diversified funds. For the diversified funds limits the fund up to 5% to a single asset security and in aggregate not to extent more that 25% to any family assets. For the non-diversified funds the total limit arises to 50%. Dividends are not reinvested and are distributed to the shareholders in a quarterly basis. The most numerous ETFs under the aforementioned structure names the QQQQs (Qubes), DIAMONDS, S&P 500 SPDR and S&P 400 SPDR.

The last legal structure is Exchange-traded grantor trust and the funds are not registered under the SEC Investment Company Act of 1940. The limits on the allocation remain. The difference with the previous structure exists on the context that shareholders have voting rights to the underlying securities. In that concept, dividends are distributed directly to the shareholders. The most numerous example in this structure is HOLDR funds.

The foremost virtue of an ETF structure reveals the inherent characteristics to trade with the similar easing properties as a listed stock and all the merits that issue (market limit or stop orders to buy or sell the securities, buy on margin or sell shares short). According to other listed investment tools stocks, bonds, and closed-end funds trading volume emerges from the daily transactions. By legislation, there is a compulsory narrow spread between NAV and floating price that the specialists and market makers should follow. Consequently, ETF investor could trade the shares at a mutually agreed upon price with another investor, or they could trade shares at any time at the market maker's bid or ask price.

ETF structure emerges another unique option, unlike equities and closed end funds. An ETF investor in order to invest on shares of ETFs can create or redeem ETF units directly from the sponsor. The process of creation consisted of inputting baskets of stocks comprising the index in large quantities in order to make 50.000 ETF shares (called creation units) that matched the underlying securities in exchange for creation units. The adverse process (redemption process) consisted of accepting a basket of shares of the underlying securities in exchange for creation units. The creation or redemption units can be created either by settling cash or by settling the exact proposition of the underlying index to the trustee. The result of the in kind process concludes to a limit of large fluctuations from the net asset value, since the in-kind transactions narrow premiums and discounts. In kind transaction by creating or redeeming units is not a taxable procedure. Creations or redemptions are settling by the respective amount of shares which indicates the underlying portfolio and have no cash transactions. The only taxable procedure is the sales of ETF shares although under this procedure can be created appealing tax free arbitrage scenarios. Investments in ETFs could avoid restrictions set by the Wash Rules[13] because ETF with similar benchmark strategies were considered different securities. Throughout, the year an investor could sell interests in ETFs recognize a gain or loss and immediately buy a different ETF with the same strategy. The opportunity to create gains without strategy risk or better with the same investment strategy is a noteworthy merit for both institutional and individual taxable investors.

By the side of shareholders, in kind transactions when it is delivered by shares of the underlying index does not include cash transaction, unlike the conventional funds which redemption process may create a cash drug problem as well as tax inefficiencies to the remaining shareholders. In addition, when an investor purchased a share class of a conventional mutual fund, the manager subtracts load fees and invests the remaining amount to replicate the current fund composition only at the closing price. On the contrary, ETF shares mainly of diversified portfolios, obtain continuous price disclosure during the market's trading session. A different aspect is that index funds charge front-end load fees or deferred sales charges. Unlike ETF structure hurdle all the aforementioned obstacles. The above distinctive properties that

[13] Wash rules indicates that if an investor sells a stock with losses and buys shares of the same strategy within a month this in not considered as a cash transaction and there are no tax obligations.

an ETF inherently delivers offer efficiency and rationality in a portfolio strategy[14] since they are fully invested all the time contributing the extra profits that the cash drag problem cuts out, concluding to a quite profitable and rational investment option.

On the concept of similar behaviour with the conventional mutual funds consist the ownership of the underling shares that held by the manager or trustee with no voting rights for ETF shareholders unless the EFT is registered under the last category. To sum up, there are other exchange traded products with congener properties of ETFs, like ETNs exchange traded notes, ETCs exchange traded commodities ADRs American Depository receipts or GDRs Global Depository Receipts.

To sum up, ETFs can be considered as a high liquid passive worldwide investment strategy. The real evolution of ETF industry is believe that is on its enfant with the prospects to be extremely positive[15] and the forecasts to predict that ETF industry will have under management \$2trillion in 2011.[16]

3.1. From Passive to Active ETFs: An exploration to a new Financial Invention

ETFs considered as a passive investment solution, on the contrary, evolutionary decision of Securities and Exchange Commission on 4th of March 2008, explode a new era on asset management field approving the listing and trading Active Exchange Traded Funds in the US market. The decision is a breakthrough for the ETF industry,

[14] Also, ETFs, unlike mutual funds that are priced always on NAV, are priced by the power of demand and supply and may differ to NAV, concluding to investment opportunities.
[15] According to Morgan Stanley, there have been submitted 550 files for new ETFs: 423 in the US, 58 in Europe and 69 in the rest of the world.
[16] Morgan Stanley estimation on ETF Global Industry Review publication

allowing investors to access actively managed portfolios within an ETF structure, on the limitation of a major obstacle of full transparency.

The main disadvantage of the approval of active ETFs consists on the fundamental properties of mandatory disclosing of the constituent holdings in addition of any rebalancing of the allocation at real time. At the previous section, we referred to the structure of passive ETFs and the behaviour to be consisted based on a specific underlying index. This is consistent to the rule of disclosure of the allocation to every potential investor.

We point out the cause for the prompt disclosure. The legislation by the SEC, reports for the investors and market-makers information, stock exchanges is bounded to publish every 5 seconds the indicative NAV. On that extent, dissemination of INAV requisites the full knowledge of the underlying portfolios. Dissemination of INAV was the major obstacle, which forepassed 18 years after the inception of the first passive ETF in order the actively managed ETF to be born in the US[17]. Active ETF structure must overcome the aforementioned obstacle. Ellipse knowledge of the constituents of the underlying portfolio violates the process of proper trading. The respect of full transparency means daily disclosure for the entire portfolio and emerge the issue as it is known "front run problem". Front run problem is the disclosure on real time of the portfolio allocation and any entity involved in the market potentially could replicate the allocation prompter than the fund. In the extent of front run problem, fund managers in real world are reluctant to disclosure their allocation on real time. The obstacle of full transparency refers mainly to professional investors but by the side of the retail investors are reluctant to pay a sponsor to purchase an

[17] Active ETFs first launched on Germany on November 2000 in Deutsche Börse Exchange

exchange traded fund since they can replicate the same allocation without paying ETFs expenses.

Let's define further the option of retaining the allocation hidden. In this solution, there are two important issues that require an answer. The first is the legislation barrier and the second one is the dissemination of the intraday NAV, so the market maker to be rational informed to provide a "fair" price to the investors. As known, the supplementary participants, specialists, stock exchange, and investors should be informed about the extract portfolio allocation and the tracking error of the underlying portfolio. As Gastineau (2001) proposed that the problem can be alleviated by the creation of a hedged portfolio with identical risk profile. The disclosure of the proxy portfolio permits to market makers, specialists, investors and arbitrageurs to consider their quantity of the risk exposure.

Full transparency is under the major interest to the participants on the creation of an active Exchange Traded Fund. However, to great interest there are sequences of difficulties that have to be withdrawn for active ETFs to become an appealing product in asset allocation market. Passive ETFs demonstrated as cost efficiency funds with low expenses ratios. In contrary, the rule of full transparency increases operational and management fees as the manager needs to correspond to daily information procedures. Management fees increase both from the higher frequency of the trades and from the hire of a well-known manager. Gastineau (2008) initiate a different angle of full transparency associated with increased trading transparency costs under the rule of liquidity demands. Daily disclosure of the allocation map and "front running problem" trades leads to an implicit increase of the demand of the underlying securities with a respectively loss for the ETFs performance and respectively shareholders.[18] More than one business day to execute the total number of the required trades implicitly increases demand and drifts upwards the prices of the underlying securities. An extra benefit names tax efficiency and provide the distinctive merit that passive exchange traded funds keep as an arrow in their quiver in order to expand the last decade. Take under consideration that the increase in the number of transactions alleviates this virtue.

Passive ETFs have predefined constant strategy allocation and investors select ETFs by their corresponding investment strategy without to look for manager's ability to generate positive returns. On the contrary, on active managed funds, investors and basely institutional investors depends their decisions on the manager ability to generate profits and a resignation of a fund manager often have negative impact both on the performance of the fund and on the investment strategy's orientation. From the manager's perspective are very reluctant to entry ETFs industry and have the day by day evaluation of their strategy unless they offset the aforementioned mandate with a high compensation of other in kind benefits which inherently increases management fees. To the extent of that, passive ETFs investors are independent from this dilemma which exchange traded fund under the same strategy to prefer. In real world, active managers benefits by high compensations due to their ability of efficient market timing and any type of disclosure reduces their glisten to the market moreover if that disclosure is mandatory to be announced simultaneously with the buying orders. By the rule of thumb, actively managed funds prefer limited disclosure portfolios and with no doubt after the full execution of their investment strategy.

By the inception of the first active ETFs, on their prospectuses demonstrate the imposed constraint to limited number of trades and not to get over more than three

[18] The liquidity demand is greater in small cap ETFs and generally to illiquid securities and is beneficial to small in volume trades

times during a week. The requirements of prompt disclosure that legislation imposes can be merely alleviated by two specific solutions. The first solution refers to the option to hidden portfolio reshuffling for the event day. In practise, the execution of the reshuffling could occur every Friday. The manager has the time to mark and reveal his investment strategy before the next business, on Monday.[19]

In this section up to now, we referred to the obstacles that active ETF structure faces on the implementation and versus to traditional ETFs. Apart from the significant difficulties the creation of active ETFs embeds distinguishing advantages. Active ETF provide an alternative choice on market timing approach, that conventional ETFs and funds fail to provide. In the universe of transaction costs, the empirical investigation of the first active ETF proves lower expenses ratios than the conventional mutual funds.

With no doubt the rule of full transparency provides a distinctive privilege, especially to the retail investors with less and delayed access to information than the specialists or institutional investors, ensuring to a more efficient diffusion of information across different types of investors in means of access.

3.2 Active ETFs structure and Quantitative Funds

In this section, we are examining the challenging prospects that hedge fund industry and quantitative funds encompass into an active ETF structure. Taking under consideration the merits of daily disclosure and the aim that quantitative funds are

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[19] Unlike equity index ETFs front running declines on ETFs with a fixed income strategy, which are not so easy to conquer to arbitrage activities and may trade more frequently.

oriented, there is a crucial question to be answer in the near future; If active ETFs are the optimal path for Hedge Funds and more broadly alternatives industry to be regulated vehicles? Are an active ETF share class the efficient and rational development for quantitative hedge funds or more generally quad funds?

In quantitative industry, the rule of full transparency, do not emerge any increase in transparency costs. Their operation nature, with frequent rebalancing, implicitly has developed a rational mechanism to monitor allocation performance and daily disclosure will not arise any additional costs. The second aspect names the side of manager appraisal. Managers in hedge funds industry are evaluating already into a very intensive horizon since their performance is the most valuable capital into a fund and do not emerge any reluctant to this point. For specific type of quantitative funds, recommended allocation comes out from an optimizer system, where there is no need for extended manager's comprehension. To that extent, any type of disclosure increases transparency and aid offshore funds to increase their solvency and so their credibility to investors.

Already, there are quantitative ETFs based on the Rules Based Indices, mainly listed on AMEX. Many of the newest exchange-traded funds (ETFs) known as quantitative based ETFs are supercharged by rules-based, quantitative algorithms, in their attempt for market timing. The underlying index is based on an algorithm and allocation strategy is defined by the computer forecasts. Rule-based ETFs merely confirm the rhetorical question if is possible for the transfer of quantitative funds on ETF industry.

3.3. A relative comparison of active ETFs versus to conventional mutual Funds

In this section, we are examining active ETFs structure against the structure of the conventional open-end funds and the similarities or significance differences that may arises by the inception of the new financial tool.

In that context, we are investigating the potential answers to the question if actively managed ETFs will comprise an additional share on the traditional open end funds or a detached innovative fund type? Recent developments consists a challenge whether active ETFs substitute conventional mutual funds, be just a counterpart solution or can accomplish an extra ETF share class on the traditional open end structure. The core attribution on the recent proposed rule is the transformation of legislation of active ETFs with respect to the respective regime of conventional mutual funds. The replacements attribute to the disclosure of the performance - NAV opposite to the benchmark, to literature and marketing material and finally to statutory limits.

On that concept, the main distinction that the legislation imposes to an active ETF structure is the obligation to a daily disclosure. The conventional open end fund is restricted to a quarterly disclosure where the disclosure of the portfolio allocation is required to accomplish within the next two months, and come up to 6 calendar months horizon.

The major matter on the relative comparison could be summed up that the attribution of an additional ETF share class to a conventional open end fund has a controversial affect to existing shareholders benefits. Gastineau reports about the effect (2003) and argued that new shareholders is possibly to be benefited from the addition of an ETF share class since transparency costs will reduce the final performance. Although, there is an offsetting positive factor "fund portfolio scales trades". The manager remains stable to the portfolio allocation, and limits trades only to inflows and outflows, keeping costs as low as possible. Edelen et al (2007) assessed that trading costs on mutual funds consist the highest proportionally costs for mutual funds and the proportion to depend to the capitalization scale of the fund. As Zhao (2002) refers conventional mutual fund managers face the dilemma to launch either a single or multi-class fund portfolios or to add one or more classes to the existing fund, however, lead to dissimilar performance. New classes in existing portfolios are primarily the results of the expansion of traditional front end load and institutional funds and occur on the situation of a successful record track for the respective portfolio. Adverse front load funds have no reason to introduce a new share class. On a different concept, Gastineau (2001) argued that an inherent constrain arises by the nature of ETFs as the index based funds as S&P500 or Nasdaq 100, is useless to be launched 4 shares classes.

A different perspective is the comparison of an active ETF with the traditional index funds which is consisted by more than one share class. Passive ETFs do not face this problem since it was structure as a single equity, however, active ETFs have been structured as funds with the opportunity of creating multiple share classes. In a traditional index funds the addition of extra share classes will not hazard the current investors, however, it is not clear if the same issue happens in an active ETF in means of treatment in tax behaviour, expenses and final performance. The daily disclosure requires additional facilitation to the reveal of the price, which can be translated into more expenses.

A further obstacle for a conventional fund to add an ETF share class in the existing share classes is the distinction with respect to the time horizon. Conventional mutual funds requires a holding period to mature and cannot be an efficient tool for short term investors and more specific can not be a rational solution for market timers and other mutual fund traders. In that concept, an active ETF presents an "ideal" market timing investment instrument with low cost which attending to low budget investors in order to achieve profits through distinguish investment strategies. At the inception of actively managed ETF appears extraordinary a replication of conventional index funds with multiple separate shares classes. However, emerge the born of a new generation of funds with a single class and the trivial stance remains the final performance which actively managed ETFs have to prove the ability to outperform conventional funds.

4. Conclusion

Tremendous expansion of Exchange Traded Funds of the recent years is under investigation in this chapter. We divided the evidence into a brief literature review on passive ETFs, analyse the properties and the structure of passive ETFs and define active ETFs.

The most appealing properties of passive ETFs can be summed up to the dual behaviour to react as a traditional open end fund and simultaneously as a traditional stock. Among the prevailing advantages include in kind transactions, tax efficiency and the wide spectrum of investment opportunities.

The evolutionary decision of the SEC to permit the creation and trading of active ETFs created a new era on asset management industry. On that concept, the major obstacle remains the issue of full transparency. The resolution of full transparency will create a different perspective and will draw the direction of future development. The most challenging direction exhibits the transformation of conventional and mutual funds into an active ETF structure.

The coming years will be under investigation for the empirical evidence of active ETFs to prove the potentials and the percentage that can achieve on asset management industry.

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Chapter 2: Pair Trading on International ETFs: An anatomy on relative value statistical arbitrage methodology

Introduction

The ample existing literature of trading strategies is relying on the conjecture that time series of returns follows a pattern. Profitable strategies base their profits mostly on past performance. The most appealing aspect since the foundation of trading strategies is oriented by the term "market timing" which names the unique objective to outperform the market. As a rule, market timing is implemented by the traditional momentum trading strategies and contrarian strategies.

Besides to the aforementioned traditional strategies a successful trading strategy raised the late years is known as pair trading strategy and reverses the intuition of market exposure to market neutral concept. Gatev et al. (2006) reports that the exploration of this kind of strategy came in the mid 1980s by Nunzio Tartaglia who developed a high technology trading program with the intervention of statistical methodology. The program recognized matched securities with high degree of correlation (prices are moving together). Conceptually, pair trading is constructed under the rules that constituencies expose correlation (moving together) and reduce net market exposure when long and short components implemented simultaneously. In the early 1990s, pair trading strategy flourished as it was utilized by many individual and institutional investors, mostly hedge funds, in their attempt to reduce market exposure. A successful pair trading strategy requires the following: (1) a fundamental behaviour of pairs which creates profits and names the assumption of mean reversion, (2) identification of stocks that move together and (3) a decision for the optimal distance metric to identify divergence.

In the practical implementation of an arbitrage strategy a crucial issue arises and can be named as "optimal timing". Optimal timing concerns the critical decision when to exit the trade if the mispricing has been eliminated or the divergence may continue to widen prior to convergence. In the literature, there are two dominant theories regarding the timing when a trade position is unwinded. The conservative trading rules propose the liquidation of the trading when the spread reverts to the long term mean and the alternative perspective suggests that assets are held until a new minimum or maximum is detected according to a predefined trading rule. According to Gatev et al (2006) no convergence means to leave the pairs to trade within the next 6 months and if they do not converge within this horizon to liquidate the trade. An alternative and simultaneously shorter perspective applied by Engelberg et al (2008) is called "cream-skimming strategy" and limits the trade only to the first 10 days. Solving the optimal exit time, the question that arises by the intuition of pair trading is how can we achieve profits by a market neutral strategy? The answer can be found on Jacob and Levy (1993) which argued that a pair trading is a market neutral strategy although in practise it is solitary a market neutral investing strategy.

In this chapter, this intuition is closely related to the exploration of the optimal formulation of pair trading strategy and the mechanism of profitability. They are three main contributions in this chapter. The first contribution is the examination of the optimal formulation mechanism for a successful pairs trading due to different levels of divergence, different trading horizons and different number of eligible pairs.

The second contribution investigates the motive behind the profits and explores if there is a systematic pattern that generates these profits. In the aforementioned attempt, we investigate if the Fama and French factors can adequately explain the pair trading strategy. The examination is extended both in US national and international oriented framework. However, the explanatory power of Fama and French traditional factors on strategies motivated by statistical arbitrage rules and fundamental factors appear to be vague. The aforementioned statement names the purpose for a pairwise investigation of profitability in cross-sectional regressions framework. More precisely, there is ample evidence in literature about the contribution of Fama and French factors to the total profitability, however there is a lack of empirical evidence according to individual factors that correspond to each country that constitutes pairs portfolios. The explanatory variables that are identified comprise three sets-levels of variables, industry level, market level and macro-country level. Among the variables that are used GDP grwoth, Default Premium, the Dividend Yield, the Discount Rate, the Unemployment Rate and the Inflation. Previous studies incorporated the empirical examination of the entire calendar excess returns to a common set of state risk variables. I consider the decomposition of a pairwise framework in a time-varying set and I regress each pairs country specific risk factor in a cross sectional panel.

The third contribution names the incorporation of international evidence to pair trading profitability incorporating ETFs and testify if ETFs leads to higher profits than strategies motivated by mean reversion on US equities returns. The literature on ETFs incorporated in the creation of winning strategies is limited, nevertheless, for first time integrate international evidence on pair trading strategies.

In conclusion, Nath (2003) presented the steps and the decisions in pair trading formulation which we reproduce below adding more several issues. In this work, we are investigating the motivation behind the first and second phase and we are illustrating the optimal mechanism for each separate concern.

Phase 1: First thoughts of a pairs trader

- Looking for the optimal historical training period
- Selection of the optimal subset from the universe of available securities
- Decision how to form pairs
- How long to trade into the future "Trading period"

Phase 2: The implementation

- Decide the length of training period
- Find a subset of securities within an asset class
- Find the optimal metric model to look for the ideal partner for a security
- Use filters to cut-off points when pairs are too unstable to mean revert with
- The optimal time for a spread to open
- The optimal time for a spread to close
- Robust mechanisms for risk management

Phase 3: In practise

- The access of a broker in cash and repo markets
- Reduce commission payments
- Availability to raise capital debt at a short choice
- Lines of credit for financing margin payments and excess of any equity capital to starts with
- The behaviour of the owners of equity capital when her P&L is under duress
- Access to alternative trading venues and how quick is the execution

The remainder of this chapter is organized as follows: Section 2 refers to a brief review of the existing trading rules and describes the several factors that affects the implementation of pair trading. Section 3 describes the data and their properties. Section 4 provides a detailed overview of the existing methodology and outlines the mechanism of our trading Section 5 provide the implementation of the robustness tests. Section 6, describes the empirical estimations and represents the decomposition of the different strategies that we applied. Sections 7, is based on the debate of pairs trading profits and the generating mechanism behind them. Finally Section 8 offer some concluding remarks.

2. Existing Trading Rules and Literature Review

The existing pairs trading literature or relative value arbitrage strategies can be derived into three major groups. The most widespread methodology on pair trading is that presented by Gatev, Goetzmann and Rouwenhorst (2006, hereafter GGR) known as the minimum distance methodology and founded under the concept of mean reverting of the returns of the pairs. They modelled the co-movement of assets into a pair under the rule of the minimum sum of squared differences between the two normalized price series and implemented the strategy into a six month trading period. They enhanced their empirical evidence with the used of various tests.

Their algorithm was replicated by Engleberg, Gao and Jagannathan (2008, hereafter EGJ). They examine a shorter trading interval of 10days which they named "cream-skimming" methodology. Their main contribution in pair trading is the examination of the risk factors that affects profitability. The evidence testifies that pair trading is related to the information diffusion across pairs portfolios.

Jurek et al (2007) applied relative value trading of two related securities via the "Siamese twin formula". The trading rule is formulated between two assets with common fundamentals and proposes a long position for an undervalued security and a short position for overvalued asset. Conceptual difference of Siamese and mean reverting strategy names the resource of deviations. Siamese refers to fundamental reasons and it's a non-directional strategy since the long position is being offset by the short position.

The second peer group of identifying pairs is based on technical patterns. Lo et al (2000) in their publication defined the most popular technical methods, which are: Head and shoulders (HS), Inverse head and shoulders (IHS) broadening tops (BTOPS) and bottoms (BBOT) triangle tops (TTOP) and bottoms (TBOT), rectangle tops (RTOP) and bottoms (RBOT), double tops (DTOP) and bottoms (DBOT). The technical analysis is based on thresholds. HS is based on maximum threshold and IHS is based on minimum threshold where within the distribution there are 5 local thresholds where are distinguished as they are 1.5 per cent of their average. Broadening tops and bottoms are based on thresholds. Tops are based on maximum threshold and bottoms are based on minimum threshold. With the distribution there are 5 local thresholds where are distinguished from bottom to top and reverse. Double tops (DTOP) and bottoms (DBOT) are constructed by locate the highest local maximum which takes place after the predefined local maximum. Those two local maximum should be within 1.5 percent and should occur the most within every 22 days. The reverse should happen on double bottom.

Lucke et al (2003) examined the profitability of chartist trading rules under the rule of the head and shoulder (SHS). SHS trading strategy requires three thresholds in a time series which represent the trading signals for the implementation for the strategy. However, the results from the exchange rates are not significantly positive and the majority of this strategy generates negative returns.

Brock et al (1992) applied two widely used technical rules in the world of pair trading strategies (1) moving average-oscillator, (2) technical range break out. The first technique is defined by two periods, short and long period while in the short run if the moving average exceeds the long run moving average they go long. They used many periods as 1-50, 1-150, 5-150, 1-200 and 2-200 where the first number represents the short period and the second number the long period. The trading range break out methodology is consisted by a resistance level, a band which in the top there is maximum threshold and on the bottom there is the trough. The upper bound presents the sign for going sort and the lower bound for going long. The thresholds are based on moving averages and the results testify that technical rules contain predictive power.

Nath (2003) applied an approach based on the empirical distribution. He kept a record of the distance of pairs and opens a trade when the spread cross 15 percentile. He kept the distribution at price levels which means that distance is static overtime. Moreover, he liquidates the trade when distance widens more than 5 percentile.

Bock et al (2008) applied Markov regime-switching models to detect switching in mean and variance between temporary and long run in equilibriums. Their captured the dynamics of pairs trading when series deviates 1.645 (so their approach to standard deviation equals to 1.645). Their trading rules without trading costs adjustments generate positive profits.

Do et al (2006) applied a parametric formula to the literature of pair trading, named as "stochastic residual spread". They considered as given the existence of mean reversion and modelled the spread by a residual spread function. They open a trade when the accumulated residual approach spread widens.

Elliot et al (2005) proposed a mean-reverting Markov chain model for the spread which is observed in Gaussian noise known as stochastic spread approach. They defined the spread to be the difference between the two assets. So, x is the driving leading factor of the spread since represents the time that the process will revert to its own mean, under a Vasicek process: $dx_t = \kappa\,(\theta - x_t)d_t + \sigma\, dB_t$ where (dB_t) is a standard Brownian motion and (θ) the long run of the mean.

Mitchell et al (2001) estimated 4,750 stock swap mergers, cash mergers, and cash tender offers during 1963 – 1998 and argued that risk arbitrage can generated positive excess returns and is positively correlated with market returns in specific environments as in stable and uptrend markets.

On an early approach of mean reversion of stock markets around the world Poterba et al (1988) argued that mean reversion is significant larger in less broad based and less sophisticated markets and De Bondt et al (1989) proved that mean reversion is more negative for the portfolios of smaller firms and for the equal-weighted index than for the larger firm portfolios or the value weighted index[20].

Pairs trading are a narrow part of the existing literature on trading strategies. Balvers et al (2000) examined mean reversion on US equities using parametric contrarian strategies without apparent conclusion. The relative comparisons between parametric contrarian investment strategies versus buy and hold and standard

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[20] By definition negative slope confirms mean reversion.

contrarian strategies proved that parametric contrarian strategies exhibits mean reversion and outperform the alternatives specifications.

Conrad et al (1998) implemented momentum and contrarian strategies during eight different horizons across several time periods and examined the source of profits. Their evidence testify that less than half of the strategies (total number 120 strategies) provide substantial profits with momentum strategies to outperform on the medium run and contrarian on the long run. The decomposition of the profits showed that cross sectional differences in mean returns considers only a minor proportion in the profitability of momentum strategies. On the other side "contrarian" profits are insignificant as offsetting by the losses. They argued that the results depends on the supposition that mean returns are constant and the source of profits names cross sectional variation in mean returns.

A different concern is the issues that arise from the practical implementation of pair trading. Bushee et al (2005) concentrate on the different approach between academic trading models and implementation in real world. They summed up that main issues are transaction costs, price impact to block trades, restriction on short sales and legislation constrains. Focus on relative value strategies the identification of arbitrage opportunities and the decision of time exit are the main leaders on the formulation on a strategy.

2.2. The Essential Role of Arbitrage to Optimal Exit Time

Statistical arbitrage trading models implicitly are grounded on the importance of arbitrage mechanism that could create profitable arbitrage opportunities. Arbitrage opportunities emerge either under the spectrum on the convergence to the long run or to the extreme price differential. The result of an arbitrage transaction should a risk free process generated positive returns. How those opportunities affect final profitability of statistical arbitrage strategies?

In this section we are referring to arbitrage opportunities under the same perspective that Shleifer et al (1997) presented on the performance of arbitrage strategies. The major evidence proved that arbitrage mechanism transform to ineffective in the extreme circumstances where all arbitrageurs are fully invested and the profits have to shared to a pool of participants and concludes to be extremely limited. From the pool of the investors only a small incremental group of specialists could identify promptly abnormal returns and can utilize them. When the majority of the investors realize those abnormalities, the superior profits have diminished and the vast majority of the investors will invest messily to the overpriced assets. So, it's a key decision to know when to enter a trade and when to exit in addition with the optimal identification mechanism of an arbitrage opportunity. An indicator to avoid market interaction names the presence of extreme volatility. According to empirical evidence the significance of historical returns are extremely vital to arbitrage (hedge) funds. In the relative comparison with traditional funds, as more sophisticated and well experienced, arbitrageurs may avoid extremely volatile arbitrage positions even those positions potentially terminate to attractive returns. The avoidance of trade on high volatile sentiments is followed by individual investors as well. Thus, a high volatility environment, will force investors to increase their redemptions and fund managers to exit the market with increased probability of potential loss. On that concept, extreme circumstances do not reflect a direct consequence of fundamentals and macroeconomic risks but arbitrageurs attempt to diminish those extraordinary events due to high idiosyncratic return volatility.

Jurek et al (2006) confirm Shleifer et al's (1997) work where arbitrageurs are reluctant to increase their allocation in a high volatility environment even when mispricing has widened. There is a trade off between horizon and divergence risk, where after the crucial cut off point any mispricing, even in the case of expanding divergence and creates highly profitable opportunities, conclude to a decline in the allocation. They argued that the trade off creates a time-varying boundary, where outside the bounds even the opportunity map increases rational arbitrageurs will diminish its exposure. Their evidence is confirmed as increasing opportunities are offsetting with the nearer exit horizon and they arbitrageurs are not willing to bear any potential losses.

Kondor (2008) confirmed the vital role of arbitrage in the success of trading strategy under three perspectives: (1) competition of arbitrageurs leads the prices out of the long run mean, and predictability of the direction of change concludes to false sign (2) the competition of arbitrageurs can lead to substantial loses in the majority of extremely short horizon (3) the absence of arbitrage from the market helps predictability power and the prices to converge. Jacob and Levy (2003) on the hypothesis of optimal time exit argued that statistical arbitrage strategies and optimal forecasting of the spread time series should be considered as unique factor which affects profitability of a pair trading strategy. [21]

On a totally different perspective, Do et al (2006) referred to the main problem of non-parametric trading methodology which lack of forecasting ability to predict the convergence time horizon. Jurek (2006) referred to the proximity of arbitrageur's terminal evaluation date as one of the two main factors that affect a strategy.[22] Kondor (2008) confirmed that the prompt reflection of the first arbitrageurs could terminate

[21] They referred that a pre-selection should be accomplished by fundamentals factors.
[22] The alternative factor refers to the expectations of positive returns.

with high probability to positive profits at any time point as far as they are not affecting the prices. He referred to the unique advantage of a finite time exit and sum up that the two factors affecting the price spread are allocation and the unknown duration of the local demand pressure. On that concept, we are investigating several time intervals in order to find out whether there is an optimal trading horizon.

2.3. Liquidity and Short Sales Constrains

The level of liquidity affects the implementation of a trading strategy and plays a vital role in the explanation of the source of the profits. Literature confirms that mean-reversals, both on a short and long run, are driven by the level of liquidity and the distinction is referring to the direction of the transition (Conrad, Hemmed and Niden (1994), Cooper (1994)).

This behaviour odds arbitrageurs that leads to an extensive period of inequilibrium and keep the prices in divergence. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996) and Brennan, Chordia, and Subrahmanyam (1998) argued that illiquid stocks presents on average higher returns. Amihud (2002) and Jones (2000) model liquidity as endogenous variable and proved that there is a link between market liquidity and expected market returns in means that innovations affects persistent equities. Eleswarapu (1997) confirmed the existence of liquidity premium on equities and found a strong evidence utilizing data from Nasdaq stock exchange for the horizon from 1973-1990. Engelberg et al (2008) proved that liquidity factors have limited power to explain pair trading profits which declines further on short-term horizon. Llorente et al (2002) argued that short-term return reversals are driven by non-informational hedging trades where illiquid stocks are more vulnerable.

Chordia et al (2000) concentrate on aggregate spreads, depths and trading activity on US stocks, indicating that on daily basis there is negative correlation between liquidity and trading activity. Liquidity collapses on bear markets and is positive correlated by long and short interest rates. Increasing market volatility has a direct negative effect in trading activity and spreads. Major macroeconomic announcements increase trading activity and depth just before their release.

Knez et al (1997) under a different perspective proved that the difference between quoted depth and order size is strongly correlated with conditional expected price, so the profits depends on the size of the positions.

Short sale constraints prohibit the application of market neutral strategies and cancel the hedging ability that arbitrageurs and investors have to reduce their market risk. EJG on pair trading implementation argued that short-sale constrain is not correlated with the risk and return of pair trading. D'avolio (2002) provided evidence that size affects is negatively correlated with the availability of borrowing equities, while small size decile exhibits the most obstacles.

3. Data

3.1. Data Sample Span

Our empirical analysis focuses on 22 international, passive ETFs. We study international ETFs of the major developed markets as well as the major emerging markets. Our sample have been broken down with respect to specific criteria like market capitulation, wide historical tracking record, well-know issuers and trying to capture the whole range of global asset allocation with respect to country indices exposure as well as regional dynamics through international ETFs.

Our dataset primary listing is on the American stock exchange and the majority of them are provided by Barclays Global Investors - (Ishares). The list of our series includes the following countries accompanied by their ticker: MSCI Australia (EWA), MSCI Belgium (EWK), MSCI Austria (EWO), MSCI Canada (EWC), MSCI France (EWQ), MSCI Germany (EWG), MSCI Hong–Kong (EWH), MSCI Italy (EWI), MSCI Japan (EWJ), MSCI Malaysia (EWM), MSCI Mexico (EWW), MSCI Netherlands (EWN), MSCI Singapore (EWS), MSCI Spain (EWP), MSCI Sweden (EWD), MSCI Switzerland (EWL), MSCI Japan (EWJ), MSCI S. Korea (EWY), MSCI EMU[23] (EZU), MSCI UK(EWU), MSCI BRAZIL (EWZ), MSCI TAIWAN (EWT) and S&P500 (SPY), the biggest ETF worldwide.

The majority of the ETF records started on April, 01 1996. Exceptions are MSCI S. Korea started on 10.05.2000, MSCI Taiwan started on 20.06.2000 and MSCI EMU incepted on 25.07.2000 and. International ETFs peer group listed on AMEX includes 53 ETFs[24] although we crop the group for adequacy purpose of the dataset (sufficient number of observations). The set consist a heterogeneous group in means of inception date, for the estimations we considered every ETF by the objective inception date until March, 11 2009.

Our analysis is based on daily observations including open, high, low and closing prices for each separate ETF series. ETFs series has been downloaded dividend adjusted since dividend payments are not made simultaneously for all series and those variations may affect spread fluctuations. The calculation of dividend adjusted series done with the implementation of the annual dividend across all months

[23] EMU corresponds to the performance of publicly traded securities in the European Monetary Union markets.
[24] According to the official leaflet of AMEX dated on May 30, 2007.

of the year after the cut off of the divided since the next cut off with the new amount. However, the series downloaded dividend adjusted[25] and the calculations adjusted electronically from the provider.

The respective ETFs have futures contracts (some of them have also options[26]) and the vast majority of our sample ETFs can be traded, over the counter, to electronic platforms (ECN). The trading hours of AMEX are at the opening 09:30a.m. to 4:15p.m.

The ETF have been spilt into two categories. The first group defines the segmentation between Developed versus Emerging markets to investigate if our strategy is driven by mature countries with a complete financial system. The second group have sorted the ETFs according to market capitalisation. This group consists only from large capitalization funds, however, we separated our sample into two portfolios based on market capitalization in order to check for liquidity effects on the profitability of the strategies.

In addition to the results regarding the full sample, we divided our sample into four different sub periods. The first subperiod covers the inception of our set April, 1 1996 and is extended since the end of December of 1999. The second subperiod starts at January, 01 2000 and is extended until December, 31 2002, the third subperiod covers the period from January, 01 2003 until the end of 2005, and the last period is extended since January 01 of 2006, till the end of the set. The contribution of decomposing the sample into different horizons is to examine if there are any patterns that lead our strategy only on specific periods and to verify the correlation of our trading methodology according to different conditions of the capital markets. The

[25] Campell et al (1997) argued about the importance of dividend-price proxies for variations in expected future returns.

[26] Options have the following ETFs: MSCI Australia, MSCI Brazil, MSCI Canada, MSCI Germany, MSCI Hong-Kong, MSCI Japan, MSCI UK, MSCI Taiwan, S&P500. Options increase the liquidity of the respective ETFs.

reasons that I selected these specific periods are several with the main motivation being that of looking inside and back test the strategy into different business cycles. The first period is referring to an upside trend on the capital markets while the second period captures the reverse downtrend. The pre last period is related to the recovery period and the last period is mainly linked to the bull market of the last years, embedded by the subprime crisis.

3.2. Properties and Data-Snooping

The definition of data snooping includes a model that explodes an excellent fit with spurious results. In time series analysis, data-snooping is inherent and unavoidable, and the ellipse of customized methods leads us to face every situation as unique. In this section we refer to the methodology to identify any spurious patterns and the treatment of our datasample during the calculations of our estimations.

Our datasample is based on MSCI international indices with many advantages and the most crucial is that there is survivor bias free. MSCI indices according to Fama and French (1998) include firms that disappear and simultaneously do not include data from newly firms so there is no survivor bias. On that concept, the rules that MSCI indices are compiled are clear and disclosed to every investor. The importance of the aforementioned aspect is crucial and compared with competitor's hedge funds databases (since pair trading strategies is mainly applied by hedge fund industry) which suffer from survivor bias. On a similar perspective, Fama and French (1998) argued that MSCI primary include large capitalization companies of a country index. The included companies mostly appear to include 80% of existing market capitalization and consists a robust proxy of market performance for each respective country. MSCI is one of the largest and regulated index providers regulated all over the world.

On an extended direction of the previous statements appear to be the lack of bankruptcy risk. GGR (2006), consider bankruptcy risk as one reason that individual securities returns cannot considered as stationary. A characteristic example arises by the properties of twin stocks. A negative announcement on the first stock wills identical influence by the same direction the second stock and the pair trading between twin stocks will be unsuccessful. Considering ETFs, bankruptcy risk alleviates, as implicitly are aggregate major indices of the stock exchanges with no survivor bias as we refer extensively on the previous paragraph.

Data-snooping issue arises when many specifications have been conducted or the datasample has been used many times in order to conclude to the final model. The problem gets larger dimensions when we conduct non-linear methodology and trying to achieve a robust and successful out of sample estimations including random trends as well as genuine nonlinearities patents. A naïve rule to detect overfitting is too many degrees of freedom or two many parameters which leads to unfortunate out of sample estimations. Lo & MacKinlay (1990) state that a corrected distribution could be a merely solution to the problem. Another test to mitigate the effect of data-snooping is out of sample evaluation across different tests and datasets. Brock et al (1992) confirm existence of the problem and note that technical analysis can uncover spurious patterns although can not alleviate them. Their solution named the reporting results from several trading strategies, to utilize a very long data series (Dow Jones Index 1897 -1986) and to focus on the robustness of results across different no overlapping sub periods. The above concerns have being taken under consideration at section 5, where we conducted robustness tests.

4. Methodology

4.1. Time and Formation Horizon

The formation of the pairs is established after a rolling horizon of 120 trading days (formation or estimation period) and the implementation of the basic trade occurs for 20 days (trading period). The selection of the formation period has been done after testing several different horizons[27]. We start the formation period at April the 2, 1996 and complete the first period at September 21, 1996 which corresponds to 120 business days. The length of the formation period is constant over the entire sample and we roll over every formation window aligned with the length of trading period. More analytical, the first formation period begun on April 2, 1996 and completed to September, 21 1996. The pairs are eligible to open at September, 22 1996. We roll over 20 business days for the second period and finishes at October, 21 1996 (when we implement 20 days trading) and so on. Our calendar formation periods are overlapping at 120 days minus the trading period which is the horizon that we roll over the formation space. The implemented estimation period is shorter than the existing literature applied (GGR (2006) and Engelberg et al (2009)) when they incorporate one year formation period. In the way we calculate the segmentation of formation periods, we consider overlapping formations periods but we avoid overlapping trading periods.

[27] We conducted estimations with a rolling window length of 52, 104, 200 and 320 business days, however we do not present these estimations

4.2. The Formation and the Eligible Number of the Pairs

In the formation of the pairs our base was the empirical algorithm that proposed by GGR with a modification of their algorithm. At the beginning of the formation period, at day *t=1,...120*, we record each ETF price dividends included, P_i^t under equation (1):

$$P_i^t = \prod_{t=1}^{N} (1 + r_t^i) \tag{1}$$

Where the ETF *i*'s price by the closing price at day t, N is the total number of days from the start, and r_t^i is the return on day t. For each formation period, we compute equation (2), for creating the rule for identifying pairs.

$$\Delta = \frac{1}{N} \sum_{t=1}^{N} \left| P_t^i - P_t^j \right| \tag{2}$$

where t=1,..., N is the total number of days for each estimation period, P_t^i and P_t^j are the prices of each separate asset on trading date t. The distinguish of our selection pairs rule and GGR rule consist on that our rule identify pairs that minimize sum of absolute deviations of the two underlying price series during the same formation period. On the contrary, GGR identifying pairs that minimize the sum of squared deviations between the two price series. The implementation of GGR rule is known as minimum-distance criterion and conceptually is developed on the naïve rule that two stocks move together historically. The intuition of the formation pairs algorithm appears to be the similar, nevertheless, the rules in means of absolute differences permits to identify opportunities with smaller divergence than the sum of squares. Economic interpretation of the modification lies in the decreasing level of divergence which increases the frequency of opportunities and potentially could lead to higher profits.

Our datasample is consisted by 22 ETF price series, so the available number of pairs for consideration at the beginning of each formation period calculated by the following rule $P_m \times (P_m - 1)/2$, where *Pm* is the total number of ETFs and the total sum stands for 231 pairs. We limit the number of pairs at each formation period, up to 20 pairs that have the smallest price difference during the formation period[28]. The best 20 employed pairs is the cap in our estimations and we consider pair portfolios with 2, 5 and 10 eligible pairs to examine profitability distribution to different levels of pairs portfolios.

The formation of pairs portfolio requires as perquisite identification of the optimal pairs distance. The motivation is to examine the optimal distance of identifying pair opportunities. Figure 2, represents pairs mean return under 3 different distances of deviations, 0.5, 1.0 and 2.0 standard deviations. Outlining graph 1, clearly reveals the negative relationship between profitability and increasing distance spread. Clearly, optimal distance outlined to be 0.5 standard deviations. Previous studies, GGR and EGJ incorporated 2.0 standard deviations to identify pairs divergence, however, narrower distance achieves to identify small divergence, increasing the probability of arbitrage opportunities which can lead to potentially higher profits. In

[28] In order to conclude to 20 pairs with the minimum historical distance we conduct the estimations with more pairs however, the results worsen substantially.

pairs trading strategies the perspective to create profitable winning strategies loading small divergence opportunities is novel. The relative comparison of three different distributions reveal from k=1,..., 20days exhibits a negative relation between proportion of distance and volatility. The narrower distance reveals advanced volatility. The calculation of the distance is measured in terms of return distribution. GGR stated that the number of pairs increases the optimal spread of standard deviations as a result of the distance of the assets in price spread declines. A related issue that EGJ reports and hedge funds industry mainly face in practise is the widening of the spreads is usually translated to margin calls, with direct consequences either an additional capital inflow where on down markets hedge funds liquidity is constrained either liquidation (partial or complete) and exit of the market which distorts additionally market returns.

The next step is the practical implementation of the trading. The criterion for the execution of the trading requires price of the underlying assets in each eligible pair the last day of the formation period to diverge more than 0.5 standard deviations. When a sign emerge we invest in long position to the asset which ranges below the mean and we short the asset that lies above the mean. During the trading period, we evaluate for opportunities on a daily frequency under the distance observed rule and we separate the transactions into three different cases: (1) if the divergence exists, we continue to trade with no reactions (2) naïve case names that prices convergence less than 0.5 standard deviations, accordingly we liquidate the positions of the trade and we are evaluating sign innovations of the pairs (3) the most complicated execution occurs when the assets of the eligible pair move to the opposite direction and cross the average mean. Here, we reverse our positions according to the movement of the respective assets. During the time that the prices are around to cross the mean and are less than 0.5 standard deviations we liquidate and we are waiting for the divergence to open a new trade position.

So far, we referred to the formation of unrestricted pairs as GGR named the rule to evaluate only pairs divergence. In addition, we estimated several restricted pairs constrained by the rules of academic literature and practitioners as the segmentation between developed and emerging markets and different level of market capitalization. The universe of pairs trading executed the next business day after the event day of divergence. Intuitionally, the implementation of pair trading based on the sign at the event day, we are not eligible to implement after the trading session. A different aspect according to GGR, names the waiting of one business day checks for abnormal microstructure effects as first order negative serial correlation and the negative effect of bid-ask bounce. Literature confirms that a contrarian strategy, as pair trading belongs to, is affected positively by the bid-ask bounce.

4.3. The Computation of the Excess Return

Calculation of the profits is considered as a buy-and-hold portfolio as GGR followed on their publication and stated that prevent from exaggerated transactions costs. Equation (3) represents excess returns of a pair during a single trading. Excess return is defined as the net flows between long and short exposure. L represents the long constituent of the portfolio and S represents the short constituent of the pair. So, p^{i} introduce excess return of a pair at the specific time t, and equation (3) cumulates the total number of trading days.

$$\sum_{t=1}^{N} R_t(p^i) = \sum_{t=1}^{N} (R_t(L^i) - R_t(S^i)) \qquad (3)$$

In other words, at the day of divergence we start keeping a daily record and we calculate the cumulative excess return at the day that a transaction occurs. For the terminal wealth of the pairs trading portfolio apart from the first part of right hand side of equation (4) which is straightforward and represents the return of the current trade

$$R_t^{portfolio} = (1 + R_t(p^i)) \times r_{t-1} \qquad (4)$$

The second part (where is r_{t-1}) is defined as following:

$$r_{t-1} = \sum_{i=1}^{N} \frac{w_{t-1}^i r_{t-1}(p^i)}{w_{t-1}^i} \qquad (5),$$

$$w_{t-1}^i = (1 + r_1(p^i)) \times \ldots \times (1 + r_{t-1}(p^i)) \qquad (6)$$

For the cumulative return ending at the prior day t-1, we are calculating the wealth at every single trading with respect to the number of N pairs that opened on this specific trade. After the calculation of the portfolio of every single trade, we apply equation (6) for the outcome of the terminal pairs trading profits. Calculations are considered as a pay off of one dollar.

4.4 Optimal Trading Horizon and Profit Sensitivity

Continuing the examination of the optimal pair trading mechanism, we are examining the rational trading horizon. Figure 1, exhibits the empirical distribution of the mean pair trading returns according to k different days, where k= 1, 2, 3, ..., 60,...,120. The distribution of the mean returns illustrates that within a maximum horizon of 120 business days, the optimal trading period correspond to 20 days. Figure 1, illustrates clearly two interesting assumptions: (1) the mean pair returns are more volatile the first 4 days (2) the interesting empirical evidence arises from k=20 when the allowance of the trading up to k=120 mean returns are declining monotonically. The first day mean return is 0.025% and increases at k=8 days to 0.065%. Clearly, the higher mean return occur the 20day with a mean of 0.075%, as we referred after the 20^{th} day mean pair trading falls substantially. On the left side of the figure we represent kernel density. In risk adjusted terms, economic and statistical evidence confirms the hypothesis of k=20 days as the optimal trading period. The naïve algorithm on trading period is to let the assets to converge to historical means. However, the economic statement behind the profits of the pairs trading strategy is not motivated only by the speed of the mean-reversion but also from different factors. To comprehend the vital role of optimal time exit, we have to understand the increasing risk that an arbitrageur faces when the position remains opens for several months.[29]

The short horizon of trading is called a cream-skimming strategy. Our empirical findings stand in contrary to EGJ evidence as the confirmed 10days as the optimal time exit period. The main empirical evidence, we employ in this work, is contributed by appling cream-skimming strategy of 20days trading. However, literature on pair trading (GGR, EGJ) applied a longer trading horizon, 6months period and we desire to investigate the profitability on longer horizon. The second reason for applying a longer strategy consists on the second part, which we investigate pairwise cross-sectional variations and the robustness of the empirical evidence demands a longer trading period. Going further to dual trading horizon, divergence and profitability are not contributed by the same factors on a short and long horizon according to EGJ evidence. The aforementioned aspects name the motivation behind for applying 60days trading horizon.

4.5 Pairs Divergence, Trading Horizon and Statistics

This section motivates and performs a combined analysis of the sensitivity according to the trading horizon and the number of eligible pairs that opens during each separate trading horizon. In Table 1 panel A, we constrain the trading horizon up to 20 days as the optimal horizon. During 20days trading horizon, we reveal the summary statistics that arise by the interaction of the pairs. In Panel B, we also

[29] The rationality behind optimal time exit is expressed as well by the market side. Brunnermeier and Nagel (2004) argued that from 1998-200 hedge funds investing in the bubble of technology realize substantial profits, while one that sold early suffered extraordinary large outflows that liquidate the entire fund.

distribute the number of pairs portfolios that divergence in every trading horizon and we represent the survivor analysis in the time constrain up to 120 days. Survivor analysis as defined by Lo, MacKinley and Zhang (2003) represents the decomposition of time-to-converge. Panel A, on first row reveals that on average all pairs opened during the eligible period of 20days. The number of opened pairs declines as more eligible pairs included in the estimations.

Panel B, investigates the results that the selection of the constant trading horizon under the distribution of profitability for individual trading horizons. The results inference that more of the half opened pairs, convergence within 40 trading days. The most appealing result indicates that one out of four pairs convergence within a week. The latter assumption substantially confirms the selection rule of wide spread divergence (0.5 standard deviations).

In Table 2, we provide the pairs traded matrix, which includes the names of each opened pair and the respective number of relative value trades in each trading session. Panel A, plots the trades for the first pair, 30% (920trades) of the opened pairs are the relative pricing between Eurozone and France regions. In number of trades, the second pair, Eurozone and Germany region traded the most time, which translated to 177 times out of 3.137 executable trades (5.6%). Briefly analysis of the remaining panels (B and C) arise intensive relative pricing between countries of Eurozone (France-Germany, Italy-France) and between Eurozone (Eurozone-Italy). The relative value trades uncover a hidden pattern of economics fundamentals behind the opened pairs. The latter assumption, motives to investigate pairwise for cross-sectional variation on the second part of the paper.

Figure 4, illustrates the empirical distribution of the means returns for the top 5 eligible pairs from the opening of the trade at day k=1,...,20, until the last day that we exit the trade. Panel A, demonstrate a spike between day 4 and 5. Panel B, demonstrate the risk of the distribution to be extremely volatile around k=10day. To sum up the results, confirm our empirical motivation of 20 days and the hypothesis that the profits are short lived and declines over time (EGJ).

5. Robustness Methods

5.1. Properties of Time-Series Estimations

In this section, we analyse the tests we conduct in order to capture the dynamics of the dataset. First, we check for the existence of autocorrelation and thus we conducted the Ljung-Box and squared Ljung-Box statistic (Granger's and Anderson's (1978)). By the rule of thumb, financial series should not present any autocorrelation patterns, and hence no forecastability power. Squared Ljung-Box statistic checks and exhibits the ability to indentify nonlinear patterns under the assumption that since the residuals are independent $\overline{e_t}$ then the square $\overline{e_t^2}$ will be also independent. The next test checks out for departures from normality. We applied Cramer–von Mises test to determine the behaviour of the variables.[30] The asymptotic power of CVM test is the flexibility to estimate under certain local (contiguous) alternatives and is applied by an EDF joint statistic for the composite hypothesis of normality. The test statistic is given by equation (7):

$$W = \frac{1}{12n} + \sum_{i=1}^{n}\left(p_i - \frac{2i-1}{2n} \right) \quad (7)$$

where $p_i = \phi\left(\frac{x_i - \bar{x}}{s} \right)$. Here, p_i is the cumulative distribution function of the standard normal distribution and $\bar{x}$, s are mean and standard deviation of the observations respectively.

A successful strategy should accomplish that the combination of the selection of the assets is stationary. The concept behind co-integration is that a successful strategy has a perquisite: The selection of assets should accomplish that the linear combination between the prices of the assets ensures that any deviations of their price is aimed to be temporary and in the near future will revert to zero (mean-reverting rule). GGR (2006) in their publication refers to co integration as a vital perquisite to the implementation of pair trading. They referred to the literature of asset-pricing models framework with nonstationary common factors like Bossaerts and Green (1989) and Jagannathan and Viswanathan (1988) applied. The co-movement between the long and short components, arise the evidence of nonstationarity between the prices of the portfolios, nevertheless, the pair strategy is expected to perform significantly well.

5.2. Stochastic Dominance Test

A plausible answer to the robustness of our estimations can be occupied by the stochastic dominance approach. Stochastic dominance is defined as a ranking scale between two assets according to their risk taking under consideration their probability distribution function. The comparative advantage of stochastic dominance theory is the ability to utilize risk evaluation and create accurate results (particularly the third order) under the minimum possible quantity of information.

The implementation of the methodology includes three orders. The first order stochastic dominance exists if F(x) dominates G(x), the expected value of F(x) is higher than the expected value of G(x). The second-order stochastically dominates if for any two distributions F(x) and G(x) with the same mean, F(x) second order stochastically dominates G(x) for every no decreasing concave function u: $R+ \rightarrow R+$. The function of stochastic dominance is given:

$$\int_{0}^{+\infty} \mathrm{u}(\mathrm{x})\,\mathrm{dF}(x) \geq \int_{0}^{+\infty} \mathrm{u}(\mathrm{x})\,\mathrm{d}\,G(x) \quad (8)$$

The third order stochastically, when Fu(y) > Gu(x) for all increasing, concave u, with u'''()>0. The economic interpretation of the higher order derives investor's behaviour to decrease risk-aversion aligned with the increasing wealth. To that context, methodology allows to observe decision makers reaction without knowing their utility function and their sensitivity of optimal decision to different levels of risk. In the context of pair trading, Jarrow (1986) examined the existence of arbitrage opportunities incorporating first order stochastic dominance and argued that "*The condition is that the price of a particular contingent claim, defined in terms of the distribution involving the stochastically dominated assets, is non positive. These* *conditions are both necessary and sufficient in complete markets for the existence of an arbitrage opportunity*". Moreover, he confirmed that in continuous trading models the condition of completeness implicitly exists. Fong et al (2005) reveal the evidence for international momentum strategies. They strongly argued that the non-parametric nature allows noticeably to distinguish between profits and loses. On the same concept, the understanding of the utility function is adequate for the investors to decide without being aware of the distribution of the returns. In contrary, ranking is sensitive to outliers. Their major outcome was that traditional asset pricing model fails to explain momentum profits with respect to non-satiated and risk adverse investors. However, asset pricing models that integrate behavioural biases of the investors could insist an optimal alternative solution. Post (2003) compared the power of stochastic dominance efficiency into a portfolio with bootstrapping techniques and asymptotic distribution theory. His evidence revealed the strength power of stochastic dominance in the concept of portfolio selection and evaluation. Under their tests, Fama and French market portfolio is insignificant compared to portfolios based on market capitalization and book-to-market ratio (referring extensively in section 7).

In our work, we applied the theory up to the third order and we to examine the dominance between pair trading profitability and S&P500. We used the median p-values for all block lengths between N^0.3 to N^0.7.

H_0: pairs profitability stochastically dominates S&P500 profitability

H_1: pairs profitability does not stochastically dominates S&P500 profitability

Table 6, illustrates the results according to third order stochastic dominance theory. The results accept the null hypothesis (as p-values exhibit) so the distribution of pair trading returns dominates the distribution of S&P500. Under the concept of utility function in the decision making framework, a rational investor who choose to invest on a net exposure to the market will prefer to invest in pair trading strategy rather than to a buy and hold strategy on S&P500.

5.3. Omega Function

The ample literature of asset pricing concentrates its analysis to the conditional beta and the motivation behind the slope of the market. In recent years, investment strategies evaluation, especially in hedge funds, concentrate their attention to the evaluation of the "alpha". To that scope, we employ omega ratio developed by Keating and Shadwick (2002). The fundamental of omega ratio is based on the incorporation of all the moments of the distribution and for a given targeted return (r), Omega Ratio is the weighted gain/loss ratio relative to r.

$$\Omega(L)=\frac{\int_L^b [1-F(r)]dr}{\int_a^L [F(r)]dr} \quad (9)$$

Omega Function is produced by equation 9, where (a, b) is the interval of realised returns and F(r) is the cumulative distribution of returns. The importance is getting higher if we take under consideration that the distributions of the trading profits are not normally distributed. Figure 5, plots the results under the segmentation of positive returns (r=0). The figure plots the best 5 eligible pairs of the main trading strategy against the long and short component, S&P500 and an equally weighted portfolio constructed by the long and the short components. The evidence confirms the limited upside mean for the pair trading, however, the S&P500 and the equally weighted portfolio exhibit a steeper curve applied under a zero threshold.

6. Empirical Results

6.1. Profitability of Pair Trading Strategy

In this section, I represent economic and statistical interpretation of the empirical results that arise by the implementation of pair trading methodology. Before I begin the comprehension and evaluation of the empirical results, let me a prompt review to the constituents of the estimations on the formulation of trading methodology that represented earlier at section 4. Trading strategy started at September, 23 1996 with the first 19 ETFs. At June, 20 2000 I add the latest ETF and I incorporated all the available set in the estimations. The number of best employed pairs incorporated to portfolio construction is 2, 5, 10 and 20 pairs. The formation period integrated after 120 observations and I allowed for a maximum of 20 business days for the standard strategy. I also implement a long strategy which stands for 60 trading days. To formally investigate for divergence I consider 0.5 standard deviations. The implementation of the strategy occurs one day after the sign of divergence, considering the closing prices.

Table 4, provides the summary statistics of the empirical distribution for the baseline pairs portfolios. For illustration purposes only, Panel A reveals estimations considered on the event day as GGR (2006) represents[31]. Many interesting issues arise from the examination of the table. The different number of pairs creates a significant effect on the terminal performance. Table 4, provides a clear evidence that the employment of more pairs, using 20 days trading constrain, influence negative the performance of the trading strategy. The results come up in contrary, with GGR evidence that eligible 20 pairs portfolios exceed in means of economic and statistical performance the eligible 5 pairs portfolios. Panel B, summarize the statistics that estimated the next business day after the divergence. Mean return drops monotonically by the inclusion of more eligible pairs and ranges from 0.05% to 0.08%. Turning next to the standard deviation the evidence is not straightforward and ranges between the bounds of 0.45% to 0.87%. As can be figured out, the intention of daily risk declines with slower growth than the daily average return as we moving to the right of the table. The last finding most likely reflects the diversification benefit as the inclusion of additional series reduces variation, with no added value on average returns of the included portfolios.

Arbitrageurs are interesting for a combined return-risk profile evaluation and the conventional Sharpe ratio provides an adequate evaluation between the numbers of the eligible pairs portfolios. Construction of Sharpe ratio requires excess return less than the risk free rate. However, I considered zero free rate and the ratio is a pure division of excess return to the respective risk. Sullivan et al (1999) demonstrate that the effect of considering a risk-free rate can only undercover a time varying drift adjustment and can not provide any substantial significance in the evaluation of the portfolio success. The magnitude of the best Sharpe ratio is constrained to the top 5 pairs portfolios. To the extent of the robustness of Sharpe ratio, Goetzmann et al

[31] To remind that, their argument of waiting a day after the divergence consist a defence against of microstructure effects like first order negative serial correlation as a result of bid-ask bounce.

(2002) argued that the results can be misleading if return distribution exhibits negative skewness, however the disability disappears where positive skewness adjoins all the eligible pairs portfolios. Comparing with Brock et al (1992) the best performing trading rule produced a Sharpe ratio 0.39 in comparison my highest pair portfolio strategy generates a Sharpe ratio equal to 0.12[32].

Analysis of the properties of empirical distribution utilizes a different perspective against the risk. In the context of the higher moments, the distributions covering all the different number of the eligible pairs are exhibiting skewness on the right and excess positive kurtosis. Distribution of the excess return reveals a maximum drawn down which ranges from 4.4% to -7.4% according to the number of the eligible pairs. So, our trading rule limits significant the losses and generates strong uptrend when abnormalities in mean returns arises. Pair trading profitability reveals to be uncorrelated with S&P500 as expected by the concept of a market neutral strategy. However, the addition of more eligible pairs conveys the strategy closer to S&P500 with a correlation coefficient 0.13. The crucial assumption is that expanding the number of the eligible pairs portfolios increases the correlation with a buy-and-hold strategy and accordingly declines market neutral conceptuality. The implementation of the trading among higher number of available pairs increases the intension of percentage observations with positive excess return. During the entire trading period, top 5 pairs exhibit 1.680 days of positive excess returns and 1.460 days of negative excess return.

Figure 6, plots the cumulative excess return for the trading period between September 1996 and March 2009. The terminal wealth increase monotonically and if we concentrate our focus on the best 5 eligible pairs, the initial invested wealth of one

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[32] French and Poterba (1991)) argued about the specific risk coming form the countries index that is affected by home-bias observation. They argued that the marginally switching positions between the countries do not affect Sharpe ratios of the countries that investors liquidate their positions.

dollar terminated at 9.8 dollars for the trading horizon of 13 years. On the same universe and horizon a buy-and-hold strategy (S&P500) suffered from smooth up and down trends with poor terminal performance. Moreover, pair trading profitability never declined more than the initial invested wealth. This assumption is of major importance mainly in hedge funds industry where investor's decision to liquidate their position in a fund depends on the proportion of losses out of the initial invested wealth.

Table 5, represents the relative comparison between the short implementation (20days) of pairs strategy and an alternative long version (60days) of pairs trading. The relative examination for the same number of eligible pair portfolios, clearly testifies that the optimal pair trading is implemented by 20 days trading. The same results emerge on risk adjusted basis where Sharpe ratio deteriorates substantially. On a different perspective correlation for the best 10 pairs is always less for the short strategy than the long strategy. On the contrary, for the top 20 pair portfolios correlation coefficient is almost indifferent between the different lengths of the trading period.

Comparing pair trading profitability with previous studies concludes to inferior results. A generic rule is the deterioration of the results is occurring across the universe of the main pairs strategy when the trading is implemented the next business day after the sign emerges. Before I continue, in order to have a unique calculation scale I refer to the methodology that I calculate the average excess returns and GGR named it as fully invested return[33].To that concept, the top 5 eligible pairs earned an average monthly excess of 1.49% and GGR 0.78%. For the top 20 eligible pairs, I

[33] GGR provide two methods for calculation of excess returns. The return on committed capital, which represents the portfolio payoffs by the number of pairs that have been signed for trading. The second method is that we incorporate and is called the fully invested return and includes the payoff from the number of pairs that traded during the trading period.

achieved a monthly mean return of 0.93% and the respective mean return on GGR's work is 0.81%. The results provide an apparent outperforming excess return for my trading algorithm. To the conclusion of my baseline results, even the universe of selecting pairs is significantly smaller, I generate higher profits.

At the conclusion, I refer to Conrad et al's (1998) statement about the mean reversion behaviour of the prices: "*Cross-sectional dispersion in mean returns appears to also be responsible for the paucity of statistically significant price reversals at virtually all horizons, the profits emanating from these reversals are typically neutralized by the losses due to the large cross-sectional variance in mean returns*".

6.2. Different Level of Capitalization and Pair Trading Profitability

In this section, I split the dataset between two portfolios according to their market capitalization. The concept behind the segmentation reveals my expectations to capture the dynamics that different levels volume and liquidity may embedded[34]. A large number of studies have argued about the importance of liquidity levels and market capitalization in mean reversion both at short and long run horizons[35]. Moreover, arbitrageurs are always concerned for liquid and illiquid ETFs and as I refer at section 2.3 practical implementation of trading strategy are conditional to the level of market capitalization. In the context of pair trading and contrarian strategies, Avramov et al (2006) testify that large mean reversal exhibits positively link to

[34] Level of liquidity in the literature of stocks is examined by the trading volume. In the context of ETFs, there is substantial activity over the counter and we consider total market volume instead of trading volume.

[35] GGR argued that an examination of different levels of capitalization provide robustness tests against short-selling. Profits of higher percentiles of large stocks can survive against short-selling abounded.

illiquid stocks and high turnover. A different perspective accommodates that low level of liquidity is more vulnerable to non-informational trades and Llorente et al (2002) argued that short-term reversals are correlated to non-information driven hedging trades.

In my segmentation, capitalization of the first portfolio ranges from 65 billions to 384 millions[36] while capitalization of the second portfolio ranges from 330 millions to 59 millions. Table 3, provides a detailed representation of the returns, trading characteristics and the empirical distribution, for the maximum holding period of 20 days. We realize that there is no detectable pattern between first and second portfolio funds. The mean return for both groups reveals to be identical with respect to the same number of pairs and ranges from 0.021% to 0.052%. However, the results slightly affect the ample evidence of the literature that information diffusion is more efficient in higher capitalization funds. Aligned with the main pairs trading strategy the addition of more pairs deteriorates the empirical distribution where the number of pairs performing the higher means return correspond to the first two employed pairs. The evidence in means of risk, arise strange with the higher market capitalization funds to exhibit higher variation. As I discussed earlier on the discussion of risk arbitrage, the interaction of high number of investors and arbitrageurs generate volatility in the determination of the price. On that context, evidence conforms existing literature, as higher market capitalization run into higher volatility. Results originates higher Sharpe ratio for smaller portfolio which ranges between 0.047% and 0.064%. The second portfolio performs better in mean of maximum drawn downs. The percentage of observation with positive excess returns is almost identical between

[36] On the first quintile belong the following ETFs: Australia, Brazil Canada, EMU, Hong Kong, Japan, Singapore and South Korea, Taiwan, UK, S&P500. On the second quintile belong Austria, Belgium, France, Germany, Italy, Malaysia, Mexico, the Netherland and Spain. Sweden and Switzerland

the two portfolios while the only exception is observed on the best 10 eligible pairs where small capitalization outperforms significantly.

EGJ (2008) split their sample into two portfolios with respect to the criterion of average market capitalization and level of liquidity, however they demonstrate no interaction to profitability. On the context of traditional segmentation in the literature between large and small capitalization, extended literature provided evidence of the outperformance of small versus to larger capitalization countries (Bondt et al (1989), Conrad et al (1989), Rouwenhorst (1998), Zarowin (1990), Richards (1997), Chan (1988) and Ball et all (1989) and Knez et al (1996)).

6.3. Portfolio Profitability between Developed and Emerging Countries

In this section, I am examining economic and statistical properties that may arise by the separate implementation of developed and emerging countries. Expansion of emerging markets at the late years and the increasing interest of the investors could arise significant relative value opportunities. Bekaert et al (1998) defined that on the concept of portfolio allocation to threat emerging markets identical as developed markets could lead to error assumptions. They results are referring to higher volatility and deviations from the normality. Fung et al (1999) argued that emerging markets utilize limited opportunities on the implementation of statistical trading strategies.

Investment strategies have on the top of the agenda investors risk profile and this categorization helps to decompose deeper the profits of the strategy and take into consideration risk adverse of the investors. As widely known, emerging markets are more volatile, incorporates higher risk and match specific investors risk profile. Rouwenhorst (1988) provided evidence to the question if similar return factors are contributed between emerging and developed markets. His evidence was supportive to my decision to include emerging markets to the base pair trading strategy since emerging markets exhibit momentum, and is affected by the same factor as developed.

The sample is heterogenic and is consisted by 5 ETFs exposed on emerging markets and 17 ETFs exposed on developed markets. Thus, we are facing limitations on the implementation of the emerging markets and the empirical evaluation terminates to the ten pairs portfolios. Since two out of five ETFs incepted on 2000, the estimations conducted on the common data observations and started by the inception of the last ETF (Taiwan) on June, 20 2000. The set of ETFs considered as emerging markets includes Brazil, Malaysia, Mexico, Taiwan and South Korea. The segmentation of the ETFs according to developed and emerging countries completed according to MSCI indices of world and emerging countries respectively.

Tables 7, represents the summary statistics. On the practical limitations, on emerging markets we consider only the best 2, 5 and 10 eligible pairs. Pairs portfolios of developed markets outperformed emerging markets for the best 2 and 5 eligible pairs and underperformed for the best 10 pairs. Risk on emerging markets is substantially higher than developed markets and ranges from 1.0% to 1.3%. On the contrary, pairs portfolios invested only on developed markets exhibit a daily volatility which ranges from 0.42% up to 0.84%. On that concept, for the same number of employed pairs, emerging funds Sharpe ratio starts from 0.030% and developed funds Sharpe ratio starts from 0.082%. The investigation of distribution and statistical properties proves that both emerging and developed markets exhibits positive skewness and excess kurtosis. The evidence clearly testifies that a market neutral strategy based on emerging markets can generate positive profits, conversely there is no compensation for the substantial higher risk that an investor bears.

Poterba et al (1988) examined the existence of mean reversion on the stock exchanges around the world. Their results proved that mean reversion is significant larger in less broad based and less sophisticated markets. Their empirical evidence on emerging markets justifies that mean returns do not reflect mean reversion behaviour.

6.4. Portfolio Profitability between Long and Short Components

In this section, I are trying to determine if there a systematic pattern between long and short positions that generates superior excess profits. The key assumption is that long and short term separate evaluation confirms cross-sectional variation in mean returns and uncovers any patterns of time series returns. GGR argued about the necessity of examining separately long and short constituents and their conception can be determined to the following statements: Firstly, decomposition of the returns between long and short should confirm mean-reversion, in means that reversion would exploit equal returns between long and short constituents. Suppose that would conclude to neutral market exposure and consequently to zero returns. Secondly, if short returns dominated long returns then it is crucial short-sale legislation in order to implement the strategy. This point becomes more precious under the current global crisis where stock exchanges worldwide, have forbidden short sales. Lastly, each trading position is motivated by different factors, and the evaluation of each different position can lead us to the profits generator.

Table 8, illustrates the performance of long and short pairs for each eligible pair portfolio individually. An interesting result arises from the best 2 and 5 employed pairs where the 93% and 80% of the mean return respectively is generated by the short component. Mean return for the long component ranges from 0.005 to 0.016 percent and for the short component ranges from 0.041 to 0.082 percent. As we add more pairs to the trading matrix the importance of short component is decreasing and respectively the important of long components increases. The most interesting point emerges from the evaluation of the risk when long and short variations are roughly identical. Conversely, combined analysis of the first and second moment concludes to a significant higher Sharpe ratio for investors who choose to follow a short strategy than investors who invent in a buy-and-hold strategy (long component). From risk management perspective long component as I add more employed pairs decline local maximums and short factor controversially increases its power in local maximums. Intention of positive excess returns improving by the inclusion of extra pairs in the final profitability.

Figure 6, clearly arises the implication that trading rule produces significant positive returns when the spread between long and short widens. Observing the movement of trading through out the implementation period long crosses short component only at the beginning of the trading. The terminal cumulative return for the best 5 employed pairs is \$6.4 and the respective wealth for long component ends at \$1.5. During the trading period short component is positive while for specific periods 2002- till the last months of 2003 and the final one and half years of subprime crisis there are large spikes which boost our strategy to outperform.

Mean return of short factor declines monotonically as I expand the number of employed pairs. Recall main's strategy behaviour which exhibits identical behaviour, I conclude to the empirical verification that pair trading is a short driven strategy. Our evidence aligned with GGR evidence that pair trading validate short against long dominance.

6.5. Subsample and Sensitivity Analysis

To investigate the robustness of long term return reversals I provide evidence about the performance of basic pair trading portfolios into different incremental periods. We divided the formation and trading horizon into four intervals. The first period includes the calendar dates from the beginning April 1, 1996 until the end of 1999. The second calendar period starts on January, 1 2000 and is corrupted on December, 31 20002. The first subset is extended from January 2003 until December 31 2005 and the final available period extends from January, 1 2006 until the end of the data on March 11, 2009.

The logic behind the approach of the separation of different horizons reveals the endeavour to investigate the dynamics of main pair trading strategy under different market environments. The first period (04.1996 - 12.1999) reflects the uptrend sentiment of the global financial markets and terminates almost at the peak of the capital markets[37]. During the subperiod between 2000 and 2002, the sentiment reversed and the markets suffered from a strong downtrend momentum. At the third calendar period between (01.2003- 12.2005) the execution of the trading occurs at the time that financial markets started to recover. Lastly, the calendar period between the start of 2006 and March, 11 2009 represents a combined sentiment when the uptrend

[37] The proxy for the track movement of capital markets is the dominant index of S&P500

of the first two years, reversed into the chaotic environment that subprime crisis fabricated.

It is expected during the markets suffering from a downturn momentum, pair trading strategy to survive and to achieve significant profits confirming the definition of market neutral concept. Several crucial features emerge as we can observe by table 9. A key point is that in contrary with the main strategy performance, for the second and third periods, as I employ more pairs the results are improving both in mean returns and standard deviation. Let's stay on the first subperiod where the addition of extra eligible pairs substantial decline profitability and the magnitude of diversification diminish as can be extracted by the Sharpe ratio evaluation. Based on correlation against S&P500, profitability is not linked with a buy-and-hold strategy.

Examination of the second trading period (01.2000 to 31.2002), the global financial system is suffering by substantial losses and extreme volatility. As I expected, a market neutral strategy offer positively to the limitation of losses as can be withdrawn from Sharpe ratio evaluation. The employment of more pairs increases the diversification benefit. Increasing correlation with S&P500 in a downturn market environment confirms short factor dominance. The proposition of positive excess return concludes to be the highest among the different periods.

The third subsample mirrors the start of recovering in capital markets and simultaneously pair trading started to underperform substantially. In that concept, mean return turn up as the worst among the different trading horizons and starting from the lower number of employed pairs is negative. The results reflect that trading profitability is driven by the performance of the short asset.

The last period involves two controversial movements the uptrend and the downturn as imitate the crisis in US sub-prime market. Evidence demonstrates the second worst daily mean return (after the period of 2003-2005) and ranges from 0.02% to 0.03%. The evidence also reports that the number of the available pairs is uncorrelated with the final performance apart from the top 20 eligible pairs.

Overall, the key assumption can be summed up that pair trading achieved the higher profitability for the first two trading sub-horizons (April 1996 until December 2002). If I exclude the first 3 years of the trading horizon where the market neutral conception is not established, the following periods confirm the conjecture where I achieved to limit the losses. The stronger evidence arises from the uptrend calendar period between January 2003 and December 2005, where pair trading collapses to generate significant profits. The increased profitability of the first period and the reversion on the following years probably confirms the hypothesis that the increasing number of hedge funds and generally investors diminish the proportion of profitable opportunities. By the perspective of a practitioner, a market neutral strategy, apparently, will be abandon during strong uptrend movements, investing intensively market exposure. However, the examination of the aforementioned implication is beyond of the empirical score of our analysis.

7. Pair Trading Portfolios and Fundamental Factors

7.1 A brief overview on Fundamentals

This section contributes to the ongoing debate about the economic significance of Fama and French risk factors on asset pricing framework and the significance of the explanation of pairs trading profitability. In dept analysis on the anatomy of trading strategies names the exploration of cross sectional variation in excess returns that we examine on the second part of this section. The empirical estimations provide evidence in three different levels, based on fundamentals, on trend reversals and cross sectional regressions with respect to individual pairs. In the conduction of the empirical evidence we incorporated both US and International factors. The basic question that the literature has tried to answer is what factors are responsible for global equity returns? Are there any universal factors that explain adequately cross sectional returns? The identification of those common factors pioneered in an early stage by cross sectional analysis of Fama–MacBeth (1973) where individual stock returns can been weakly explained by average returns and market betas compared to industry-sector, local and global portfolios. The implementation of the theory requires the construction of mimicking portfolios respect to the market that is considered to be tested.

Ample literature can be segment into three major categories according to the purpose that asset pricing model has been constructed (1) Firm –Level Characteristics (Idiosyncratic) and the same factors exists on common (industry-level news) (Hou, Karolyi and Kho (2006), Cavaglia, Brightman and Aked (2000), Carrieri, Errunza and Sarkissian (2005), Engelberg (2008)), (2) market level characteristics (local and global market) (Fama and French (1992, 1996,1998), Griffin (2002), Rouwenhorst (1998)) (3) macro-economic or country characteristics (Chan, Chen and Hsieh (1985), Liew and Vasalou (2000), Vasalou (2003), Brennan, Wang and Xia (2004), Petkova (2006)). Briefly, factors affected on each category can be named on the first level as

Size, Earnings/price, Cash flow/price, Dividend/price, Book to Market equity, Leverage. Second level is Risk Free Rate-One month Treasury bill, SML, HML, DY, DEF- The default premium, Market Risk/Volatility and Trend Reversal Factors. Lastly, GDP, Interest rates, Inflation rate, Unemployment and FX. Before I report the relative literature of each separate level, I will refer to Fama and French risk factors which dominate the literature among all levels but most in market level. Fama and French (1992) considered that size and book to market equity variables explains average returns. Their research based mainly on three factors SMB (small minus big), HML (high minus low) and a market factor (Market factor in stock returns is the excess market return, RM-RF) which become the most popular factors in the literature. SMB is risk factor that mimics the return behaviour relative to the size and is constructed between the simple average of the returns on the small-stock portfolios (S/L, S/M, S/H) and the simple average of the returns on the three big-stock portfolios (B/L, B/M, B/H) between portfolios with the same book-to-market equity. HML is risk factor that mimics the risk factor in returns related to book to market equity and it is constructed as the average on the two high BE/ME portfolios (S/H and B/H) and on the two low BE/ME portfolios (S/L, B/L). Lastly, market factor as FF mimic the return on the value weighted portfolio in the six sizes BE/ME, add the negative BE stocks excluded from the portfolios. As RF has been considered one month bill rate. On their publication (1995), took under consideration the importance of stock evaluations on the final decision making. The proved that book-to-market is affected by relative profitability and also size and book to market behaviour in returns are correlated by the pattern of earnings. They examined the returns of both stocks and bonds against market and mimicking portfolios for size book-to-market equity. The 6 portfolios are constructed by sorting stocks based on ME and BE/ME. The rule is median NYSE size is used to break American stocks included in the data sample into two groups of small and large. The other factor named by book to market equity. In order to construct the factors they divided the sample into three sub-categories the lowest presents the bottom (30%), the medium (40%) and the highest one with the remaining 30% of the value form the stocks that are listed on NYSE. Fama and French (1997) extend their research on risk factors on a global basis. They provided that value stocks seem to have higher returns all over the world and especially on emerging markets. They evidence confirms that there are significant positive returns for value stocks is US. Returns on value stocks have been justified by book to market ratio, earnings to price and cash flow to price ratios. On average returns of global portfolios of high and low book to market stocks are significant to the level of 7.60%.

Rouwenhorst (1998) in his research used those risk factors to look for their implication to international momentum strategies. His trading rule was to invest on medium term winners and short medium term losers. His results indicated positive monthly excess return of about 1% where the strategies assign insignificance versus to size and market factor. Although the international momentum returns showed to be correlated to the U.S. market, however, they did not indentify the common factor.

Griffin (2002) examined country specific and global versions factors of Fama and French and their explanatory power on variation in international stock returns. His results indicated that none of the models (domestic, world and international) completely captures average returns when used as asset pricing models. Although among them country specific explain better equity returns than world model. He argued that adding foreign factors in econometric terms is significant although economically the added value in small. So, there is no benefit to conduct extend FF factor model to an international context.

Cooper et al (2001) load FF factors and answer the question whether SMB and HML among with other size based and BM sized portfolios is responsible for the variations of the returns. Their perspective is different from previous studies since the created dynamic trading strategies with long and short positions in different deciles portfolios. They proved that fundamental factors state of economy and more precisely interest rates and default risk are crucial for predicting the returns of the size and B/M portfolios.

Petkova (2006), examined relationship between innovations and FF factors (HML and SMB) and conclude that can adequate predict market return and its variance rather than the level of predictive returns. As Campbell's (1996) and Merton (1993) ICAPM which predict the changes in variables that forecast future market returns should be factors in the cross-section of average returns. Then, she applied those compared the model with predictive variables innovations with the traditional FF model as factor for the cross-section of excess returns of 25 portfolios sorted by the size and book-to-market for the period 1963-2001. She proved that the model based on innovations in dividend yield, term spread, default spread, one month T-bill yield combined with the excess return has better performance than the traditional FF model (where variables are insignificant). Third, she argued that innovations factors are able to capture common time-varying patterns in returns. The innovation model performed better, than HML and SMB (sorted on the same basis) as the portfolios they are designed to explain and also in light of Ferson, Sarkissian, and Simin's (1998) criticism. Moreover, she linked cross-sectional and time-series return predictability, while se compared FF factors and variables based on time-variation in returns.

Liew et al (2000) tested the relation between the profitability of 2 FF factors (HML, SMB) as well WML and future economic growth. They argued that future GDP growth can be examined by HML and SMB based only on ten developed markets, we found that at least HML and SMB contain significant information about future GDP growth (also with positive coefficients). Although, WML factor is insignificant to explain future economic growth. Moreover, argued that there is no information in the market factor to explain the above results. Their results confirm FF that HML and SMB are able to predict future changes in the investment opportunity set as Merton's (1973) defined in ICAPM.

Chan et al (1991) argued that market factor, with common movements in returns associated with size past returns, book-to-market and dividend yield. Although expect from default premium and term premium the other macro factor are insignificant. Also, the decomposition of their estimations proved that significance of book to market ratio declines as the calendar year unfolds (the higher degree of significance was on January). On the other hand the momentum factor improved as the calendar year goes on. Lastly, dividend-yield had good performance in down-market months.

Ferson et al (1993) built a risk factor model based on global framework. They used the following factors. World excess return based on MSCI world equity index minus short term interest rate, trade weighted US dollar prices of the currencies of 10 industrialized countries, the unexpected component of a monthly global inflation measure of the G7 countries, monthly change in a measure of long-term inflationary expectations, TED variable where is the change in the spread between 90-day Eurodollar deposit rate and the 90day US Treasury-bill yield, the weighted average of short-term interest rates in the G7 countries, crude oil, where they considered the change in the monthly average US dollar price per barrel, industrial production where is the weighted average of the industrial production growth rates in the G7 countries.

Chordia et al (1998) for each stock calculated in monthly frequency natural logarithm of the following variables size, BM book-to-market, volume price, dividend yield, cumulative return into two different variables, the first one was lagged two months and the second was lagged 3 months. The reason for this discrimination was to avoid spurious patterns based on thin trading or bid-ask spreads. Their evidence argued that size and book-to-market factors are diminishes in the presence of momentum and trading volume effects.

Vasalou (2003) estimated a model in order to examine is news related to future GDP growth can explain cross-section returns. In comparison, FF two factor model (HML, SMB) contains information related to future GDP growth. Although, when news related to future GDP growth FF factors power declines to their ability to explain cross-section returns.

Carrieri et al (2005) examined the relation between firm specific levels versus geographic diversification. Under the sample of US equity market, 16 equity markets and 10 local industries proved that the average correlation across countries has increased in relation to that across industries.

Hou et al (2006) examined the factors that could affect time-series and cross sectional variation in global equity returns. Among their model they included firm characteristics, such as size, earnings/price, cash flow/price, dividend/price, book to market equity, leverage, momentum. Their results indicated that, for 49 countries over 1981-2003 horizon, momentum, cash flow/price, factor-mimicking portfolios and global market factor are the major factors that affects equity returns. At their publication, reported also the respective research about he factors and the decomposition of cross sectional equity returns worldwide but this time by the side of the practitioners.

So far, the review referred to academic literature, but also the practitioners have employed several risk models including factors as Market, FX, Macro as well as industry-specific risk factors in order to capture the wide spectrum of style, fundamentals, financial-statement ratios and bottom-up factors. According to Hou et al (2006), the most popular are BARRA Integrated Global Equity Market Model (Stefek, 2002; Senechal, 2003), Northfield's Global Equity Risk Model (Northfield, 2005), ITG's Global Equity Risk Model (ITG, 2003) and Salomon Smith Barney's Global Equity Risk Management (GRAM, Miller et al., 2002).

7.2. Pair Trading Profits survivorship against fundamentals

Going further to the empirical evidence, in the second section market neutral conceptuality is evaluated in means of risk characteristics and risk management behaviour. To explore the systematic risk exposure I employed the most widespread methodology as proposed by Fama and French (1993). In this section, I am testing pair trading profitability against the three common risk factors, market factor over risk free rate (MKT_RF), two ad hoc factors linked to economic fundamentals, book to market value (HML), firm size (SMB) as they introduced by Fama-French in several studies and three market trend factors according to the trading horizon, a short-term reversal, a long term reversal and a momentum factor. Table 10, provides evidence of monthly log excess returns of baseline results are they introduced in section 6.1. To test for heteroscedasticity, we conducted Newly West standard errors with 4 lags[38].

Pair trading come up to a significant monthly alpha across the including pairs portfolios both for the standard short strategy (20days) and for the long strategy (60days). Short strategy alpha ranges from 16basis points to 9basis points compared to the longer strategy while the highest level of alpha stands for 13basis points and the lowest for 6basis points. In the longer trading horizon alpha diminished significantly. Compared with raw excess return, on section 6, alpha insists to be lower. According to FF (1993) intercept close to zero testifies that the cross sectional average returns can be adequately explained by the 3 risk factors[39]. Insignificance pair trading profitability due to market factor confirms the expectation of market neutrality. The evidence from 6 factors model appears to be identical for the short and long strategy, with two exceptions which however, lacks of economic interpretation. Book to market factor (HML) loads negatively on the profitability of pair trading portfolios. To concentrate our attention only on the significant factors, on the short trading implemented with the best 20 pairs, momentum factor loads positively, while on long strategy the first 5 pairs portfolio is explained by the long term reversal factor. Monthly profitability based on our international evidence expose different dynamic than US evidence as reported by GGR. Their trading profits are not affected by any of the 3 traditional factors but exists an explanation behind profitability on reversal and momentum factors.

Robustness evaluation is given by R^{2}. Goodness of fit ranges from 4.9% to 12.3% for the standard strategy and from 5% to 6.5% for the longer strategy. We

[38] The reason why refer to 4.1 section with data and descriptive statistics

[39] I conduct the estimations separately, however we don't report them, with the 3 common risk factors and in comparison with the two factor model, adding excess market return removes downwards strong positive intercepts values close to zero.

expected long trading to be more vulnerable to fundamentals however our hypothesis is rejected. The second evidence for both horizons indicates the absence of pattern between the numbers of eligible pairs. The corresponding values on FF (1993) range between 6% and 21% and GGR basic strategy provided a R^{2} range from 15% to 40%.

Economic interpretation of empirical evidence can better comprehend by the separation of the factors according to economic fundamentals and market environment. FF (1993) state that size and book to market are eligible to explain substantially variations in average returns, where market factor is skilful to explain excess market returns. On the same concept, explanatory power of returns limit to a certain degree related to SMB and HML and depends on the idiosyncratic power of each strategy.

The second categorization pertains to market conditions. Jegadeesh (1990) and Lehmann (1990) supply the empirical explanation of pair trading profitability and market conditions and confirm that explanatory power of predictions is concentrated into momentum and reversal factors. The horizon of predictions is limited from momentum to medium-term reversals and the lack of sufficient exposure restricts any substantially explanation of pair trading profitability. However, the dramatic assumption loads the significance of the excess returns on risk-adjusted basis which appears to be fundamentally dissimilar to the concept of contrarian strategies. Mitchell et al (2000) stated the existence of independence between risk arbitrage and market returns.

On the conclusion, we need to defence any critical perception that may arise according to the dissimilarity of the sample that we apply national factors against to an international dataset. According to Griffin (2002) domestic risk factor produces better outcomes compared with world three-factors on country indices both in full and subsamples. In absolute terms, international evidence lacks of explanatory power. For the robustness of our work we conduct the estimations on international FF factors and not in the world three risk factors. Estimations are represented at section 7.5.

7.3. Sub-period Pair Trading Profitability survivorship against fundamentals

In this section, I utilize FF risk factors and their attribution to sub-samples profitability for the regular strategy of 20 days. For the duration of each subperiod refer to section 6.5. Several interesting results arise from Table 11. Alpha profits appear to be significant only within the trading horizon between 1996 up to the end of 2002 and ranges from a high of 24basis point to a low of 11basis points. Exception consists the trading utilization based on the 2 eligible pairs. Clear evidence confirms the success of pair trading only on the first 6 years. Back in period 1996-1999 markets sentiment dominated by an uptrend momentum and profitability are not explained by the loaded risk factors. Long term reversal factor explains profitability as generated by 20 eligible pairs. The utilization of the second period (2000-2002) the significant risk factors are concentrated to 20 eligible pairs and explains profitability due to the market factor, the long term reversal and the momentum factor. The next two years (2003-2005) pair eligibility for the first 2 and 5 pairs loaded positively to market factor. Between the calendar horizon of January 2003 and December 2005 top 2 and 5 eligible pairs trading profitability exhibits unexpected conditional significance to market exposure. Khandani and Lo (1997) state that in short period of time the outcome is driven due to financial contagion. The first two pairs profitability explained by the size factor (SMB) and by the long term reversal. Top 10 pairs also affected by SMB factor. On the last period 2006-2008, the only factor that can explain excess return is size factor when I implement the trading with the best 10 eligible pairs. The results similar to raw estimations from section 6.5 subsamples strongly confirm that profitability opportunities fractionally deducted after 2000 and the relevant explanation is that the increasing number of market participants.

7.4. Emerging and Developed markets Profitability Survivorship against Fundamentals

In this section, the motivating framework is the segmentation between emerging and developed markets and to detect if it emerges any continuation risk pattern. A brief analysis between the regions is presented at Table 12, which demonstrates monthly excess returns and their exposures to FF risk factors. Emerging markets profitability can only been explained by the market factor on the top 5 and 10 pairs and by the momentum factor for any number of eligible pairs. The estimations reject tracking ability as can be outlined by the rejection of the intercept. On the evidence emerged from developed markets, I concentrate on the tracking ability of the constant term. Trading portfolios reveal a significant and positive alpha which ranges from 13basis points to 10basis points, however, the degree of alpha deteriorates as I include more eligible pairs. The first two pairs exhibit the higher degree of profitability dependence against size, book to market and long term reversal. Especially size factor established as a crucial factor for profitability, when the trading constrain to the best ten pairs. With a positive coefficient equals to 0.26, pair trading portfolios exhibit a reversal on long term for the best two pairs.

The importance of the empirical evidence become tremendous important if I recall the results of section 6.3 where both emerging and developed markets corresponds to the proportion of the terminal profitability. However, according to risk factors the importance of pair trading strategies is constrained only to developed markets.

7.5. Capitalization and Pair Trading Profitability survivorship against fundamentals

In this section, I examine pricing performance of FF 6 factors model that is based on the sensitivity analysis according to market capitalization. Table 13, presents the dependent and explanatory returns in time-series regressions segmented by two portfolios with respect to different levels of capitalization. On both groups of capitalizations, alpha existence is significant and positive. On the relative comparison there is no distinguishable dissimilarity between the two portfolios even though the second portfolio for the same number of pairs, accomplish slightly higher alpha. Summarize the left side of Table 13, higher capitalization profitability can not be explained by risk factors and market reversals. On the right side, created factor between small versus high equities (SMB) exhibit significant power on monthly excess return up to ten pairs portfolios. Finally, top 20 portfolios profitability is affected by the short term reversal factor. FF (1993) argued that slopes on SMB are related to size and moving from small to big quintiles slope declines monotonically.

Moreover, testified that SMB mimicking return is supplemental to the other two risk factors and captures variation that is missed by the other two factors (Market and HML). "*Similarly the slope on HML are systematically related to BE/ME. In every size quintile of stocks the HML slopes increase monotonically form strong negative values for the lowest BE/ME quintile. HML clearly captures shared variation in stock returns related to book to market equity that is missed by the market and by SMB*".

7.6. Profitability and International Evidence of Fundamentals

At this section, I particularly interesting if there is any motive emanates from international factors in the exploration of pair trading profitability. I incorporated value and growth portfolios as they are presented by Kenneth French's website and are formed in composite countries using four fundamental ratios (book-to-market (B/M); earnings-price (E/P); cash earnings to price (CE/P); and dividend yield (D/P)) and the market factor. Firms in the country portfolios are value-weighted. To construct the index returns we subtract high minus low returns for each separate variable. Table 14 considers the monthly excess returns for the period started at September 1996 to February 2009. Estimations include both the regular strategy of 20days and the long strategy of 6odays. Residuals have been corrected by Newly-West with 4 lags.

The empirical results reveal interesting interpretations. The analysis of the results indicates a significant monthly alpha for both trading horizons, nevertheless, compared with the raw returns that I have discussed earlier, is diminished. The evidence of a positive alpha consist the tangibly evidence that pair trading profitability implies positive returns independent from the market conditions.

Formally, the exposure of profitability to international factors is limited. For the strategy that holds the position for a short window there is a negative conditional dependence with cash to earnings ratio (CE/P). The direction of the relation is negative and declines monotonically as we add more eligible pairs to the trading implementation. The next significant factor that explains adequately pair trading profitability, only for the case of the top 5 and 20 eligible pairs, is earnings-price ratio (E/P).

Compared to the standard strategy, the 60 days mean return ranges between 4 basis points and 8 basis points below. The long strategy (60 days) tends to be explained by more international risk factors than the standard strategy. However, the most interesting result is that the long strategy loads positive at the market when the trading is implemented with the best 2 and 5 pairs. Also, for the top 5 and 10 employed pairs Book-to-market ratio loads negatively pair trading returns. Moreover, the best two employed pairs load negatively on the cash earnings to price factor and but positive on the dividend to price factor.

At the end, the relative comparison of the standard strategy (20days) and the long strategy (60days) appears to be affected by different risk factors which strengthen our perception for individual examinations as EGJ conjecture.

7.7. Subsamples Profitability and International Evidence on Fundamentals

In Table 15, I analyse pairs trading profitability after I split the sample into four sub horizons. The first period extends from April 1996 to December 1999, the second period extends from the start of 2000 to the end of 2002, the third period includes the start of 2003 until the end of 2005 and the last period covers from January 1996 until the end of December 2007. The most dramatic evidence arises if we observe the constant term of the strategies while different subperiods emerge significant different levels of alpha. Depending on the trading implementation until the end of 2002 pair portfolios generates a positive monthly alpha but a reversal trend is followed the following years. Limit the examination on the first period and for the best 5 employed pairs significant factors are B/M and CE/P. Adding more pairs, the top 20 pairs profitability is exposed to CE/P ratio.

Moving to the second period trading and based on the top 5 to 20 employed pairs portfolios the variable that is reliably related to the profits is the market factor. For the third period, pair trading profits are not related to nay risk factors, however, a minor importance exception is the negative correlation between profitability and B/M ratio when the implementation is constrained only to the best 2 employed pairs. On the last period, profitability is affected significant by D/P ratio and E/P ratio only for the top 5 and 20 pairs portfolios.

Comparing international subsample evidence with section 7.3 which explain subsample profitability against the US local factors, I do not find any notional dissimilarities. The major attributions concentrated to the rejection of intercept on the last two periods and the positive correlation of the market conditions.

7.8. Cross-Sectional Regressions and Profitability of Pair Trading

Thus outlying pair trading profitability, I look behind the profitability against a common panel of risk factors. Previous studies incorporated the empirical examination of the entire excess returns to a common set of state variables and the overall evidence as stated by GGR and my work on the previous sections, conventional risk factors models fail to capture the dynamics of systematic risk. Literature fails to cover the motivation of the empirical examinations that I examine in this section. The only work that examined separately each employed pair to a set of pairs characteristics was EGJ's work, however, they concentrated only on US local factors and only on the narrow universe of industry level factors.

My motivation consists on providing a broad international evidence of long and short component of every single employed pair against to a set of common characteristics. I match each traded pair with its own state variables in a time varying set and I regressed logarithm excess return into a cross sectional panel. The approach of cross-sectional framework unfolded in the days of divergence and convergence between the pairs. The purpose outlining into the three following statements: (1) initiation of the pairs, (2) convergence of the pairs, which separated into the category of natural convergence and the constrain stop according to the trading period (3) the pattern behind the profitability of the pairs. International evidence provides conditionality both on systemic risk and local factors, the latter statement confirmed the empirical evidence that each country exhibits its own idiosyncratic characteristics. On that concept, I load in the following factors which I outline underneath:

Dividend Yield Ratio: the countries daily dividend yield at day t.

Forward Earnings per share ratio: defines earnings per share of the next 12 months for each respective country index. Forecast included the median of the consensus of the market specialists. Earnings are the consensus at day t and prices calculated by the last traded day t.

Default Premium: defines the daily change premium as the difference of US 10 year government bonds minus daily change 10year government bond of each individual country. Default premium is based on the perception to examine potentially financial contagion (Khandani and Lo (2007)).

Market Volatility: define a continue time series variable constructed as range based volatility estimators at day t, based on the daily prices of individual ETFs during the trading period. Market risk is the average cumulative return over the prior 5 days.

Macroeconomic Variables: In macros, we include a set of 3 variables, GDP, Inflation and Unemployment Rate and are represented as growth rate. Chen Roll and Ross (1986), Ferson and Harvey (1991) Chen, Karceski and Lakonishok (1998) mentioned the relevance of macro variables on equity returns. Variables are transformed to daily frequency to be adapted to the respective trading days.

Exchange Rates: represents the daily exchange rate of each country against to US dollars and is the rate of each day t relevant to prior day.

Central Bank Interest Rates: outline monthly rates that central banks of each country offers and we transformed to daily rates.

Money Market Rates: outline interbank rates of each country.

Market Capitalization: The daily market capitalization of each ETF in millions US dollars at day t. Market capitalization is the average return over the prior 5 days.

Daily Turnover: The daily turnover of individual ETFs in Us dollars. EGJ (2008) referred to market capitalization and daily turnover ratio as proxies on examination of liquidity effect on profitability. Daily Turnover is the average return over the prior 5 days.

Average Return of the previous quarter: Each country daily excess return over the previous 60 days, with respect to day t.

International Portfolio Flows: The difference between portfolio inflows and outflows of each country. Brennan and Cao 1997, Froot, O' Connell and Seasholes (2001), stated about the importance of international portfolio flows in the equity returns and loaded in their estimations. Taylor and Sano (1997) argued about the importance of global and country specific factors in determining the long-run movements in equity flows. International portfolio flows are expressed on the difference of the event daily minus the prior day.

International Equity Flows: The difference between equity inflows and outflows of each country. International equity flows are expressed on the difference of the event daily minus the prior day.

Fundamental data has been downloaded by Factshet database. Economic variables have been provided by both IMF and Bloomberg database. The empirical estimations are represented on Table 16. In the decomposition of individual pairswise approach I consider the first 5 eligible pairs and I examine profitability generator according to the standard strategy of 20 days. I followed the event-time approach, which contains only the days of the divergence. The scope of the approach is to concentrate my analysis only to the economic and statistical significance of my main variables of interest to the event of divergence. I begin the analysis of the intercept which appear to be insignificant, while the only exception arises on the fourth pair which loads a positive excess return equal to 12basis points. Before I continue the analysis with the significant factors, I distinguish the default premium and market capitalization factors that find to be insignificant across the number of the employed pairs. On average the first pair is affected positive by inflation, discount rates, dividend yield and past cumulative returns. The second pair, at both long and short component appears to be independent from fundamental factors on pair matching and divergence. The only distinguishable occasion is restricted on short component which appears to be loaded on money market rates. The third pairs profitability is affected by two factors for each investment position. Thus, long position is statistical significant and positive with unemployment rate and equity inflows. On the contrary, GDP and market volatility provide explanation for the divergence of the short position. Both variables affect short position on negative basis. The fourth pair exhibits a sharp contrast with the alternative pairs in means of statistical and economic significance of the risk factors. The pairwise regression loads a positive alpha of 12 basis points. At both the long and the short component pairwise formations are explained by inflation, unemployment rate and equity inflows. The slope is negative for the unemployment rate and positive for the GDP and equity inflows. Long position is also loaded to portfolio inflows and market volatility and EPS are loaded for the short position. According to EGJ work, profitability divergence occurred by EPS factor is due to firm-specific news and tends to be permanent. In the last pair different variables explain profitability. For the long investment position Inflation, GDP and past returns confirms the source of divergence. For the short investment horizon discount rates, equity inflows and market rates explains divergence.

To sum up, it is statistically significant that cross-sectional event regression, do explain much the time-series variation in pairs trading return as confirmed by R^2. Finally, I point out that the interaction between pairwise positions (long and short) does not exhibit any consecutive pattern among the pairs divergence. Among the variables, inflation and GDP appear to explain the profitability for the majority of the pairs.

8. Conclusion

In this chapter I investigate the properties of a market neutral, pair trading strategy when applied to data on international ETFs and, moreover, I offer some possible economic explanations about the source of pair trading profitability. Among the many issues that are important in the context of a pair trading strategy, I examine whether one can identify an optimal trading horizon and offer evidence that, for the ETF data used, there is such a trading horizon which is close to 20 trading days. I also present a number of interesting characteristics on the returns of the pairs trading strategy and compare them to international indices and the S&P500. The statistical and economic superiority of the pairs trading strategy can be confirmed from a variety of factors. However, the significance of profitability is short lived. The major proportion of profits is diminishing after the first month. Contrary to the existing literature a small fraction of divergence leads to substantial profits and open a novel perspective to the implementation of pairs trading methodology.

I then examine the possible underlying economic factors that can potentially explain the profitability of the pairs trading strategy. A novel part of this analysis is that I use both national (US) and international factors in examining this profitability and connect it with various aspects of the fundamental evolution of national and international markets. I examine whether the traditional Fama and French 3-factor model can explain profitability but these factors (as well as three additional financial factors added to the above) cannot explain pairs trading profitability.

The international factors, linked to the state of the economy of each international ETF, offer limited explanatory power and the results are not consistent across countries. In particular, with the exception of inflation and GDP growth, many of the economic variables are significant across different countries and pair trading specifications.

Summary of Chapter 2:

In the epoch of crisis the impressive performance of market neutral strategies has spurred an enthusiastic debate in the finance literature over the source generator of the market neutral profitability and the underlying economic interpretation that could revealed. Pairs trading apparently consists one of the most popular formulation of market neutral trading among the practitioners based on the fundamentals of mean reverting prices in a time-varying framework. In this chapter, I am scrutinizing the interpretation of pair trading strategies, the anatomy of the profits and the economic interpretation looking behind the risk factors that affect profitability. In the ample literature, pair trading strategies was tested on US equities, however, for the first time we provide international evidence of pair trading profitability incorporating Exchange Traded Funds.

Several aspects discussed and received attentions in this chapter. The pioneer element explored the fundamental implications for a winning model. Literature derived many important implications about relative value statistical arbitrage strategies but on totally different perspective. I quantify the impact of trading horizon, distance divergence and I am founding a novel modification of the existing rule of identifying pairs. To translate these indicators, my pair trading approach proved that minor divergence, into monthly time framework resulting to substantial and attractive profits.

The second part of the chapter incorporates risk approach to evaluate profitability and explain the source generator. The state variables that proxy for the empirical evidence is important determinants of risk returns. The state variables are separate into two groups. The first group include the traditional Fama and French factors. The second group is designed to explain in a cross-sectional regression model the prediction power of country specific factors into arbitrage opportunities. Traditional FF factors provide limited economic and statistical power. Besides, the pairwise analysis of the life-cycle of pair trading appear to be insignificant to explain adequately profitability, even if there is a dependence between excess return and GDP and inflation factors.

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Tables and Figures

Table 1

Summary of Trading Statistics

table represents the trading statistics of the excess return portfolios. Due to different inception dates of dataset, I initiate the ılations with the first 19 ETFs and we add each separate ETF by its own inception date. The sample period is from April, 01 1996 to ch, 11 2009 (3.140 observations). The "top n" represents the "n" best eligible ranked pairs according to the historical distance of mean price. On Panel A, we open the trade when the divergence between the pairs exceed 0.5 standard deviations, and if does converge within the next 20 business days we stop the trade. The implementation of the strategy take place the next business day ıe divergence. Panel B, represents pairs that convergence according to different trading periods.

Panel A: Trading Statistics				
Pairs Portfolio	*Top 2*	*Top 5*	*Top10*	*Top 20*
Average Number of Trading Days per pair	19.115	19.070	19.056	18.951
Standard Deviation Average Number of Trading days	1.416	1.506	1.645	1.813
Average Number of Round-Trips per pair	0.952	0.920	0.857	0.805
Standard Deviation of Average Number of Round-Trips	1.064	1.042	1.021	0.997
Average Number Pairs Open in 20days	1.913	4.772	9.537	18.969
Standard Deviation of Average Number Pairs Open	0.099	0.161	0.281	0.472

Panel B: Pairs that Convergence within N trading days				
Trading Horizon	*Top 2*	*Top 5*	*Top10*	*Top 20*
5 Days	26.8%	26.9%	25.6%	25.5%
10 Days	33.5%	33.2%	31.9%	31.6%
20 Days	42.7%	41.3%	40.4%	40.9%
40 Days	57.7%	53.3%	52.1%	51.8%
60 Days	69.2%	65.4%	61.5%	60.7%
120 Days	80.8%	74.6%	72.3%	72.1%

Table 2

Pair Traded ETFs Matrix

The table represents the number of traded pairs of the eligible top 5 number of pairs. The sample period is from April, 01 1996 to March, 11 2009 (3.140 observations). We open the trade when the divergence between the pairs exceed 0.5 standard deviations, and if does not converge within the next 20 business days we stop the trade. The implementation of the trading occurs the next business day of the divergence.

Panel A: 1st Pair

	Australia	Canada	Sweden	Germany	Hong Kong	Italy	Belgium	Switzerland	Malaysia	Netherlands	Austria	Spain	France	Taiwan	UK	South Korea	EMU	S&P500
Australia																		
Canada																		
Sweden																		
Germany		20																
Hong-Kong		20																
Italy																		
Belgium	20			40														
Switzerland				20		20	20											
Malaysia																		
Netherlands	60		20	60		20	20	60										
Austria		20																
Spain				20		20		80										
France		20	40			60	40	60	20	40		20						
Taiwan											20							
UK				20		20	80	80		20	20	20	140					
South Korea			20															
EMU				177		100	80	40		120		60	920		20			
S&P500	20	20	20				20	20		20		20	40		120		20	

Panel B: 2nd Pair

	Australia	Canada	Sweden	Germany	Hong Kong	Italy	Japan	Belgium	Switzerland	Malaysia	Netherlands	Austria	Spain	France	UK	EMU	S&P500
Australia																	
Canada	20																
Sweden																	
Germany		20															
Hong Kong																	
Italy																	
Japan					20												
Belgium	40			40		120											
Switzerland						60		60									
Malaysia																	
Netherlands			20	60		20	20	120	60								
austria	20								20		20						
Spain						60			20		40						
France		60	40	80		160		60	80	20	60	20	40				
UK				40		80		40	120		60	40	20	120			
South Korea											20						
EMU			40	60		177		100	40		80		20	160	80		
S&P500	40	20	20		20		20	20	20		20		20		120	40	

Panel C: 5th Pair

	Australia	Canada	Sweden	Germany	Hong Kong	Italy	Japan	Belgium	Switzerland	Malaysia	Netherlands	Austria	Spain	France	Singapore	UK	Mexico	South Korea	EMU	S&P50
Australia																				
Canada	20																			
Sweden		20																		
Germany			20																	
Hong Kong		20		20																
Italy		20		57																
Japan																				
Belgium				40		20														
Switzerland	20	40		80		60		40												
Malaysia	20						20													
Netherlands			40	100		60		60	100	40										
Austria	20								40											
Spain				20		20		20			120	20								
France	20	20		140		120		80	60		60	20	60							
Singapore					20	20				40				20						
UK	20	20		20	20	80		20	80		40	20		40						
Mexico														20						
South Korea			20	20											20					
EMU	20	20	40	80	40			40	40		60		20	100	20	60				
S&P500	60				40	20	20		20		40		20	20		40			20	

Table 3

Summary Statistics for Stochastic Dominance Test

The table represents stochastic dominance test of the excess return portfolios. For definitions of pair trading refer to table 1. The sample period is from April, 01 1996 to March, 11 2009 (3.140 observations). One day waiting estimations represents the implementation of the strategy the next business day. We implement three order stochastic dominance test. Stochastic dominance test examines the order of dominance between two assets according to their distribution. The test refers to the zero hypothesis that pair profitability stochastically dominates S&P500 profitability

Panel A: Event Day				
Pairs Portfolio	*Top 2*	*Top 5*	*Top10*	*Top 20*
1st Order	0.0000	0.0000	0.0000	0.0000
2nd Order	0.0005	0.0000	0.0000	0.0000
3rd Order	0.0042	0.0037	0.0096	0.0101
Panel B: One Day Waiting				
Pairs Portfolio	*Top 2*	*Top 5*	*Top10*	*Top 20*
1st Order	0.0000	0.0000	0.0000	0.0000
2nd Order	0.0008	0.0000	0.0000	0.0000
3rd Order	0.0043	0.0042	0.0050	0.0056

Table 4

Summary Statistics of Daily Estimations of Baseline results

The table represents the summary statistics in percentage basis of the excess return portfolios. Due to different inception dates of the our dataset, we initiate the calculations with the first 19 ETFs and we add each separate ETF by its own inception date. The sample period is from April, 01 1996 to March, 11 2009 (3.140 observations). The "top n" represents the "n" best eligible ranked pairs according to the historical distance of their mean price. We open the trade when the divergence between the pairs exceed 0.5 standard deviations and if does not converge within the next 20 business days we stop the trade. One day waiting estimations represents the implementation of the strategy the next business day.

Panel A: Event day

Pairs Portfolio	*Top 2*	*Top 5*	*Top10*	*Top20*
Terminal Excess Return	18.284	20.041	13.786	8.965
Mean	0.097	0.098	0.085	0.071
Standard Deviation	0.887	0.667	0.551	0.454
Sharpe Ratio	0.109	0.147	0.155	0.156
Maximum	9.420	8.860	7.070	4.720
Minimum	-7.450	-7.780	-6.030	-4.080
Skewness	1.050	1.340	1.740	1.400
Kurtosis	13.700	26.800	28.600	16.700
Correlation with S&P500	0.065	0.069	0.101	0.146
Observations with Excess return>0	52.55%	54.14%	55.41%	55.73%
Mean of Excess Return >0	0.660	0.502	0.406	0.344
Mean of Excess Return <0	-0.543	-0.380	-0.317	-0.273
Mean of top ten excess return	5.778	4.729	4.099	3.347
Mean of bottom ten excess return	-3.504	-2.644	-0.020	-1.629

Panel B: One day waiting

Pairs Portfolio	*Top 2*	*Top 5*	*Top10*	*Top20*
Terminal Excess Return	10.994	9.769	5.502	4.183
Mean	0.080	0.075	0.056	0.047
Standard Deviation	0.869	0.637	0.534	0.448
Sharpe Ratio	0.092	0.117	0.104	0.104
Maximum	6.150	6.300	7.060	4.650
Minimum	-7.440	-7.760	-6.860	-4.440
Skewness	0.637	0.470	0.822	0.938
Kurtosis	10.200	17.600	27.000	15.700
Correlation with S&P500	0.049	0.070	0.086	0.128
Observations with Excess return>0	51.91%	53.50%	53.18%	53.50%
Mean of Excess Return >0	0.647	0.476	0.387	0.330
Mean of Excess Return <0	-0.552	-0.389	-0.323	-0.279
Mean of top ten excess return	5.204	4.035	3.657	3.038
Mean of bottom ten excess return	-3.582	-2.798	-2.329	-1.957

Table 5

Summary Statistics of Relative Comparison between Two Trading Horizons

The table represents the summary statistics in percentage basis of the excess return portfolios. Due to different inception dates of our dataset, we initiate the calculations with the first 19 ETFs and we add each separate ETF by its own inception date. The sample period is from April, 01 1996 to March, 11 2009 (3.140 observations). The "top n" represents the "n" best eligible ranked pairs according to the historical distance of their mean price. We open the trade when the divergence between the pairs exceed 0.5 standard deviations, and if does not converge within the selected trading horizons we stop the trade. The selected trading horizons are 20 and 60 business days respectively. The implementation of the strategy occurs one day after the divergence.

Trading Horizon	*20 days*				*60days*			
Pairs Portfolio	*Top 2*	*Top 5*	*Top10*	*Top20*	*Top 2*	*Top 5*	*Top10*	*Top20*
Terminal Excess Return	10.994	9.769	5.502	4.183	5.744	3.361	2.471	2.298
Mean	0.080	0.075	0.056	0.047	0.059	0.040	0.030	0.028
Standard Deviation	0.869	0.637	0.534	0.448	0.814	0.590	0.468	0.432
Sharpe Ratio	0.092	0.117	0.104	0.104	0.072	0.068	0.064	0.064
Maximum	6.150	6.300	7.060	4.650	6.820	3.110	2.580	3.090
Minimum	-7.440	-7.760	-6.860	-4.440	-3.250	-3.340	-2.360	-3.130
Skewness	0.637	0.470	0.822	0.938	53.500	15.400	6.350	24.800
Kurtosis	10.200	17.600	27.000	15.700	7.340	5.310	4.790	7.740
Correlation with S&P500	0.049	0.070	0.086	0.128	0.028	0.064	0.051	0.134
Observations with Excess return>0	51.91%	53.50%	53.18%	53.50%	50.96%	52.87%	51.91%	51.59%
Mean of Excess Return >0	0.647	0.476	0.387	0.330	0.624	0.447	0.361	0.327
Mean of Excess Return <0	-0.552	-0.389	-0.323	-0.279	-0.543	-0.419	-0.329	-0.294
Mean of top ten excess return	5.204	4.035	3.657	3.038	4.231	2.564	1.882	2.177
Mean of bottom ten excess return	-3.582	-2.798	-2.329	-1.957	-2.933	-2.270	-1.711	-1.949

Table 6

Summary Statistics of Daily Estimations between Large vs. Small Capitalization Portfolios

table represents the summary statistics in percentage basis of the excess return distribution including the segmentation of the ı set into two portfolios according to their capitalization: The first portfolio includes the first 50% of the sample with the larger talization and the supplementary 50% included in the second portfolio. Due to different inception dates of the our dataset, we ıte the calculations with the first 19 ETFs and we add each separate ETF by its own inception date. The sample period is from , 01 1996 to March, 11 2009 (3.140 observations). The "top n" represents the "n" best eligible ranked pairs according to the ɔrical distance of their mean price. We open the trade when the divergence between the pairs exceed 0.5 standard deviations, if does not converge within the next 20 business days we stop the trade. The implementation of the strategy occurs the next ness day after the event of divergence occurs

	First Portfolio				Second Portfolio			
Pairs Portfolio	*Top 2*	*Top 5*	*Top10*	*Top 20*	*Top 2*	*Top 5*	*Top10*	*Top 20*
ninal Wealth	4.352	3.511	2.301	2.000	4.766	3.197	2.038	1.873
n	0.052	0.043	0.029	0.024	0.053	0.039	0.024	0.021
ıdard Deviation	1.010	0.785	0.667	0.647	0.829	0.595	0.517	0.447
pe Ratio	0.051	0.055	0.043	0.037	0.064	0.065	0.046	0.047
imum	8.300	7.940	6.260	4.790	4.400	2.940	3.340	2.620
num	-5.810	-5.050	-4.740	-4.190	-7.200	-2.660	-2.320	-1.980
vness	0.385	0.934	0.679	0.525	0.009	0.020	0.133	0.183
osis	7.260	12.100	11.000	8.700	7.180	4.690	5.280	5.340
elation with S&P500	-0.022	0.037	0.066	0.112	0.094	0.110	0.135	0.178
ervations with Excess return>0	50.32%	50.32%	50.96%	51.27%	50.96%	53.18%	51.59%	51.91%
n of Excess Return >0	0.767	0.579	0.485	0.466	0.628	0.448	0.393	0.338
n of Excess Return <0	-0.693	-0.504	-0.444	-0.440	-0.565	-0.427	-0.369	-0.320
n of top ten excess return	5.004	5.078	3.966	3.690	3.590	2.327	2.307	2.061
n of bottom ten excess return	-4.222	-3.128	-2.943	-2.698	-3.614	-2.225	-1.944	-1.698

Table 7

Summary Statistics of Daily Estimations of Developed vs. Emerging Countries

The table represents the summary statistics in percentage basis of the excess return distribution including the segmentation of the data set into two different subsets: Developed and Emerging markets. Due to different inception dates of the our dataset, we initiate the calculations for developed markets by its own inception date and we add additional ETFs based on developed markets by the inception date. The sample period is from April, 01 1996 to March, 11 2009 (3.140 observations). For emerging markets, we initiate the calculations, at June, 20 2000 where the last ETF on emerging market incepted (2.050 observations). The "top n" represents the "n" best eligible ranked pairs according to the historical distance of their mean price. We open the trade when the divergence between the pairs exceed 0.5 standard deviations, and if does not converge within the next 20 business days we stop the trade. The implementation of the strategy occurs the next business day that the event of divergence occurs

	Emerging Countries			*Developed Countries*			
Pairs Portfolio	Top 2	Top 5	Top 10	Top 2	Top 5	Top 10	Top 20
Mean	0.063	0.050	0.764	0.069	0.056	0.049	0.047
Standard Deviation	1.320	1.060	0.709	0.842	0.603	0.486	0.415
Sharpe Ratio	0.048	0.048	1.078	0.082	0.093	0.100	0.113
Maximum	6.890	8.050	4.960	6.050	3.500	2.580	3.050
Minimum	-5.710	-4.620	0.001	-4.480	-2.900	-1.900	-2.020
Skewness	0.225	0.813	1.880	0.386	0.385	0.206	0.341
Kurtosis	6.050	9.070	8.190	7.710	5.670	4.900	6.060
Correlation with S&P500	0.075	0.077	0.061	0.066	0.087	0.107	0.129
Observations with Excess return>0	51.71%	49.76%	50.73%	52.55%	52.23%	52.55%	53.18%
Mean of Excess Return >0	0.983	0.811	0.764	0.625	0.472	0.388	0.327
Mean of Excess Return <0	-0.939	-0.694	-0.726	-0.565	-0.399	-0.329	-0.274
Mean of top ten excess return	5.886	5.589	4.168	4.516	2.849	2.149	1.920
Mean of bottom ten excess return	-5.079	-3.741	-3.489	-3.571	-2.281	-1.695	-1.681

Table 8

Summary Statistics of baseline results according to Long and Short decomposition

The table represents the summary statistics in percentage basis of the excess return portfolios decomposed into long and short components. Due to different inception dates of the our dataset, we initiate the calculations with the first 19 ETFs and we add each separate ETF by its own inception date. The sample period is from April, 01 1996 to March, 11 2009 (3.140 observations). The "top n" represents the "n" best eligible ranked pairs according to the historical distance of their mean price. We open the trade when the divergence between the pairs exceed 0.5 standard deviations and if does not converge within the next 20 business days we stop the trade. One day waiting estimations represents the implementation of the strategy the next business day

Pairs Portfolio	*Top 2*		*Top 5*		*Top10*		*Top20*	
	Long	Short	Long	Short	Long	Short	Long	Short
Terminal Wealth	0.940	10.722	1.506	6.424	1.438	3.810	1.249	3.464
Mean	0.005	0.082	0.016	0.062	0.013	0.044	0.008	0.041
Standard Deviation	1.160	1.150	0.751	0.781	0.519	0.560	0.437	0.472
Sharpe Ratio	0.004	0.072	0.021	0.080	0.025	0.079	0.018	0.086
Maximum	16.000	8.670	7.810	5.700	3.640	6.010	3.400	4.200
Minimum	-8.860	-9.160	-6.700	-7.610	-3.940	-4.570	-3.890	-4.060
Skewness	0.709	0.389	0.174	0.323	-0.246	0.911	-0.248	0.650
Kurtosis	21.700	12.100	16.700	14.500	9.960	15.700	12.900	15.700
Correlation with S&P500	0.364	0.379	0.380	0.439	0.441	0.531	0.437	0.503
Observations with Excess return>0	49.04%	51.27%	50.00%	53.18%	50.96%	52.23%	50.64%	53.18%
Mean of Excess Return >0	0.742	0.797	0.502	0.535	0.361	0.395	0.292	0.325
Mean of Excess Return <0	-0.755	-0.722	-0.473	-0.476	-0.352	-0.339	-0.286	-0.282
Mean of top ten excess return	7.319	6.834	4.710	4.915	2.623	3.707	2.468	3.033
Mean of bottom ten excess return	-6.316	-6.171	-4.639	-4.535	-2.883	-2.748	-2.553	-2.603

Table 9

Summary Statistics of Daily Estimations of Subsamples Portfolios

The table represents the summary statistics in percentage basis of the excess return portfolios. Due to different inception dates of the our dataset, we initiate the calculations with the first 19 ETFs and we add each separate ETF by its own inception date. The sample period is from April, 01 1996 to March, 11 2009 (3.140 observations). The sample period has been divided into 4 subsamples: The first period is from April, 01 1996 to December, 31 1999 (827 observations), the second period is from January, 1 2000 to December 31 2002 (631 observations). The third period is from January 1 2003 to December, 31 2005 (635 observations) and the last period is from January 1 2006, to March 11 2009 (681 observations). The "top n" represents the "n" best eligible ranked pairs according to the historical distance of their mean price. We open the trade when the divergence between the pairs exceed 0.5 standard deviations, and if does not converge within the next 20 business days we stop the trade. One day waiting estimations represents the implementation of the strategy the next business day.

Sample Range:	*1996:04-1999:12*				*2000:01-2002:12*				*2003:01-2005:12*				*2006:01-2009:03*			
Pair Portfolio	Top 2	Top 5	Top10	Top20	Top 2	Top 5	Top10	Top20	Top 2	Top 5	Top10	Top20	Top 2	Top 5	Top10	Top20
Mean	0.133	0.093	0.077	0.044	0.061	0.087	0.081	0.083	-0.002	0.018	0.019	0.023	0.033	0.031	0.032	0.022
Standard Deviation	1.070	0.682	0.524	0.465	0.923	0.669	0.564	0.494	0.513	0.367	0.284	0.261	0.524	0.434	0.389	0.333
Sharpe ratio	0.124	0.137	0.146	0.094	0.066	0.130	0.144	0.167	-0.004	0.050	0.066	0.089	0.062	0.070	0.083	0.065
Maximum	6.050	3.230	2.340	3.560	4.220	3.760	2.450	1.730	2.070	1.360	1.210	1.030	4.790	3.580	3.140	2.300
Minimum	-3.740	-2.470	-1.480	-2.540	-3.350	-2.340	-1.510	-1.520	-3.200	-1.980	-0.961	-0.817	-1.940	-1.820	-1.330	-1.300
Skewness	0.457	0.231	0.189	0.445	0.351	0.264	0.337	0.154	-0.550	0.090	0.187	0.297	1.390	1.610	1.350	0.988
Kurtosis	5.540	3.910	3.470	7.910	5.510	4.710	3.880	3.630	6.510	5.200	4.630	3.650	15.000	15.300	12.600	9.650
Correlation with S&P500	0.050	0.014	0.007	0.042	0.203	0.185	0.201	0.253	0.045	0.047	0.053	0.057	0.183	0.155	0.210	0.190
Observations with Excess return>0	52.36%	54.66%	54.17%	53.81%	51.35%	55.31%	55.63%	54.99%	49.13%	51.34%	49.92%	52.28%	50.37%	51.84%	52.13%	52.72%
Mean of Excess Return >0	0.896	0.575	0.454	0.368	0.718	0.547	0.464	0.426	0.378	0.283	0.220	0.199	0.381	0.310	0.282	0.240
Mean of Excess Return <0	-0.749	-0.490	-0.369	-0.334	-0.648	-0.482	-0.398	-0.337	-0.379	-0.262	-0.201	-0.176	-0.329	-0.271	-0.241	-0.223
Mean of top ten excess return	3.851	2.201	1.562	1.605	3.267	2.146	1.840	1.527	1.345	1.150	0.889	0.737	2.069	1.920	1.736	1.339
Mean of bottom ten excess return	-2.867	-1.755	-1.320	-1.233	-2.602	-1.656	-1.253	-1.238	-1.731	-1.031	-0.812	-0.556	2.069	-1.198	-1.045	-0.923

Table 10

Profitability of Pair Trading Strategies

ne table represents the results of monthly excess log returns from pair trading portfolios where the independent variables are 6 risk factors as represented by Fama and ench. The implementation of the strategy occurs the next business day of the divergence and the trading horizon is constant 20 days. Daily returns are compounded to ılculate monthly returns. The independent variables are: Value weighted market excess return (MARKET), a size portfolio based on small equities minus big equities (SMB), book-to market portfolio of high minus low stocks (HML), a portfolio of year long winners minus year long losers (MOMENTUM), a portfolio of last month losers minus last onth winners (SHORT TERM REVERSAL) and finally a portfolio of 4 year long winners minus 4 year-long losers (LONG TERM REVERSAL). The corresponding p-values are ported for each separate variables and statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West estimator with 4 lags. The sample period is ›m September 1996 to February 2009. The p-values and R^2 from each time-series regression are reported in nominal form.

Trading Horizon	20 days				60 days			
Monthly Pairs Portfolio	*Top 2*	*Top 5*	*Top 10*	*Top 20*	*Top 2*	*Top 5*	*Top 10*	*Top 20*
Intercept	0.016	0.015	0.012	0.009	0.013	0.008	0.007	0.006
	0.000	0.000	0.000	0.000	0.004	0.001	0.000	0.000
Market	-0.026	-0.014	-0.024	-0.029	-0.039	0.006	-0.007	0.010
	0.680	0.841	0.621	0.521	0.704	0.918	0.841	0.806
HML	-0.257	-0.225	-0.204	-0.122	-0.283	-0.157	-0.118	-0.101
	0.003	0.0107	0.0011	0.065	0.065	0.046	0.024	0.040
SMB	-0.101	-0.080	0.031	0.022	-0.082	-0.010	-0.007	-0.026
	0.509	0.436	0.677	0.721	0.599	0.903	0.886	0.589
Long Term Reversal	0.188	0.108	0.036	0.032	0.145	0.166	0.073	0.032
	0.143	0.321	0.686	0.661	0.451	0.092	0.179	0.587
Short Term Reversal	-0.043	0.113	0.053	0.054	-0.083	0.004	-0.001	0.008
	0.663	0.210	0.507	0.427	0.314	0.921	0.983	0.787
Momentum	0.054	0.094	0.036	0.070	0.013	0.002	-0.006	-0.006
	0.472	0.127	0.466	0.098	0.785	0.946	0.731	0.798
Observations	150	150	150	150	150	150	150	150
R^2	0.049	0.087	0.123	0.098	0.061	0.065	0.058	0.050

Table 11

Regression of Monthly Returns of the Subsamples Estimations

The table represents the results of monthly excess return from pair trading portfolios segment by regions of emerging and developed markets where the independent variables are 6 risk factors as represented by Fama and French. The implementation of the strategy occurs the next business day of the divergence and the trading horizon is constant 20days. Daily returns are compounded to calculate monthly returns. The independent variables are: the value weighted market excess return (MARKET), a size portfolio based on small equities minus big equities (SMB), a book-to-market portfolio of high minus low stocks (HML), a portfolio of year long winners minus a year long losers (MOMENTUM), a portfolio of last month losers minus last month winners (SHORT TERM REVERSAL) and finally a portfolio of 4 year long winners minus 4year long losers(LONG TERM REVERSAL). The corresponding p-values are reported for each separate variable and statistics are corrected for autocorrelation and heteroscedasticity using Newey-West estimator with 3 lags. The p-values and R^2 are reported in nominal form. The sample period has been divided into 4 subsamples.

Period:	*1996:04-1999:12*				*2000:01-2002:12*				*2003:01-2005:12*				*2006:01-2009:02*			
Pair Portfolio	*Top 2*	*Top 5*	*Top10*	*Top20*	*Top 2*	*Top 5*	*Top10*	*Top20*	*Top 2*	*Top 5*	*Top10*	*Top20*	*Top 2*	*Top 5*	*Top10*	*Top20*
Intercept	0.024	0.017	0.017	0.011	0.010	0.016	0.019	0.024	-0.005	0.002	0.003	0.003	0.004	0.004	0.006	0.003
	0.081	0.078	0.003	0.016	0.205	0.068	0.003	0.000	0.263	0.347	0.221	0.307	0.338	0.126	0.009	0.120
Market	0.024	0.018	0.030	0.041	0.101	0.204	0.129	0.256	0.574	0.302	0.214	0.092	-0.167	-0.127	-0.077	-0.103
	0.924	0.919	0.795	0.715	0.593	0.150	0.262	0.055	0.041	0.049	0.114	0.414	0.341	0.422	0.262	0.014
HML	-0.180	-0.215	0.006	0.047	0.020	0.210	0.019	0.031	-0.051	-0.181	-0.053	0.121	-0.089	-0.164	-0.126	-0.145
	0.733	0.506	0.979	0.827	0.921	0.247	0.876	0.789	0.821	0.462	0.718	0.390	0.522	0.198	0.138	0.015
SMB	-0.473	-0.057	0.144	0.148	0.016	0.085	-0.009	-0.071	-0.815	-0.325	-0.291	-0.082	-0.106	0.133	-0.245	-0.106
	0.250	0.833	0.410	0.311	0.945	0.539	0.936	0.436	0.062	0.216	0.093	0.527	0.650	0.561	0.067	0.337
Long Term Reversal	0.282	-0.006	-0.201	-0.333	0.225	-0.042	-0.041	-0.271	-0.536	-0.078	0.029	0.096	0.222	0.242	0.070	0.039
	0.677	0.989	0.397	0.089	0.412	0.803	0.798	0.066	0.063	0.640	0.843	0.524	0.266	0.181	0.413	0.419
Short Term Reversal	-0.030	0.041	-0.054	-0.069	0.057	0.028	-0.013	-0.067	0.160	0.125	0.172	0.043	0.102	0.114	0.078	0.054
	0.919	0.845	0.685	0.519	0.540	0.698	0.799	0.130	0.581	0.508	0.189	0.684	0.514	0.439	0.186	0.106
Momentum	-0.125	-0.047	-0.059	-0.032	-0.129	-0.023	0.002	0.104	0.238	0.096	0.052	-0.013	0.143	0.155	0.030	-0.012
	0.674	0.742	0.571	0.726	0.209	0.605	0.975	0.072	0.279	0.565	0.711	0.895	0.248	0.190	0.656	0.794
Observations	40	40	40	40	31	31	31	31	31	31	31	31	33	33	33	33
R^2	0.053	0.044	0.064	0.125	0.138	0.129	0.079	0.320	0.315	0.143	0.182	0.120	0.192	0.230	0.289	0.377

Table 12

Profitability of Pair Trading between Developed and Emerging Countries

The table represents the results of monthly excess return from pair trading portfolios segment by regions of emerging and developed markets where the independent variables are 6 risk factors as represented by Fama and French. The implementation of the strategy occurs the next business day of the divergence and the trading horizon is constant 20days. Daily returns are compounded to calculate monthly returns. The independent variables are: Value weighted market excess return (MARKET), a size portfolio based on small equities minus big equities (SMB), a book-to-market portfolio of high minus low stocks (HML), a portfolio of year long winners minus a year long losers (MOMENTUM), a portfolio of last month losers minus last month winners (SHORT TERM REVERSAL) and finally a portfolio of 4 year long winners minus 4 year long losers (LONG TERM REVERSAL). The corresponding p-values are reported for each separate variable and statistic are corrected for autocorrelation and heteroscedasticity using Newey-West estimator with 4 lags for developed and 3 lags for emerging markets. The sample period extended from September 1996 to February 2009. The p-values and R^2 from each time-series regression are reported in nominal form.

	Emerging markets			Developed markets			
Monthly Pairs Portfolio	*Top 2*	*Top 5*	*Top 10*	*Top 2*	*Top 5*	*Top 10*	*Top 20*
Intercept	0.013	0.010	0.005	0.015	0.013	0.010	0.010
	0.039	0.032	0.137	0.000	0.000	0.000	0.000
Market	-0.296	-0.440	-0.364	0.018	0.011	-0.014	-0.021
	0.148	0.023	0.029	0.771	0.863	0.770	0.653
HML	-0.193	-0.369	-0.219	-0.239	-0.271	-0.135	-0.087
	0.559	0.250	0.395	0.008	0.001	0.053	0.225
SMB	-0.044	-0.076	-0.103	-0.285	-0.129	0.038	-0.047
	0.829	0.741	0.641	0.022	0.113	0.613	0.443
Long Term Reversal	0.230	0.327	0.365	0.259	0.098	0.018	0.039
	0.400	0.136	0.076	0.034	0.383	0.843	0.568
Short Term Reversal	-0.137	0.002	0.076	-0.111	-0.083	-0.008	0.007
	0.353	0.989	0.623	0.164	0.294	0.885	0.895
Momentum	-0.238	-0.214	-0.222	0.020	-0.036	0.002	0.041
	0.077	0.013	0.074	0.711	0.384	0.923	0.135
Observations	98	98	98	150	150	150	150
R^2	0.072	0.182	0.206	0.080	0.108	0.075	0.040

Table 13

Profitability according to Market Capitalization

The table represents the results of monthly excess return from pair trading portfolios segment by regions of emerging and developed markets where the independent variables are 6 risk factors as represented by Fama and French. The implementation of the strategy occurs the next business day of the divergence and the trading horizon is constant 20days. Daily returns are compounded to calculate monthly returns. The independent variables are: the value weighted market excess return (MARKET), a size portfolio based on small equities minus big equities (SMB), a book-to-market portfolio of high minus low stocks (HML), a portfolio of year long winners minus a year long losers (MOMENTUM), a portfolio of last month losers minus last month winners (SHORT TERM REVERSAL) and finally a portfolio of 4 year long winners minus 4year long losers (LONG TERM REVERSAL). The corresponding p-values are reported for each separate variable, and statistic are corrected for autocorrelation and heteroscedasticity using Newey-West estimator with 4 lags. The sample period extended from September 1996 to February 2009. The p-values and R^2 from each time-series regression are reported in nominal form.

	First Portfolio				Second Portfolio			
Monthly Pairs Portfolio	*Top 2*	*Top 5*	*Top 10*	*Top 20*	*Top 2*	*Top 5*	*Top 10*	*Top 20*
Intercept	0.009	0.008	0.005	0.005	0.013	0.009	0.005	0.005
	0.016	0.015	0.033	0.059	0.000	0.000	0.002	0.003
Market	0.001	-0.113	-0.063	-0.047	-0.014	0.040	0.066	-0.001
	0.992	0.224	0.294	0.404	0.833	0.511	0.148	0.975
HML	-0.124	-0.107	-0.009	-0.027	-0.295	-0.064	0.033	0.006
	0.323	0.449	0.927	0.802	0.001	0.361	0.472	0.900
SMB	0.179	-0.023	0.035	0.080	-0.214	-0.164	-0.104	-0.071
	0.211	0.857	0.724	0.368	0.067	0.026	0.047	0.165
Long Term Reversal	0.174	0.136	-0.008	-0.120	0.046	-0.030	0.038	-0.002
	0.305	0.350	0.942	0.164	0.732	0.760	0.585	0.974
Short Term Reversal	0.050	-0.046	0.006	0.040	0.056	0.004	0.073	0.098
	0.768	0.655	0.954	0.682	0.458	0.958	0.170	0.031
Momentum	0.028	0.045	0.074	0.014	-0.049	-0.011	-0.003	-0.031
	0.824	0.569	0.314	0.822	0.211	0.793	0.919	0.233
Observations	150	150	150	150	150	150	150	150
R^2	0.063	0.058	0.037	0.026	0.078	0.071	0.093	0.105

Table 14

Profitability of Pair Trading Strategy against to International Factors

The table represents the results of monthly excess log returns from pair trading portfolios where the independent variables are 4 risk factors as represented by Fama and French constructed from international indices where the weighted is according to the weights of MSCI EAFE. The implementation of the strategy occurs the next business day of the divergence and the trading horizon is divided into two periods of 20 and 60 days. Daily returns are compounded to calculate monthly returns. The table reports loadings on 5 factors market excess return (MKT), book-to-market (B/M), cash earnings to price (CE/P), earnings-price (E/P), dividend yield (D/P) sorted by size. The corresponding p-values are reported for each separate regression and statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West estimator with 4 lags. The sample period is from September 1996 to December 2007. The p-values and R^2 from each time-series regression are reported in nominal form.

Trading Horizon	20 days				60 days			
Monthly Pairs Portfolio	*Top 2*	*Top 5*	*Top 10*	*Top 20*	*Top 2*	*Top 5*	*Top 10*	*Top 20*
Intercept	0.017	0.015	0.012	0.010	0.013	0.007	0.006	0.006
	0.000	0.000	0.000	0.000	0.011	0.010	0.001	0.000
Market	0.072	0.059	0.057	0.010	0.217	0.154	0.070	0.033
	0.318	0.265	0.296	0.891	0.073	0.062	0.101	0.500
B/M	-0.087	0.151	0.057	0.027	-0.247	-0.224	-0.184	-0.104
	0.779	0.462	0.681	0.837	0.332	0.097	0.077	0.220
CE/P	-0.525	-0.435	-0.349	-0.294	-0.610	-0.167	-0.038	-0.001
	0.081	0.013	0.027	0.011	0.047	0.335	0.736	0.996
E/P	0.350	0.379	0.145	0.214	0.079	0.212	-0.060	0.045
	0.233	0.032	0.253	0.065	0.812	0.220	0.724	0.762
D/P	0.262	-0.002	0.149	0.080	0.547	0.159	0.172	-0.042
	0.222	0.987	0.243	0.524	0.056	0.316	0.176	0.742
Observations	136	136	136	136	136	136	136	136
R^2	0.034	0.042	0.040	0.039	0.103	0.076	0.055	0.049

Table 15

Regression of monthly returns of the subsamples International evidence

The table represents the returns on monthly excess log returns form pair trading portfolios where the independent variables are 4 risk factors as represented by Fama and French constructed on international indices. The sample period is from April, 01 1996 to December, 2007. Daily returns are compounded to calculate monthly returns. The sample period has been divided into 4 subsamples: The first period is from April, 01 1996 to December, 31 1999, the second period is from January, 1 2000 to December 31 2002. The third period extends from January 1 2003 to December, 31 2005 and the last period extended from January 1 2006, to December 2007. The "top n" represents the "n" best eligible ranked pairs according to the historical distance of their mean price. We open the trade when the divergence between the pairs exceed 0.5 standard deviations, and if does not converge within the next 20 business days we stop the trade. One day waiting estimations represents the implementation of the strategy the next business day. International indices where the weighted is according to the weights of MSCI EAFE. The table reports loadings on 5 factors market excess return (MKT), book-to-market (B/M), cash earnings to price (CE/P), earnings-price (E/P), dividend yield (D/P) sorted by size.

Period:	*1996:04-1999:12*				*2000:01-2002:12*				*2003:01-2005:12*				*2006:01-2007:12*			
Pair Portfolio	*Top 2*	*Top 5*	*Top10*	*Top20*	*Top 2*	*Top 5*	*Top10*	*Top20*	*Top 2*	*Top 5*	*Top10*	*Top20*	*Top 2*	*Top 5*	*Top10*	*Top20*
Intercept	0.027	0.019	0.016	0.008	0.011	0.016	0.017	0.020	0.010	0.005	0.003	0.003	0.004	0.004	0.009	0.001
	0.024	0.023	0.010	0.075	0.078	0.069	0.004	0.000	0.161	0.165	0.263	0.154	0.198	0.144	0.005	0.650
Market	0.073	0.064	0.048	0.150	0.142	0.206	0.197	0.178	-0.147	0.052	0.050	0.029	-0.058	-0.166	-0.112	-0.016
	0.744	0.647	0.647	0.123	0.453	0.150	0.067	0.084	0.537	0.704	0.646	0.703	0.780	0.333	0.491	0.900
B/M	0.418	0.521	0.262	0.047	0.508	0.107	-0.308	-0.002	-0.985	-0.294	-0.183	-0.040	0.382	0.286	0.214	0.149
	0.599	0.095	0.387	0.793	0.408	0.802	0.450	0.996	0.018	0.238	0.273	0.781	0.170	0.385	0.561	0.622
CE/P	-0.694	-0.592	-0.347	-0.416	-0.819	-0.648	-0.072	-0.232	0.113	-0.166	-0.222	-0.120	0.484	0.449	-0.062	0.157
	0.240	0.071	0.131	0.027	0.432	0.327	0.890	0.489	0.791	0.577	0.253	0.404	0.306	0.130	0.695	0.178
E/P	0.383	0.202	0.048	0.099	0.884	0.804	0.063	-0.029	-0.089	0.158	0.196	-0.065	-0.980	-0.839	-0.113	-0.341
	0.441	0.371	0.727	0.385	0.377	0.235	0.892	0.943	0.862	0.565	0.276	0.630	0.247	0.052	0.517	0.013
D/P	-0.108	-0.225	0.014	0.189	-0.225	0.006	0.272	0.212	0.329	0.261	0.497	0.446	0.523	0.547	0.290	0.360
	0.873	0.493	0.963	0.373	0.707	0.984	0.267	0.502	0.598	0.430	0.101	0.024	0.010	0.013	0.093	0.032
Observations	40	40	40	40	31	31	31	31	31	31	31	31	34	34	34	34
R^2	0.049	0.114	0.064	0.167	0.077	0.137	0.111	0.103	0.212	0.076	0.199	0.189	0.377	0.589	0.310	0.477

Table 16

Pair Trading Strategy Profitability against to International Factors

The table represents a cross-sectional regression of excess returns from pair trading portfolios where the independent variables are a set defined one-by-one within the table. The implementation of the strategy requires a trading horizon of 20 days. The corresponding p-values are reported for each separate regression and statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West estimator with 3 lags. The p-values and R^2 from each time-series regression are reported in nominal form.

Trading Horizon	20 days									
Number of Pair	*First*		*Second*		*Third*		*Fourth*		*Fifth*	
	Long	*Short*	*Long*	*Short*	*Long*	*Short*	*Long*	*Short*	*Long*	*Short*
Intercept	0.0135		-0.0291		0.0258		0.1200		-0.0366	
	0.9461		0.4747		0.3697		0.0012		0.2101	
Inflation	-9.0596	1.4931	-0.8925	0.3746	0.3538	0.6187	-4.3894	1.6720	-4.3701	0.8166
	0.0802	0.0807	0.5249	0.5169	0.7371	0.1994	0.0031	0.0608	0.0685	0.4366
GDP	0.0159	0.0278	-0.0007	0.0023	0.0002	-0.0046	0.0085	-0.0199	-0.0072	0.0001
	0.2435	0.4056	0.6673	0.7187	0.8578	0.0426	0.0280	0.0012	0.0089	-0.9507
Unemployment rate	0.0757	0.7557	-0.0076	-0.0241	0.0069	0.0143	-0.0452	-0.1617	0.0079	0.0456
	0.1398	0.1071	0.4175	0.7345	0.0717	0.7729	0.0048	0.0498	0.5976	0.1301
Money Market Rates	0.3045	-0.8067	0.0433	0.0056	0.0349	0.0235	0.0355	-0.0559	-0.1661	-0.0381
	0.0561	0.0882	0.3929	0.3415	0.5686	0.5315	0.4631	0.3786	0.8091	0.0426
FOREX	-0.3614	-0.1586	-0.0264	0.3818	-0.0266	0.2503	-0.0484	0.1238	0.0625	0.7566
	0.0811	0.7464	0.5134	0.3274	0.2486	0.3322	0.3334	0.8584	0.0172	0.3025
Default premium	0.0316	0.0269	0.0040	-0.0053	0.0068	0.0005	0.0051	0.0033	-0.0073	-0.0142
	0.1187	0.6213	0.5318	0.5363	0.1346	0.9280	0.5343	0.6923	0.2228	0.2469
Dividend yield	-31.3336	16.0077	-1.2712	1.5816	-1.8411	0.8219	-0.5380	-1.5142	0.1227	0.4176
	0.0354	0.0661	0.4037	0.2778	0.1023	0.1503	0.7051	0.3361	0.9181	0.5747
EPS	-0.0006	0.0006	0.0000	0.0000	0.0000	0.0000	0.0001	-0.0002	0.0002	0.0001
	0.9452	0.0366	0.1758	0.8960	0.8583	0.7503	0.5816	0.0710	0.1999	0.4743
Equity Inflows	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.8674	0.1142	0.8893	0.3614	0.0737	0.6174	0.0301	0.0330	0.2584	0.0699
Portfolio Inflows	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.4139	0.2118	0.9727	0.6604	0.1534	0.3283	0.0910	0.1022	0.1511	0.2078
Market Capitalization	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.9380	0.5030	0.1426	0.5321	0.7430	0.3748	0.2729	0.4916	0.9457	0.8140
Discount Rates	-0.0849	0.2864	-0.0483	-0.0593	-1.8411	-0.0379	-0.0500	0.1362	-0.2692	0.4918
	0.1831	0.2959	0.3507	0.0398	0.1023	0.5146	0.2431	0.0754	0.2469	0.0410
60 days Past returns	-90.1903	133.7159	-0.0748	0.0251	1.2283	0.0336	-8.3444	7.4952	-10.4909	0.0570
	0.0181	0.0272	0.3115	0.4598	0.7605	0.1594	0.4099	0.3678	0.0744	0.1504
Market volatility	0.0480	-0.4180	0.0068	0.0645	-0.0063	-0.0178	-0.0068	-0.3148	-0.0089	-0.1162
	0.0001	0.2416	0.6272	0.4497	0.4652	0.0110	0.5512	0.0008	0.3415	0.4113
Market turnover	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.8849	0.0519	0.1433	0.5330	0.7272	0.9013	0.2263	0.1306	0.9432	0.1739
Estimation Period:	06.12.1997-11.07.2007		04.07.1997-12.28.2007		02.13.1997-03.31.2008		03.14.1997-07.28.2008		07.09.1997-03.22.2007	
Observations	41		68		85		56		48	
R^2	0.8850		0.3969		0.3187		0.6756		0.7064	

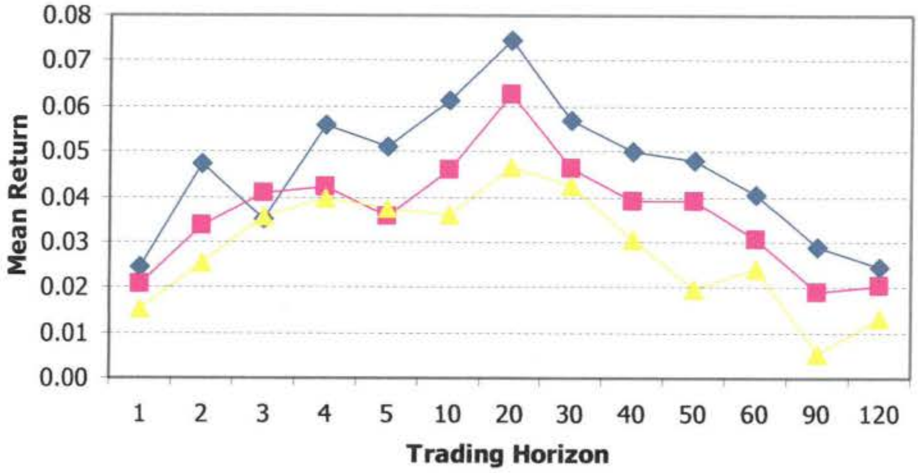


Figure 1: The lines plot the distribution of mean returns of the best 5 eligible pairs according to different measures of standard deviations on the identification of the opportunities. During the formation period (120 days), the strategy is evaluating two price absolute differences according to three different scales of distance. For different k trading horizons, where k=1,…,120, we consider three scales of deviations, 0.5, 1.0 and 2.0 standard deviations. Blue line corresponds to the distribution of mean returns for 0.5 standard deviations, magenta corresponds to empirical distribution of 1.0 standard deviation, and gold corresponds to empirical distribution of 2.0 standards deviations. The execution of the strategy occurs one day after the divergence

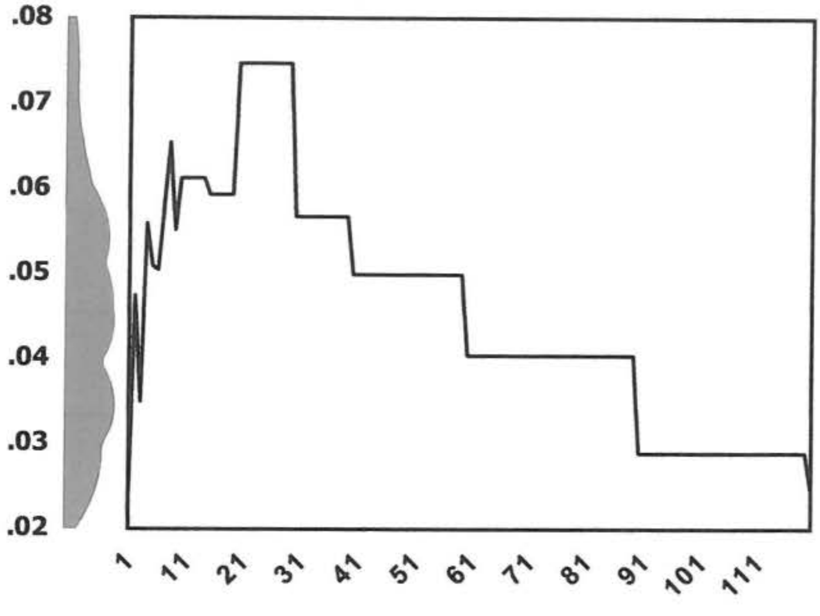


Figure 2: Distribution of Mean Returns according to different Time Exit Strategies. The testing period is between 1day and 120days. The mean returns are represented also from Kernel density on the left. The execution of the strategy occurs the next business after the divergence and the evidence have been applied to top 5 pairs. The grey bar on the left side of the plot represents Kernel Density.

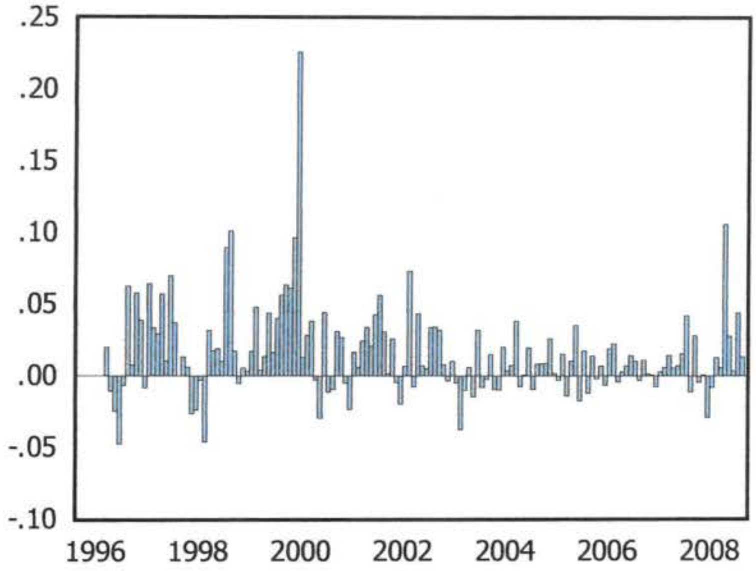
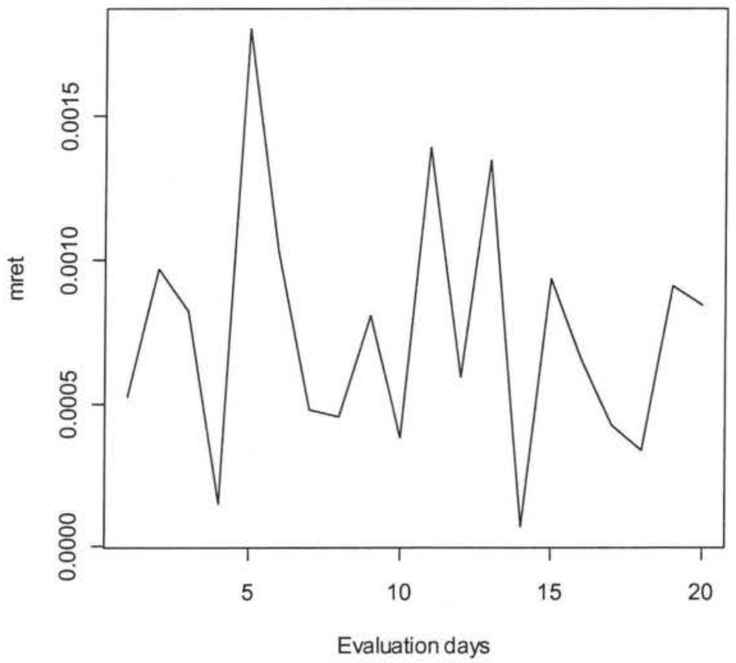


Figure 3: The line plots the distribution of the monthly Excess Return of Pair Trading Strategy for the top 5 eligible pairs. The trading period is extended from September 1996 to March 2009. The execution horizon is 20days. The strategy is implemented the next business day of the divergence day.

Panel A: Mean return distribution during the 20days execution period.



Panel B: Distribution of standard deviation during the 20 days execution period.

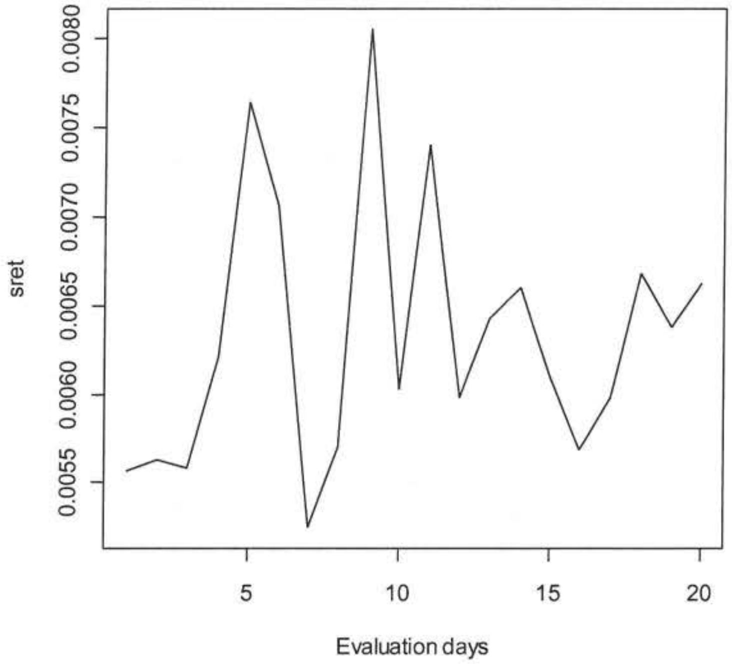


Figure 4: Panel A and Panel B plots the distribution of mean returns and standard deviation of top 5 eligible pairs of pairs trading strategy. The execution horizon is 20 days. The implementation of the strategy occurs one day after the divergence.

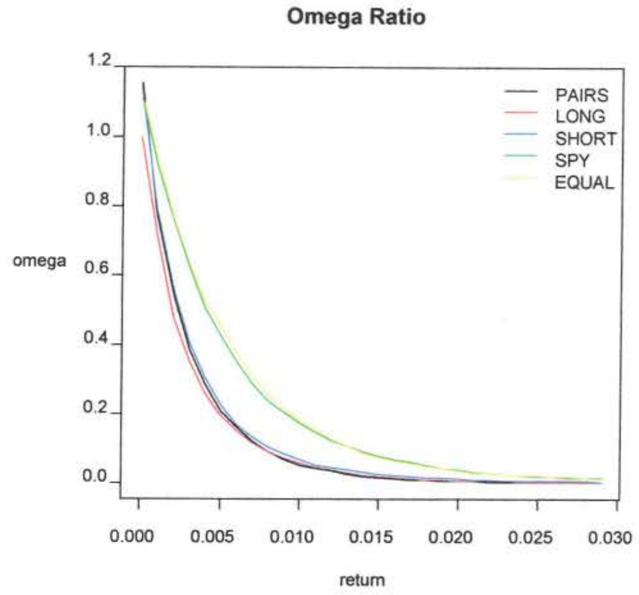
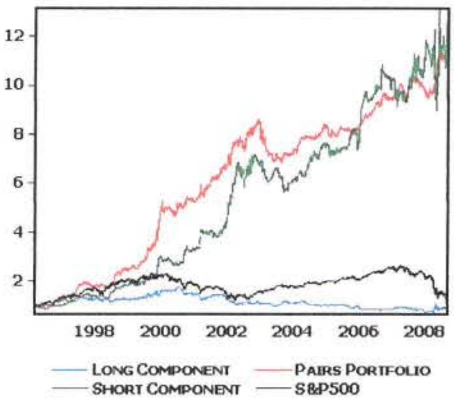
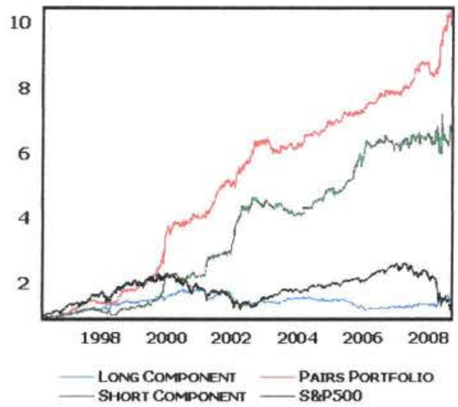


Figure 5: The plot exhibits the daily Omega Ratio produce with the best 2 eligible pairs. We set as r threshold 0 and we are considering the positive returns. In the plot, we are representing pairs trading strategy, and long and short component separately. For the relative comparison, we represent S&P500 and equally weighted portfolio.

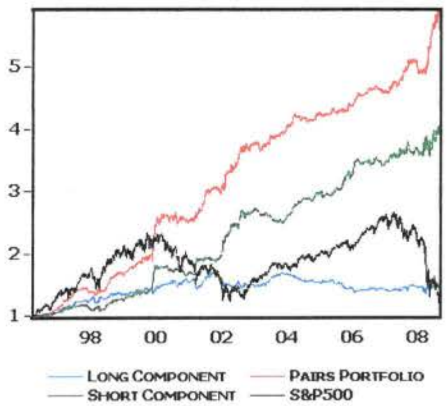
Panel A: Top2 Pairs Portfolio



Panel B: Top5 Pairs Portfolio



Panel C: Top10 Pairs Portfolio



Panel D: Top20 Pairs Portfolio

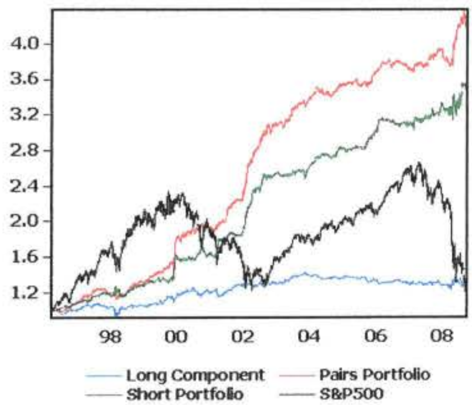


Figure 6: Presents daily terminal wealth of baseline results for different number of eligible pairs in the respective panels (A:2pairs, B:5pairs, C:10pairs, D:20pairs). In the figures, we represent in align with the terminal wealth, long and short component and S&P500 for the relative comparison.

Chapter 3: Pairwise Rotation Statistical Trading Strategies: An non-neutral trading strategy and volatility timing

Introduction

The issue of predictability of stock returns is of constant interest to academics, practitioners and investors. According to Skidelsky (1992), Keynes at the corner of 19th century examined the variation on stock returns according to the business cycle and assumed a trading strategy investing in real assets under the name of "Active Investment Policy". His strategy was based on constant rotation between short and long maturity assets under forecast estimates based on the changes in the interest rate. At the early 70's, financial markets have been dominated by the theory that markets are following random walks with no space for profits. Although the increase in volatility of that period, especially in the US market, initiated an examination of variations of stock behaviour. Johannes et al (2002) define market timing as that behaviour of the investors to increase their allocation in risky assets in periods of bull markets while volatility timing decreased as the opposite attribution when investors are decreasing their allocation in periods of high volatility. Lam et al (2004), defined market timing as the objective of outperforming a buy and hold strategy on periods of highly expected returns, and stay in cash on periods of bear markets. Market timing is an investment strategy with the unique objective to outperform the market.

Market timing requires the appropriate investment strategy (which strategy we choose) according with the fitting model selection (econometric methodology). A popular methodology for the implementation of market timing is technical trading rules. Trading rules assess the existence of patterns that can be incorporated for predictive purposes. As we referred to the previous chapter, Nath (2003) presented some practical issues in pair trading industry which we reproduce below adding some more issues as well.

The scope of this chapter is to examine the economic and financial interpretation of return predictability under the spectrum of the performance of optimal trading strategies by incorporating the impact of volatility and market timing. Applying different forecasting specifications, we try to generate profitable trading rules. We explore economic and statistical significance of "volatility timing strategies" similar to Fleming, Kirby and Ostdiek (2001, 2003) and Johannes Polson and Stroud (2002) work. Second, the outcome of trading rules applied to rotation trading methodology and I am exploring the motivation behind the strategies in order to comprehend the fundamentals of those strategies so as to improve econometric methodology. On that concept, a major contribution reveals our scope to examine the statement if different levels of volatility create different levels of forecasts. The implementation of our strategies has been based on ETFs, as in the previous chapter.

Our methodology incorporates historical information to the identification of the appropriate model and under predefined selection trading rules we implement the specification to generate one-period predictions of excess returns. The rolling forecasts are employed in a single asset portfolio rotation strategy switching between two ETFs. Intuitively, our model incorporates an amalgamation of time-varying expected returns and volatility timing. In the implementation of our strategies we analyse and test step by step the anatomy of our strategies based on widely acceptable methods from statistical and econometrical literature, and provide evidence for the robustness not only for the parsimonious model but also for the excess returns. The strategy is similar with Johannes, Polson and Stroud (2002) is based on the construction only on a single risky asset, without relying on diversification or time-varying correlations. Obstacles arises by optimal allocation is identified by Best and Grauer (1991) known as the extreme sensitivity of estimates to expected returns. Breen, Glosten and Jagannathan (1989) and Thomakos, Wang, and Wu (2007) employed switching strategies based on predictive estimates.

The remainder of this chapter is organized as: Section 2, describes a briefly analysis on pair wise rotation trading. Section 3, provides a brief overview of existing risk arbitrage research and outlines the three main groups of pair wise rotation strategies. Section 4, describes the data sample and the properties that used in this paper and the model specification. Section 5, applies robustness tests. Section 6, presents the results of the predictions of ETFs based on trading results rotation strategies, the relative comparison between market and volatility timing as well the decomposition of the robustness of the sign and the trading activity. Sections 7, represents the concluding remarks.

2. Existing Trading Strategies and Relative Review

2.1. Review on Market Timing Trading Strategies

Breen, Glosten and Jagannathan (1989) examined the performance of a market-timing switching strategy between Treasury bills and stocks for the horizon of 1954-1987 and proved that the predictions of excess stock return on the one month risk-free rate does not compensate in risk adjusted basis.

Pesaran (1994) presented evidence on the predictability of excess returns on common stocks under three different frequencies monthly, quarterly, and annual. He proved that recursive method produce best forecasts and allows us for a statistical significant proportion of the signs of the actual returns. In means of trading strategies signs predictions outperform the respective market portfolios when trading takes place on a quarterly or annual basis including high transaction cost scenario. Although, at monthly frequency switching portfolios outperforms market portfolio only when transaction costs are zero or very low.

Pesaran et al (1995) examines if a market timing strategy could outperform a buy and hold strategy. Using a forecasting methodology on U.S. equity markets found that the eclipse of a systematic predictable relationship could lead to profitable market timing but there are miscellaneous economic factors which change over the time and are affecting the volatility of returns. Moreover, they argued that during 60s where the market appears low volatility the predictions were not significant, but the trend changed on 70s where volatility dominated US market.

Gencay (1996) take as granted that forecastability of equity from their past returns or other past variables violates efficient market hypothesis and explored the aforementioned factor. Using daily data of DJAI index from 1963 to June 1988 examined the existence of linear or non-linear predictability of stock market returns using moving average criteria between short and long averages. He proved that there is strong existence of non-linear predictability.

Whitelaw (1997) used linear econometric methodology to capture the dynamics of conditional mean and volatility dependence of equity returns to forecast stock market Sharpe ratios in monthly basis. He proved that predictability leads to profitable market timing strategies and outperforms a buy and hold strategy in terms of ex ante Sharpe ratios. Moreover, assessed that mean and volatility of equity returns are not correlated.

Qi et al (1999) examined market timing has been applied under the implementation of neural networks. They incorporated linear and nonlinear predictability of the excess returns using recursive modelled neural networks which are capable of performing flexible nonlinear functional approximation. The nonlinear neural-network model compared to linear performed better forecasts both in-sample and out-of-sample. Moreover, recursive neural network forecasts outperform a passive buy-and-hold strategy and the switching portfolio which is constructed with linear recursive forecasts.

Pessaran et al (2000) on the development of their work applied a recursive modelling strategy to the UK stock market. They found evidence of predictability that can be used by the investor in order to become more efficient in means of risk-return trade off but only implemented by a passive strategy.

Lam (2000) examined the optimal trading results under the assumption that of forecasting a key summary statistic of future prices. Using neural networks and considering transaction costs to Hang Seng Index Futures Contract traded in Hong Kong, proved that forecasting the largest change before reversal outperforms the k-step-ahead forecast in achieving higher trading profits.

Racine (2001) argued that constructed switching portfolios based on linear forecasts and switching portfolios based on neural networks on Qi's methodology. He argued that NN methodology outperforms in means of return and risk linear regression. He also applied an evaluation comparison among the following indicators under the rule of 396 recursive predictions: root mean square error RMSE, mean absolute error MAE, mean absolute percentage error MAPE, correlation coefficient (COEF), the fraction of correctly predicted signs (SIGNS). He argued that switching portfolio based on linear methodology generates higher accumulated terminal wealth with lower risk that the methodology based on recursive neural-network forecasts.

Xia (2001) examined equity return predictability under the effects of uncertainty on an optimal dynamic portfolio in a continuous time frame for a long term investor. He argued that there is a strong relationship between optimal portfolio and investment horizon where is produced by the hedging demands. In a long run period the opportunity cost of innovations is substantial.

Johannes et al (2002) analyzes the factors that lead to optimal portfolio rules which named it as return predictability. He used a time-varying model of expected returns and volatility in order to generate profitable out-of-sample portfolio returns. He assessed that a strategy based exclusively on volatility timing can outperform market timing strategies, since they assumed no predictability in mean returns. His results were based on S&P 500 index for the period 1980-2000.

Lee et al (2002) considered optimal market timing strategies under transaction costs. They used a trading pair one risky and one riskless asset considering an auto-regressive model under long-term investment growth under a finite investment horizon. Their model criteria depend on two threshold values. At evaluation day, if the return is between the two values, they remain at the same allocation; otherwise they will transact from one asset to another, depending on the side of threshold value that exceeded. Moreover, they argued that as time passes the optimal strategy confirms the momentum index trading rule. Apart from the technical part using Hang Seng Index Futures they outperform the market with one-step ahead forecast. Strategy analysis with respect to transaction costs they proved that no-transaction region increases as the transaction cost decrease.

Kanas (2003) examined the out-of-sample forecast performance of two parametric models (standard and Markov regime switching) and two non-parametric nonlinear models (nearest-neighbour and artificial neural network models) for US equities market under the period of 1872-1999. Evaluation was based on forecast accuracy and encompassing. Markov switching models outperform all the other models in both accuracy and encompassing where in terms of encompassing Markov strongly outperforms the competitors. In term of accuracy, there was not any distinction between the models.

Jiang (2003) examined market timing ability and incorporated a large datasample of mutual funds for the period 1980-1999. He proved a superior timing ability among actively managed equity funds.

Lam et al (2004) assume that traditional market timing methods which hold stocks in a period with positive excess return and switching to a riskless asset in a reversal period with negative excess return under the presence of transaction cost is not optimal. They argued that under the optimal growth criterion an investor can achieve up to 80% higher return for a daily review but in case of low transaction costs. In longer review periods to outperform perfect market timing we need a higher degree of correct predictions in order to be at par with a buy-and-hold strategy. With respect to transaction costs, the correct prediction probability in order to be at par with the buy-and-hold strategy increases.

Wang (2004) argued that rotating strategies over equity styles could generate significant returns. He proposed a weight-based approach to multifactor risk adjustment of style rotation based on Sharpe's classic approach. Conventional Sharpe's approach under logit-based timing strategy leads to a different conclusion.

Thomakos, Wang and Wu (2007) applied rotation strategies based on capitalization of three indices (S&P500, S&P400, Russell 2000) and argued about the significance of the predictability of short term interest rate. Their results for the respective period of 1979-2004 extrapolate positive excess return.

Brooks et al (2008) formed a dynamic asset allocation framework. They incorporated the widespread ratio in hedge funds industry "omega ratio". The best strategy is implanted by the difference between the earnings-price ratio and short term Treasury yields. They argued that speculative methodology is the second best strategy outperforming buy and hold strategy. Moreover, they proved that fixed income yields component drives the strategy. Yields are crucial both on determination of the phase in the business cycle and as a benchmark against gauge equity valuations.

2.2 Review on Volatility Timing Trading Strategies

Breen et al (1999) argued about the importance of one-month interest rate in the prediction of the sign and the variance of the excess return on stocks. Moreover, the comparison of fund managers between 1954-1986 that use forecasting models to their allocation decisions cost them annually 2% management fees when the mean returns was only 2bps and the volatility 60% above their benchmark.

Poon et al (2001) on their review publication referred to 72 papers of forecasting volatility. The separated the literature under those that built volatility forecasts based on historical price information and the second group on those that incorporates implied volatility in option prices. According to their publication issues under the majority of the interest are forecast evaluation, the frequency of the series on volatility forecast accuracy, measurement of "actual" volatility, and the affects of outliers on volatility performance.

Fleming et al (2003) proved the benefits of realized volatility, where in means of volatility - timing strategy is willing to pay 50 to 200 basis points per year to switch from a daily returns based estimator of the conditional variance matrix to an estimator based on realized volatility. The benefits are greater to a static portfolio and do not restricted to short horizon investors. Moreover, historical volatility was very difficult to create a dynamic relationship between conditional expected returns and covariance measures of systematic risk however realized volatility overcome this obstacle. Lastly, they argued about the importance of the statistical performance of realized-volatility-based estimators and the conditional covariance matrix.

Christoffersen et al (2003) on the groundwork of the sign forecasting abridgement the three conditions that can lead to profitable volatility timing in a stochastic environment. (1) Existence of conditional mean dependence in asset returns can be translated as forecastability in asset return signs and consequently in asset return volatilities. (2) On the reserve, volatility dependence produces sign forecastability, under the condition that expected returns are nonzero. They argued that merely or no conditional mean forecastability supports the hypothesis of mean and sign and hence volatility dependence violates market efficiency. (3) Sing forecasting could not be extrapolated by the existence of autocorrelation but we must conduct nonlinear methodology to capture the nature of sign dependence. They argued that all the above conditions should be applied at an intermediate return horizon data since high-frequency data (daily) or to the contrary low-frequency data (annual) does not produces significant signs. On their extension of their research (2005) argued that improvement of sign forecasting, apart from the conditional variance information, could produced by conditional skewness and kurtosis information.

Marquering et al (2004) projected evaluation of return and volatility forecast using non-parametric and regression-based market timing tests. Realized volatility tested predictability in returns and volatility simultaneously and examined if there any other common properties between returns and volatility forecasts. They estimations used recursive regression models on S&P500 index for the extended period of 1970-2001 and produced out-of-sample forecasts for both returns and volatility. Their results indicate that there is a positive market timing ability in both means of return and volatility pairs. Furthermore, they argued that there is no any direct relationship between the quality of the return and volatility forecasts. More precisely, a good forecast in returns does not give us any evidence for a good volatility forecast and the majority produces a bad volatility forecast and vice versa. However, evidences proved that when volatility is higher than the average predictability of returns is more often correct, thus high dependence in return forecasts.

2.3. Existing Literature on Trading Strategies

Bondt et al (1985) under the spectrum of experimental psychology suggests that, in violation of Bayes rule, investors have a propensity to "overreact" to unexpected and dramatic news events. They argued that this behaviour affects stock prices and is the crucial factor for the overreaction hypothesis which violates efficient market hypothesis. They also argued that on January returns earned by prior "winners" and "losers." Investors who belong to losers experience exceptionally large January returns five years after portfolio formation.

Jegadeesh (1990) examined predictive behaviour of security returns under the spectrum of serial correlation. Based on monthly returns, he argued that stocks exhibits negative first-order serial correlation and positive higher-order serial correlation. Moreover, he confirmed that January the patterns are dissimilar to the other months. He rejects the hypothesis that stock prices follow random walks. His outcome confirm that the difference between abnormal returns on the extreme decile portfolios was 2.49 per cent per month for the respective period of 1934-1987, 2.20 percent excluding January and 4.37 percent per month including January.

A different approach in trading strategies is stocks overreaction. Chopra (1992) proved that there is a significant overreaction. They argued that extreme prior losers based on portfolios of prior five years returns outperform extreme prior winners by 510% per year during the following five years. Moreover they proved three more rules. January seasonal overreaction is affected by tax-loss selling effects. Overreaction is less for large companies than for small companies. Overreaction is getting greater as time comes closer to quarterly earnings announcements.

Kandel et al (1996) examined the decomposition of predictability of stock returns under different statistical hypothesis. Under, constrain of risk-averse Bayesian investor who allocates their wealth between stocks and cash. They argued that usual statistical measures are not adequate to describe regression relation and only recent observations of predictive variables exhibit a substantial affect on the investor's portfolio.

Conrad et al (1998) on a wide analysis of the two most broad trading strategies momentum and contrarian at eight different horizons and duration several different time periods proved that only 50% of the 120 applied strategies return significant profits. Between the 2 strategies are equally distributed inside 60 successful strategies. They proved that momentum strategies are more profitable at medium horizons while contrarian strategies are profitable at longer horizons. The most trigger result indicate that mean returns of individual securities are constant during the period of the sample, although cross sectional variation in mean returns is a factor of profitability only for the momentum strategies which considers our research since it is closer to market timing.

Sullivan et al (1999) applied White's Reality Check bootstrap methodology to evaluate the performance of 26 technical trading rules utilizing daily data of Dow Jones index.

Gatev et al (2006) et al examined the performance of a relative value arbitrage rule with daily data for over 40 years. They argue that pair trading is profitable, taking consideration trading costs, and selecting pairs under the "minimum distance criterion". They proved that relative value strategies are profitable due to mean reversion behaviour. More precisely, since the pairs historically are fully correlated will converge and this co movement leads to substantial profits.

2.4. Review on basic factors affecting the implementation of rotation trading

Bushee et at (2005) on their examination on the differences on the academic trading models and the real world remarked that main issues can be summed up to price impact to block trades, restriction on short sales and legislation constrains. Specifically, in rotation or switching trading strategies, liquidity and leverage are the main issues on the formulation and real implementation of a trading strategy.

In the implementation of our strategies we don't apply any short investments and we do not consider leverage. However, liquidity affects prices and conveys information into different directions. Llorente et al (2002) argued that short-term return reversals are driven by non-informational driven hedging trades where illiquid stocks are more vulnerable. These behaviour odds arbitrageurs which concluded to an extensive period of inequilibrium and keep the prices in divergence.

Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Brennan, Chordia, and Subrahmanyam (1998) argued that illiquid stocks presents on average higher returns. Eleswarapu (1997) argued about the existence of liquidity premium on equities and found a strong evidence utilizing data from Nasdaq stock exchange for the horizon from 1973-1990. Amihud (2000) and Jones (2001) model liquidity as endogenous variable and proved that there is a link between market liquidity and expected market returns in means that innovations affects persistent equities.

Chordia et al (2001) concentrate on aggregate spreads, depths and trading activity on US stocks, indicating that on daily basis there is negative correlation between liquidity and trading activity. Liquidity collapses on bear markets and positive correlated by long and short interest rates. Increase in market volatility has a direct negative effect in trading activity and spreads. Major macroeconomic announcements increase trading activity and depth just before their release.

3. Data

3.1. Data Sample Span

Our empirical analysis focuses on 4 broadly defined passive ETFs. Our sample have been fragment with respect to specific criteria like market capitulation, wide historical tracking record, well-know issuers very high trading volume and high capitalization. We incorporated 4 of the most active ETFs all over the world with respect to regional dynamics of US market:

- S&P500 is the first ETF in the US, launched on 29 January 1993 (second globally after the TIPS) on the American Stock Exchange, under the name SPDRs - Standard & Poor's Depository Receipts or "Spiders". It is considered to track S&P 500 index (ticker: SPY). It is the largest ETF all over the world with 61.4 billions assets under management.

- Financial Select Sector SPDR ETF (ticker: XLE) has been incepted on 16 February 1998. It belongs to the group of Standard & Poor's Depository Receipts-"Spiders" and it was primary listed on AMEX. Net assets under management 3.98billions
- PowerShares "Cubes" (ticker: QQQQ) is designed to track the NASQAD 100 Stock Index and has been launched on March, 10 1999 on AMEX. Due to the underlying index it belongs among the most popular ETFs with net assets under management 10.26 billions. The provider is Invesco PowerShares.
- Oil Services HOLDRs trust (ticker: OIH) has been designed as a basket of specified companies with exposure to oil service industry. It is consisted by 20 companies which are among the largest and most liquid with U.S. The respective ETF incepted on February, 6 2001 and has net assets under management 1.55 billions. It is traded on NYSE and the provider is Merrill Lynch.

The source for data set is Bloomberg database. Our estimations are based on weekly observations including open, high, low and closing prices for each separate ETF series. The sample period is defined as we consider every ETF by the inception date. Since, our datasample is a heterogeneous group in means of inception date we match each pair with respect to the ETF with less observations. So, the pairs match by the following dates.

SPY-QQQ formulated since 10 March 1999

SPY-XLE formulated since 22 December 1998

SPY-OIH formulated since 02 July of 2001

ETFs series has been downloaded without dividend adjusted[40]. For the results, we run estimations separately for Monday, Wednesday and Friday in order to test for day-of-week effect.

For every different strategy we cropped our sample by the inception date of the most recent ETF until the 04 April of 2008. All sample has futures contracts-options[41] and the whole range of the including ETFs can be traded, over the counter, to electronic platforms. The trading hours at AMEX are since the open at 09:30a.m. to 4:15p.m. The results have been generated by R program.

3.2. Properties and Data-Snooping

A successful trading strategy requires a careful overfitting and data snooping approach. Definition of data snooping includes a model that seems to fit excellent although the results are spurious. In time series is with no doubt inherent and unavoidable concern.

Data snooping arises when many specifications have been conducted or the datasample has been incorporated more than once to the process of the final model The problem gets larger dimensions when we conduct non-linear methodology and trying to achieve a robust and successful out of sample estimations including random trends as well as genuine nonlinearities patents. A naïve rule to detect overfitting is too many degrees of freedom or two many parameters which leads to unfortunate out of sample estimations. Lo & MacKinlay (1990) state that a corrected distribution could be a merely solution to the problem. Another formula to mitigate data-snooping

[40] In the literature of dividend payments are used to detect any fluctuations but it is beyond our scope cross variations that could affect spreads fluctuations.
[41] Options increase the liquidity of the respective ETFs.

is out of sample evaluation across different tests and datasets. One more vital issue in the examination of our strategies are referred to Christoffersen and Diebold (2003) and names the properties of the distribution. They argued that sign/volatility dependence requires evaluation measures more advanced than Sharpe ratios.

On the incorporation of the data to trading strategies Kandel et al (1996) argued bout the importance of heteroscedasticity in an asset allocation framework and the distortion that could bear to the optimal predictive variables. He argued that if the conditional mean and variance are increasing in the same direction, the existence of homoskedasticity will affect negatively the optimal predictions. In addition, distortions on the predictive PDF will be present in the case of heteroscedasticity. Relevance to hereskedasticity, our modelling approach confirms that returns on the asset are stationary and our asset returns are considered to be conditional heteroscedasticity[42]. The degree of importance in any inconsistency is crucial since could considerably change the optimal outcome of the same variables that are incorporated to the forecasting of the expected returns and the conditional volatility.

Pesaran and Timmerman (2005) argued that an extended model of potential variables, spurious relationships and emerge the problem and the importance to test and minimise the effects of data-snooping. They proposed as metric solutions, a loss function and to count the percentage of corrected predicted signs. They argued that the sequence of the cumulative returns are vulnerable to large sample standard errors and even a long cross- corroboration data sample could not avoid those negative effects.

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[42] GGR (2006), consider bankruptcy risk as one reason that individual securities returns cannot considered as stationary. They refer to that issue with the example of twin stocks, that a negative announcement on the one enterprise will also have an identical effect to the other stock so a strategy between those two stocks will be a loser. In our data sample bankruptcy does not exists or exists on a negligible basis, since it's consisted by major indices on ETF structure any bankruptcy of an individual security will have negligible effect.

According to their argument, our formulation approach concentrated on the finding and building of a parsimonious model under specification, estimation and finally model checking. The first step is the stabilization of the variance, which can be done by logarithmic transformation. The second step is the check and the transformation for stationary and the appropriate degrees of differencing. The first phase names the identification of the order of the autoregressive (p) and the moving average (q) polynomials. The identification procedure usually is conducted by comparing or better matching sample and partial autocorrelations or by information criteria. In our estimations we incorporated maximum likelihood estimates (MLE). The last step is the diagnostic checking or goodness of fit of the model and usually is referring to the analysis of the residuals where usually conducted Ljung-Box statistic. The aforementioned concerns examined extensive by the conduction of robustness tests which present at section 5.

4. Methodology

4.1 Rolling Estimation Period

The first step on the formulation of our methodology is the estimation of rolling window. In our modelling, the estimations have been conducted using a rolling horizon of 104 trading weeks. Timmerman and Granger (2004) examined the optimal data window and they defined the variable as "win", which simply is some fixed predetermined window based on the specific nature of the model. The optimal window length is under consideration according to the fundamentals of potential model instability and the timing of potential breaks. They assumed that model unsteadiness may be affected by factors like technological of institutional changes or policy changes. In our methodology, formation period has been chosen under testing several periods[43]. Decompose each separate specification of the implemented strategies concludes to different optimal formation periods, however, the selected 104 calendar observations conclude to the higher best outcome for the majority of implemented strategies[44]. We keep the formation period constant for the entire set of calculations. For the formation period of 104 observations, we calculated the returns of the assets into logarithmic format. From the beginning of the formation period at day *t*, we record each ETF logarithm return based on closing prices where i is the return of the i asset.

$$Ri_{,t} = \log\left(\frac{R_{i,t}}{R_{i,t-1}}\right) - 1$$

4.2 An Intuition to Methodology Formation

As Timmermann and Granger (2004) defined an efficient trading model should accomplish the following five issues:

1. Set the forecasting model available at any given time including estimation methods.

[43] We tested as well formation horizons of 52days, 104days, 200days, 320days rolling windows
[44] Different optimal window lengths concludes to better results for each separate strategy although is beyond of our scope, and probably would be a crucial issue of a trader

2. The search technology used to select the best forecasting model(s).
3. The available real time information set, including public versus private information and ideally the cost of acquiring such information.
4. An economic model for the risk premium reflecting economic agents trade off between current and future payoffs.
5. The size of transaction costs, the available trading technologies and any restrictions on holdings of the asset in question.

The selection approach is based on time-varying volatility and past returns variables. Intuitionally, our approach is based on the concept that realized volatility can help to accurate volatility forecasts where is combined with cross volatility creates correct sign predictions. Realized volatility is implemented by the specification of range based estimations and defined by the following equation which is the estimation and has been defined by Parkinson (1980).

$$RBV_t^i = \frac{\left(\log\left(\frac{R_{t,H}^i}{R_{t,L}^i}\right)\right)^2}{4 \times \log(2)} \tag{1}$$

where $R_{t,H}^i$ is the daily high price of the i asset and respectively $R_{t,L}^i$, is the daily low price of the i asset. Realized volatility has superior strength than historical volatility since allow considering daily deviations in comparison to historical volatility which captures the dynamics of a static moment T.

4.3. The Variables Selection

In this section, we establish the list of variables is likely to consider in the functional form of the estimated model. Before we initialize to unfold the functional form of our forecasting model, we use Pesaran and Timmerman (2005) argued about an optimal formulation and selection of a model. "*They argued that the real time nature of the decision making process recognizes that the forecasting model and its parameters might need updating at the start of each decision period (prior to opening market). This procedure requires updating of parameters of a given model (keeping the specification of the model fixed), updating the model by searching over a pre-specified set of models, or might even involve searching over new models including new variables, functional form prior to date T. These three levels of models can be viewed as "recursive estimation", "recursive modelling" and "innovative modelling". Recursive modelling involves recursive estimation and innovative modelling could encompass both recursive modelling and recursive estimation*". However, in our estimation we will define later the reasons we applied rolling estimations.

In the functional form, we separated the variables into two major sets. The first set is defined by the traditional variables of the first two moments (conditional expected return and volatility) (2), (3) and the second set includes the variables of the cross interaction between the variables of the return and the variance (4), (5). The variable (2) represents the subtraction of the returns of the two logarithm assets at time t.

$$y_t = R_t^i - R_t^j \tag{2}$$

$$x_t = RBV_t^i - RBV_t^j \tag{3}$$

$$I(y_{t-1} \prec 0) \tag{4}$$

$$I(x_{t-1} \prec 0) \tag{5}$$

where variable (3) is the subtraction of the range based estimators of the two respective assets and plays the role of volatility timing in a rotating trading framework. Variable (4) represents the non-positive values of the subtraction of the logarithm returns. Hence, the term hypothesize that there is historically propositionally relation between the two assets, and time varying fluctuations that will be reverted. Finally, variable (5) represents the non-positive values of the subtraction of the times series variation at time t, and hypothesize accordingly the existence of a variation-reverting relationship between the two assets.

4.4. The Rolling Functional Form

In this section, we are referring to the functional form of our specification. The crucial importance of variables (4), (5) can be comprehended deeper if we recall the intuition of trading rule up to now. Technical trading rules, trading range breaks or several technical indicators suppose a threshold which above or below the respective level, investors should react. Moreover, another popular, probably the most common, decision rule is moving average. The aforementioned rules requires a constant-static level where this is the decision making rule. However, in our model we incorporate this critical level, since the different implicitly ranks the overvalued (undervalued) asset at time t, and additional our decision level is allowed to be time-varying in contrast with a static threshold as RSI indicator. We incorporate endogenous the volatility of the constituents and allow to be time-varying capturing the dynamics in each rolling estimation. In the final form, we include the cross interaction of variables (2), (3), (4), (5). In our model, we can distinguish two major set or repressors. The first set includes the lagged autoregressive variables and the second part includes the cross term of our regressors. The interactions of the cross-term allow to capture informative variation among our series. So, the general formulation of the rotation specification model is given by the following equation:

$$\begin{aligned} y_t = \alpha + \beta y_{t-1} + \gamma x_{t-1} + \delta I(y_{t-1} \prec 0) + \theta I(x_{t-1} \prec 0) \\ + \kappa y_{t-1} \times I(y_{t-1} \prec 0) + \lambda y_{t-1} \times I(x_{t-1} \prec 0) \\ + \phi x_{t-1} \times I(y_{t-1} \prec 0) + \rho x_{t-1} \times I(x_{t-1} \prec 0) + \varepsilon_t \end{aligned} \quad \textbf{(6)}$$

Equation (6) incorporates mean of the daily logarithm returns, mean of realized volatility, their sign produced according to their means and their conditional return produced of both return and volatility innovations. Expected excess returns and volatility vary over time but to their extent of mean and variance reverting will revert to the long run equilibrium. In addition, cross variables depending on the sign of the expected returns and variation, reflects a time varying covariance between the conditional expected return and risk which helps in the accuracy of the predictions. In that concept, cross-interaction variables represent a stochastic discount factor that captures short term fluctuations in a time-varying framework. The stochastic discount factors for every single forecast output can be agued as a marginal rate of conditional expected returns and variation.

An alternative approach capturing the dynamics can be applied by a threshold and not by an inequality between the two assets. However, this link is static and we are persuasive that a time-varying framework considers better the historical information. The cross-term action in means of expected returns and volatility have been extensively used in literature for bounding dynamics of asset prices where the most common factor is Sharpe ratio. Hansen and Jagannathan (1991) applied a stochastic discount factor, where given the mean of the factor the variance bounds depends on Sharpe ratio. Pesaran and Timmerman (1995) argued about the proportional relation between returns and volatility is not constant regarding the risk fluctuations, so a time varying factor endogenous in the mechanism could capture some of the dynamics. In our attempt, identical to Pesaran and Timmerman (1995) we incorporated ex ante variables to the forecasting specification and allow time varying framework to consider the significance of the historical information.

The estimations have been conducted by rolling methodology. Timmermann (1993), Bulkley and Tonks (1989) based the implementation of the methodology on recursive estimations under the exact knowledge of the forecasting specification and search only for the parameter values. However, in our specification recursive estimations fails to capture the trends since adding more innovations distorts the trend.

In our formation, we consider a single-period allocation similar to Johannes, Polson and Stroud (2002), Stambaugh (1999) and Pastor (2000). The consideration of multi-period allocation requires hedging. Although, Brandt (1999) and Ait-Sahalia and Brandt (2001) argued that hedging demands affects slightly in the consideration of an optimal portfolio allocation and the significance increases only in long run estimations. Our main rotation strategy incorporate one step a-head forecast obtained by equation (6). Our model is consisted and combines time-varying expected returns and volatility timing and their interaction. The specification of our model is based on the flexibility on of the variables considers that the relation between the two assets is time-varying mean reverting. Pesaran and Timmerman (1995) argued that parsimonious models versus to model with large number of variables exacts better out of sample forecasting performance. According to their methodology, we kept forecasting equation stable and by a set of regressors. Rather than looking for variables it is better to categorize the regressors and utilize those that capture best the fundamental of the model.

According to forecasting specification, Brailsford (1996) on a relative comparison between several models argued about the superiority of forecasts of volatility of ARCH class of models and simple regression models, however various model rankings proved to be susceptible to the error statistic applied in the examination of the accuracy of the forecasts.

In the conclusion, the rational path to comprehend the methodology, we attempt to check for the "fundamentals" of our rotation strategies so we applied different specifications based on the decomposition of market and volatility timing.

4.5. Alternative Recursive Specifications

In the previous section, we represent the basic specification model. In this section we are defining alternative forecasting specifications which each specification stands as a part of the basic model and allow to evaluation the econometric behaviour of each separate part and distinguish the pattern behind profitability.

4.5.1. Market Timing in Differences

The first specification is named as naïve model and examines the dynamics of mean of the two respective assets.

$$Y_t = R_t^i - R_t^j \tag{7}$$

where R_t^i represents the logarithm return of asset i and R_t^j stands for the logarithm return of asset j at time t.

4.5.2. Market Timing in Autoregressive Integrated Moving Average (ARIMA (p, d, q)) model

The second specification is generally referred to an ARIMA (p,d,q) model where p, d, and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated, and moving average parts of the model respectively. An ARIMA model is said to be unit root nonstationary because its AR polynomial has a unit root MA component is always stationary I(0). An approach to removing nonstationary is by considering the first differenced series. General form of ARIMA model of a time series X_t at time t then the general form is:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t$$

where L stands for the lag operator, φ_i represent the parameters of the AR model, θ_i represent the parameters of MA model, d presents a positive integer that controls the level of differencing and ε_t are the error terms. An ARIMA (*p*, *d*, *q*) process is obtained by integrating an ARMA (*p*, *q*) process, if d = 0, where the model is deducting to an ARMA model. That is,

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right) X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

So, applying differencing d times to every term an ARMA (p, q) process is reverted to an ARIMA (p,d,q) process. In our study we applied the following specification ARIMA (0,0,q) for one step ahead forecast. From the above equation θi coefficient decay exponentially as i increase, so effect of shock at time t-i, has not a permanent effect and as time passes will diminish. The final form of MA (q) model, when θi ≠0, represents a constant term equal to the mean of the dependent variable,

$$r_t = \frac{\phi_0}{\left(1-\phi_{1-...-}\phi_q\right)}$$

Our general model transformed to an MA (q) in order to model the capture the impact of variance of a forecast error. The previous equation is just the confirmation of mean-reversion of a stationary time series since the coefficient approaches to 0 as time approach to +∞. More specific, one step ahead forecast with moving average process of first degree[45] has the following form:

[45] The determination of the order of MA has been conducted by ACF which cuts off at lag q.

$$r_{h+1} = c_0 + a_{h+1} - \theta_1 a_h$$

Where h denotes the forecast origin and F_h stands for the available information set at time h. The redacted specification is a simple forecast model based on MA (1) first order. In order to conclude to the final order of our specification model, we conduct tests for higher orders up to four order (MA (4)) but we concluded that the optimal order is the first.

4.5.3. Volatility Timing and AR(q)

The model is based on the conduction of an AR (1) model. The notation AR(*p*) refers to the autoregressive model of order *p*. The functional form of an AR(*p*) model is:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t.$$

where c is the constant term, $\varphi_1, \ldots, \varphi_p$ is the lagged parameters of the model and ε_t is the error term. In order the model to be stationary should the parameters to be $|\varphi_1|<1$. In the case where AR (1) is $\varphi_1| \geq 1$ is not stationary. The aforementioned model in our publication represents the naïve model. Andersen et al (2003) argued that modelling realized volatilities as a simple AR produces volatility forecasts that outperform those obtained from GARCH models. Going further they compared the performance of the ABDL (2003) specification with GARCH models structured in terms of the lagged realized volatilities.

4.5.4. Volatility Timing in differences

The aforementioned model is also widely used is stochastic volatility modelling with the substitution of $\mathbf{X}_t$ with the volatilities. We consider stochastic volatility under the specification of modelling the differences of volatility of the two assets.

$$d_t^{volatility} = RBV_{i,t} - RBV_{j,t} \tag{8}$$

where $RBV_{i,t}$ is the volatility of asset i at time t, and $RBV_{j,t}$ is the volatility of asset j at the respective time t.

4.5.5. Volatility Timing in Ratio

We consider a different modification, and we calculated the logarithm fraction of two volatilities. So,

$$Volatility_t = \log\left(\frac{RBV_{i,t}}{RBV_{j,t}}\right)$$

The MA moving average is based on an ARIMA (0, 0, q) model. Volatility benchmarks are an AR (1) process of the logarithm of volatility of the respective asset. Andersen et al (2003) argued that modelling realized volatilities as a simple AR produces volatility forecasts that outperform those obtained from GARCH models.

4.6. On the Choice of the Sign Formation Criteria

In the previous section, we establish our methodology specification. In this section, we represent our decision criteria for the formation of the trading rules. We applied 7 different criteria in order to indentify buy and sell trading signal for both single-asset rotation strategy and alternative specification models:

Criterion 1: This criterion is referring to the naïve model (NM). The trading sign is based on the difference of the mean of the respective assets.

If, $Y_t = R_t^i - R_t^j$ is the daily mean differences at time t of asset i and asset j, then *if* $\hat{y}_t \succ 0$, then invest the wealth on asset i, otherwise trade on asset j.

Criterion 2: The second criterion is referring to moving average model (MAM). The trading signal is based on the

If, $MAM_t \succ 0$ is the out of sample one step ahead forecast at time t of asset i and asset j, then invest the wealth on asset i, otherwise trade on asset j.

Criterion 3: This criterion is referring to the difference of realized volatilities DV_t. The trading signal is based on the difference of volatilities of the respective assets.

If, $DV_t = V_t^i - V_t^j$ is the differences of realized volatility at time t of asset i and asset j, then *if* $DV_t \succ 0$, then invest the wealth on asset i, otherwise trade on asset j.

Criterion 4: This criterion is referring to the logarithm ratio of realized volatilities DV_t. The trading signal is based on the direction of the result of the ratio of realized volatilities.

If, $DV_t = \log(V_t^i / V_t^j)$ is the ratio of realized volatility at time t of asset i and asset j, then *if* $DV_t \succ 0$, then invest the wealth on asset i, otherwise trade on asset j.

Criterion 5: This criterion is referring to our base trading strategy, to our rotation trading model (R.Model). The trading sign is based on the direction of the sign of the out of sample volatility forecast $Rot.V_t$.

If, $Rot.V_{t \succ 0}$ at time t where asset i and asset j are the assets of the strategy, then *if* $Rot.V_{t \succ 0}$, then invest the wealth on asset i, otherwise trade on asset j.

4.7. Portfolio Return Computation

The portfolio return computation is based on a simple continuous compounded return. So, a multiperiod compounded return is given by the following common equation.

$$\prod_{j=0}^{k-1}\left(1+R_{t-j}\right)=\left(1+R_{t}\right)\times\left(1+R_{t-1}\right)\times\ldots\times\left(1+R_{t-k-j}\right)$$

In the portfolio return, we keep the record and we construct an equally weighted benchmark in order to compare our rotation trading with a traditional benchmark. So, we construct a time varying benchmark equally contributed (50%) between the two assets to evaluate our rotation strategies. The attribution of the benchmark is based on the forecasts of our main model. Two more relative performance indicators (benchmarks) in order to compare our strategy with a buy-and-hold strategy which is the logarithm returns of each respective ETF separately. Moreover, we keep the record for the optimal true volatility and returns as we had inside information by the date of the realizations. The aforesaid variables incorporate the examination of the spread between an ideal rotations trading versus to our baseline strategy.

5. Robustness Methods

5.1. Forecast Accuracy – Forecast Error Analysis

In this section, we conduct several tests to check the robustness of our empirical evidence. For the empirical models based on rotation strategies and volatility timing, we obtain out of sample one step forecast and evaluate forecasting performance. We provide three measures of forecast accuracy. Forecast accuracy names a major significance to discriminate competing economic models and reversal when predictions failure is linked to the inadequate forecasting model. Diebold and Mariano (1996), West (1996) and West and McCracken (1998) argued that loss associated with a respective forecast error consist an asymmetric function and needed to be treated under a particular loss function. Clements (1989), and Fair and Shiller (1990)[46] argued that powerful models in terms of forecast accuracy can not be translated that the model contains higher information compared to other. Swanson and White (1995) argued about the importance of forecast evaluation criteria especially in the comparison of the forecasting models where there are two known criteria forecast accuracy and forecast encompassing. Granger and Newbold (1986) argued that forecast accuracy names the static test to compare forecasts, however in the specific case that the preferred forecasts are missing is known as the condition of checking forecast encompassing (Clements and Hendry 1993).

Pesaran and Timmermann (2004) argued that decision making process requires an examination to a "counter factual exercise" which is a comparative examination of the losses. It is well defined in the literature that even on good forecasts actual and fitted values may vary significantly. Forecast accuracy examination could lead us to improve our forecast methodology. To evaluation our forecasting models we applied the following three different loss functions.

Mean Error $$ME = \frac{1}{T}\sum_{t=1}^{T} e_{t+h,t}$$

[46] In literature is known as forecasting combination and encompassing

Mean error is the most naive among the three accuracy metrics, although it is used widely in the literature as it known simple models accomplish the parsimony principle.

Mean Squared Error $$MSE = \frac{1}{T}\sum_{t=1}^{T} e_{t+h,t}^{2}$$

Mean squared error is more accurate than mean error because incorporates not only the mean but the variance of the errors as well.

Mean Absolute Error $$MAE = \frac{1}{T}\sum_{t=1}^{T} \left| e_{t+h,t} \right|$$

Mean absolute error is the less widely used also a benefit versus to MSE is that we do not need to take square roots in order to define units.

Table 4 reveals summary statistics of goodness of fit when compared the three aforementioned errors measurements (ME, MSE, MAE). We compared only three out of five specializations while the motivation behind is to isolate time varying returns (NAÏVE model), volatility effect (ARIMA model) and lastly my specification. The estimations correspond to Monday. The comparative analysis reveals that MSE fits the best across the estimated pairs. Mean error disclosures a negative bias to the majority of the trading implementation. Decomposition of mean error exhibits the best performance when the trading implementation incorporates S&P500 and Financial Sector. MAE is ranked as the last accuracy measurement among the three models.

Table 5 and 6, illustrates forecast evaluation for Wednesday and the last day of the week respectively. Empirical evidence is identical to the first day of week. Among the models rotation strategy implies the best out of sample performance for mean error and mean square prediction error. Among the pairs S&P500 and Nasdaq 100 implies the best model encompass in sense of forecast accuracy.

Evidence arise from the literature, Meade (2002) implied a linear AR-GARCH model accompanied by four non-linear methods to evaluate FX rates under the spectrum of comparative accuracy on short term forecasts (daily and intraday dataset four-hourly, two-hourly, half-hourly and hourly). His results support the evidence that FX rates is superior captured by a simple linear method than a non-linear model. Root mean square error Peseran and Timmerman statistic indicate that higher frequency data concludes to superior forecasts and significant forecast directional accuracy exist for intraday data.

Taylor (1999) evaluated volatility forecasts by measuring the bias and the variance incorporated exchange rate data. His examination implied a different point of view and argued that confidence intervals improve forecasts but fails to improve variability. He argued that testing for bias the most acceptable procedure is conditional mean forecast. He took under consideration the evaluation of interval forecasts and presents a regression-based procedure which uses quintile segmentation to assess quintile estimator bias and variance. Empirical analysis shows that the new evaluation procedure provides useful insight into the quality of quintile estimators.

Brooks (1997) compared forecasts that produced by three models naive, linear and non-linear univariate time-series models using daily sterling exchange rate returns. The accuracy criteria of the forecasts are mean squared error and sign prediction. All methods proved slight forecast improvements to those that a random walk produces.

On the conclusion of economic significance of forecast evaluation, Pesaran and Timmerman (1995) proved that even the best models have no evidence of market timing ability.

6. Empirical Results

6.1. Baseline Results

In this section, we demonstrate the discrete role of volatility and market timing under the spectrum of baseline empirical evidence. I evaluate volatility timing in the similar concept as Fleming Kirby and Ostdiek (2001) and I compare volatility timing versus the performance of my main rotation strategy which represents the combined dynamics of volatility timing and market timing. Volatility dynamics outcome is measured with the two specifications that we represent extensively on section 4.5.3 and 4.5.4. The relative comparison between my dynamic strategy and volatility dynamics tries to decompose any patterns that may exist in the profitability of the strategy and arise exclusively by the embedded information that volatility transfers. The second contribution names the separate investigation of market timing dynamics. Market timing evaluation is implemented with the naïve specification as defined at section 4.5.1. Market timing relative judgment conducted by comparing the aforementioned specification to two buy-and-hold strategies which corresponds to the two underlying assets of each pair. Finally, we created an equally weighted portfolio (50%) by the two assets of each pair. The formation names the treatment of the equally weighted portfolio as a benchmark for the relative comparison versus to rotation generated profits. To an extended concept an equally weighted portfolio, formed by the forecasts of the two constituents rotating at each trading sign, can be considered as a dynamic portfolio following the traditional rules of the market and allows checking for the dynamic aspects that time varying returns embedded.

The formation period estimated over 104 weeks. So, the first formation period for SPY-OIL started on July 2001, for the second pair SPY-FINANCIALS started on December 1998 and finally for the third pair SPY-NASDAQ started on March 1999. Pesaran and Timmerman (1995) disengage forecasting performance and the length of the "learning period" as they name it. To remind that construction of our base strategy prerequisite the estimation of realized volatility, of past returns and the interactions of cross terms between risk-return combinations. The results have been conducted by the 3 different days of the week (Monday, Wednesday and Friday) in order to check for different patterns during the week.[47]

Table 1, reveals summary statistics of implemented specifications by the side of volatility (ARIMA model, and two alternative volatility measurement models, differences of volatility and ratio of volatilities) and by the side of market timing, naïve model and the equally weighted portfolio and the relative comparison of the two buy-and-hold strategy based on the two underlying ETFs. Finally, to measure the value and the degree of volatility and market timing, we encompass the comparison of the performance of the dynamic rotation strategies on a time-varying framework.

[47] Results for the three different days of the week are represented on a separate section

Results correspond to Monday. Panel A, provides empirical evidence between S&P500 and Oil Sector. Differences of volatility, volatility ratio and the naïve model achieve the highest mean return. On the contrary the interaction of volatility and market timing which in our empirical evidence represented by the rotation strategy fails to outperform the aforementioned models. Nevertheless, we achieved to outperform ARIMA specification. In means of terminal wealth (figure 4), rotation strategy achieved terminal profitability equivalent of $1.99 which was lower 151basis points that an investor paid by the best performing strategy (volatility ratio and differences of volatility). On the relative comparison of rotation trading versus to equally weighted portfolio, the former generates 23basis points higher profits. In the computation of terminal wealth, we assume that investors start off with $1 for each pairwise trading and trade every week according to the sign direction. Traditionally, construction of Sharpe ratio implemented by excess returns less than the risk free rate. However, we consider zero free rate and the ratio release a pure division between excess return and the underlying risk. Sullivan et al (1999) demonstrate that the effect of considering a risk-free rate can only undercover a time varying drift adjustment, and is unable to uncover any substantial significance in the evaluation of the portfolio success. By decomposition and comparison of risk-return profile, we study that rotation trading failed to improve risk-return profile compared to the basic alternative specifications as reflecting by Sharpe ratio indicator. Further examination confirms that single asset strategy outperforms ARIMA model, S&P500 and the equally weighted portfolio. Johannes et al (2002) argued strongly that volatility timing outperforms market timing strategies, in terms of Sharpe ratios, in the cases that models exhibits lack of predictability power.

Analyzing panel B -S&P500 and Financial sector-, the results are reverting regarding our rotation model in means of profitability. Rotation trading outperforms all the alternative specification in all risk metrics. Weekly mean return of standard strategy equals to 0.4%, while the proportional majority of the profits generated by Financial sector ETF. On that concept, trading strategy generates the highest Sharpe ratio 11.5% which superiors the second best strategy (volatility ratio) by 12%. The two specifications on volatility timing of the underlying assets followed rotation trading in means return. In means of relative performance versus to equally weighted portfolio, trading strategy achieved substantially to outperform with double mean return and substantial diversification benefit as the risk limited only to 19% higher. According to the empirical evidence, apparently pairwise strategy is driven by the second constituent based on the financial sector. On that concept, a buy-and-hold strategy based on S&P500 performed poorly for the respective period.

Figure 5 plots rotation trading in means of terminal wealth can be translated at $2.23, 5basis points higher than the second best strategy (volatility Ratio). The crucial aspect emerges by the side of risk management while rotation trading exhibits the minimum drawn down among the dynamic models for the entire trading period.

On panel C, the trading is switching between S&P500 and Nasdaq 100. Empirical evidence reveals the substantial outperforming of rotation strategy among the alternatives trading specifications. The implementation of the base formulation including past returns and innovations on volatility significantly improved risk-return profile as reflecting from the higher Sharpe ratio indicator compared both to volatility models and buy-and-hold strategies. Terminal cumulative wealth end at $1.28 outperforming for 250basis points the naïve model which correspond to the second best strategy. The trading activity reveals dependence between rotation and S&P500.

However, rotation between S&P500 - Nasdaq 100 performed the least in relative comparison to the other two pairs. A potential explanation for the small proposition of profits compared to alternative pairs can be that these indices belong among the most wide-known and heavily traded, so innovations are rapidly assimilate by the investors and directly diminishes the majority of excess returns.

Rotation trading implementation based on Monday innovations achieved the higher excess return on the first pair between S&P500 and Nasdaq 100. Although, in absolute terms the terminal wealth was significant lower among the days. The results are reverting in means or risk-return profile since the best strategy is implemented by the pair between S&P500 and Financials (Sharpe ratio 11.5%).

To sum up the vertical empirical evidence of trading implementation based on Monday observations and to testify the economic significance of market and volatility dynamics, rotation trading exhibits superior performance of rotation trading on the last two pairs, between S&P500 and Financial Sector and Nasdaq 100 respectively. Contradictory evidence arises on the first pair between S&P500 and Oil sector where level and spread of volatility between the two assets is substantial higher and wider (figure 1). Volatility varying specifications appears to confirm the hypothesis of volatility dependence in respect to a higher proportion of levels of volatility. On the same concept, incorporation both of historical returns and volatility in a high volatile environment keep our trading model as a laggard.

Table 2, reveals the calculation based on information gathered every Wednesday. Panel A, exhibits the switching trading between S&P500 and Oil Sector. Out of sample forecasts of rotation trading reveal a laggard behaviour comparing with volatility specification. The best performing strategy is ARIMA formulation with 0.6% weekly average mean and 2.8% standard deviation. Figure 1, plots the level of volatility of the two underlying assets and the crucial assumption that emerge names that substantial high level of Oil sector ETF volatility dynamics is captured by volatility specifications. We conclude to the same outcome if we utilize Sharpe ratio which range between 14.4% - 10.2% where the latter corresponds to pairwise strategy. To that concept trading implementation between S&P500 and Oil Sector, reveals significant economic profits which generated apparently by volatility timing. The combined calculations between volatility and historical returns which correspond to our basic modification fail to capture the dynamics.

Panel B, rotation trading narrow the distance against the leading strategies to 162bps and come up to $1.71 for the trading horizon of 9 and half years. Against, the equally weighted portfolio we outperform in terminal wealth for 281 basis points. We concentrated our analysis on equally weighted portfolio, because examining separately each ETFs there is a wide spread in means of terminal wealth between S&P500 ($1.06) and Financial Sector ($1.83). Consequently, rotation strategy is leading by the historical information of Financials Sector since it appears to represent 93% of the terminal wealth. In terms of volatility, as we expected the latter ETF is more risky and the disguisable element names that volatility timing models are conditional on Financial Sector ETF's volatility. However, volatility domination of the latter ETF is moderate than it is in the first pair and reflecting lower summary statistics for the entire specifications.

Panel C, represents the summary statistics of the empirical estimations between S&P500 and Nasdaq 100. All the specifications performed dramatically weakly, where the best strategy was performed by a buy-and-hold strategy on S&P500. Market timing strategies also terminate to low levels with the best among our competitive models (naïve model) to conclude up to $1.10. In means of volatility

S&P500 represent the lowest weekly sample volatility equals to 2.2%. Empirical evidence testifies that volatility timing models has been driven by volatility of Nasdaq 100 and respectively, the final wealth has been affected by this relationship. Figure 3, arises the crucial assumption where volatility for both assets exhibits identical behaviour and after the first half of the trading horizon remains in low levels, without any significant dominations between the constituents.

Overall, estimations on Wednesday arises the importance of differences of volatility on the generator of robust signs. The equally weighted portfolio as a dynamic portfolio itself must be admitted that measure the potential performance of the two ETFs, where is conducting on Wednesday. In addition, on the estimations between S&P500 and Nasdaq 100, the joint low level of volatility affected negatively the rolling forecast estimates and a buy-and-hold strategy based on S&P500 performed the highest wealth against the alternative modifications for the trading horizon between 1999-2008. On market timing strategies ample literature confirms that a buy and hold strategy can't be beaten by market timer in means of risk and return. Lam and Li (2004), on a relative comparison between market timing and buy-and-hold-strategies, proved that longer review horizons requires highly prediction accuracy in order to be at par with a buy-and-hold-strategy and confirmed the hypothesis that only a more frequent rebalancing could be a merely solution to propositional correct prediction. On their research Brooks, Katsaris and Persand (2006) provided evidence that over long horizon timing rules is hard to outperform the increasing drift of the market.

Table 3, represents the final estimations of our models based on past observations of the three implemented pairs on Friday. Panel A, examine the decomposition between S&P500 and Oil sector. The most dramatic element names that volatility timing strategies achieved to exceed initial wealth further than 200%. ARIMA model yields an average return 0.5% on a weekly basis and standard deviation 2.8% which conclude to a Sharpe ratio of 12.5%. The second best strategy belongs to volatility ratio, with an average return 0.5%, and sample volatility 3.7% and respectively a Sharpe ratio of 12.5%. Those results represent a spread at the final total wealth of 212bps. The optimal specification terminates (ARIMA model) to $2.4. The estimations disclosure the perfect dependence between volatility ratio and Oil ETF in all statistics. Equally weighted portfolios evaluate the success of pairwise trading and consists a naïve indicator of the leading asset in the implementation of our methodology. Under this assumption, rotation trading reveals to be motivated by both S&P500 and Oil's dynamics, even there is a bias created by Oil sector. Results clearly defines that volatility conditional dynamics dominates the trading behaviour of the specifications and the higher volatility level of Oil did not capture substantially by rotation function.

Panel B, the results between S&P500 and Financial Sector are varying between the dominance of volatility and market timing. In volatility timing the best specification considered to be constructed by the differences of volatility with terminal wealth of $2.05. Our rotation strategy achieved identical excess return as ARIMA model and the equally weighted portfolio. Those indicators reveal the absence of a dominant factor in the driving of our specification as is affected from both excess return and volatility dynamics. Taken under consideration together, the highest mean and lowest standard deviation of the returns on differences and ratio of volatility concludes to the highest Sharpe ratio among all strategies.

Concentrate our representation on the results on the bottom panel (C), rotation strategies generates the highest terminal wealth ($1.34) with a sample weekly mean

0.1% and standard deviation 2.6%. The first two moments produces a weekly Sharpe ratio of 3.8%. The second best strategy is the outcome of a static strategy of Nasdaq 100 ETF and concludes to terminal wealth of $1.23. Buy-and-hold strategy in addition, with the two volatility conditional strategies (volatility difference and volatility ratio) reveals the highest risk 3.8%. On the contrary, naïve specification between S&P500 and Nasdaq 100 ETF exhibits a terminal wealth of $1.09. For the universe of the strategies, Sharpe ratio ranges between 3.8% and 1.1% which the latter belongs to the naïve model.

Table 3, summarize the empirical evidence of trading strategies taking under consideration the last day of the week (Friday). On the first two panels, clearly the empirical evidence reveals that conditional volatility dynamics dominates market timing and rotation strategy nevertheless the third implemented pair, historical returns exhibits forecastability, which high proposition is captured by our trading model.

Before we proceed to the summary of the baseline results, we compare the directional market timing strategy performance against the market. Rotation portfolios in terms of weekly standard deviation exhibit substantially lower than standard deviation of market returns based on S&P500. The mean return of rotation portfolios selected on the basis of predictions is particularly low. The single-asset rotation portfolio in means of Sharpe ratio produces the highest statistic versus S&P500.

In the bottom line, our results confirms Pesaran and Timmerman (1995) results that predictive power of various economic factors over equities returns is time-varying and depends on market volatility. The outperforming of volatility timing compared both to our rotation portfolios and buy-and-hold strategies confirm the hypothesis that volatility timing has substantial economic value which was confirmed by Flemming, Kirby and Ostdiek (2003). On the extension of relatives comparisons between volatility timing and a buy and hold strategy Pesaran and Timmerman (1995) argued that switching portfolios strongly outperformed buy-and-hold strategy.

6.2. Excess Return Evaluation against Day-of-the-Week-Effect

A number of studies have documented the significance of the day of the week to the terminal profits. We tested the performance of our strategies into different days of the week. We compare the returns for 3 different days of the week (Monday – Wednesday- Friday). The reason we examined the aforementioned specific days names the motivation to stress test our profitability what it is known in the literature as weekend effect (Monday-Friday) and lastly, Wednesday is chosen according to Conrad and Kaul (1988) that argued about the existence of a pattern on trades in the middle of the week (Wednesday). Especially for Monday, I examined what French (1980) names "closed-market effect"[48], however argued that the causality of negative returns on Monday is weekend effect and not closed-market hypothesis. Also, Gibbons and Hess (1979) argued about the existence of negative returns on Monday. Rogalski (1984) confirmed the hypothesis of negative returns on Monday, although only for January the returns are positive.

According to the predictive ability based only on Wednesday, Conrad and Kaul (1988) argued about a pattern on trades, for the same size portfolios, which are positive correlated from Wednesday-to-Wednesday.

French (1980) on the distributions of the returns argued that returns on Monday is the most left skewed with the lower mean against any day of the week. On the other side, returns on Wednesday exhibit the highest right skewness among different days

[48] Closed market hypothesis according to French (1980) is the returns for days following holidays.

of the week and Friday reveals slightly skewed on the right. Among the days of the week Tuesday is the most symmetrical contributed day.

An alternative perspective on day-of-the-week effect, Chordia et al (2001) argued about the substantial decrease in trading activity and liquidity on Friday while the contrary effect takes place on Tuesdays.

According to the initial pair wise selection between S&P500 - Oil sector in means if terminal wealth rotation portfolios reveals the higher terminal wealth on Monday and followed by Friday and Wednesday. The evidence contradicts the literature. However, according to the alternative specifications the results confirm the literature and Wednesday is the most profitable day and followed by Friday and Monday.

Empirical estimations between S&P500 and Financial sector, attributes identical results and switching trading on Monday reveals the highest profits and nevertheless as the week passes excess wealth diminishes. According to the alternative models, Monday continues to generate the highest terminal wealth, although the results for the other two remaining days are shared. A market timing model (Naïve) and volatility model ARIMA presented highest final wealth on Wednesday, however the employment of differences of volatility and volatility ratio achieved the highest profits on Friday.

The execution of switching between S&P500 and Nasdaq 100 ETF extrapolates that rotation strategy performed strongly on Monday and lastly Wednesday. On the remaining specifications, Friday illustrates the highest profits, followed by Wednesday and Monday.

A possible explanation for contradictory results names that trading strategies conceptually performs more rational with the existence of the substantial level of volatility which can be translated as the days that arbitrageurs and investors are more likely to remain off the market due to the soaring uncertainty. Clearly, Monday confirms the hypothesis of information gathering during the weekend and the source appear to be positive asymmetric to conditional volatility rather than to historical returns.

On the relative comparison between the days of the week, our results does not confirm clearly the literature and especially French (1980) where returns tend to increase on Wednesday, decrease on Friday and reveal negative pattern on Monday. The aforementioned argument is opposite to our empirical estimations taking under examination the dynamic single asset rotation strategy.

In conclusion, the impact of our estimations, without conduct calculations for the transaction costs can be summed up as volatility and market timing dynamics can achieve substantial profits and can beat a buy-and-hold strategy. Although, our specifications reveal a high volatility behaviour comparing to a buy-and-hold strategy. This assumption can be established by observing Sharpe ratios across our estimations.

6.3. Empirical Evaluation of Forecast encompassing under the criterion of Correct Sign Predictions

In this section, I want to answer to the question: Is model weakness or data set constrains the leading factors of trading strategies? In the comprehension of the predictability of strategy I consider a non-parametric test of the proportion of the optimal predicted signs of excess return. The potential importance of analyse separately the direction (sign) is with no doubt vital to comprehend the intuition of our model and improve the methodology. On their research Henriksson and Merton (1981) argued that there is no information in the predictions of excess returns over the sign of subsequent realisations. Leitch and Tanner (1991) argued that ranking of forecasts based on sign tests is closely related to their ranking of predictions according to sign tests in simple trading strategies. Pesaran and Timmerman (2005) argued about the importance of the estimation of corrected sign predictions in a trading methodology. However, they proved that a correct sign prediction test exhibits limited power and a bootstrap methodology as applied by Sullivan, Timmermann and White (2001) could be a resolution to the weakness. We used bootstrap methodology to strengthen the power of our results. Bootstrap is a simple resampling technique that checks for robustness of the estimating parameters. The resampling data set simulated under 400 iterations and going 20 lags maximum backwards.

Table 16, represents the percentage of the correct excess return predictions under the different model selection strategies are significant upward from 50%. The results correspond to Monday. Evidence of switching trading between S&P500- Oil Sector arise sample mean ranges from 49% to 56%. The highest sample mean is revealed by the naïve model 56% and followed by rotation strategy with sample mean 55%. The sample standard errors in the majority of the specifications even on the extreme case of two standard deviations exceed 50%.

Panel B, exhibits trading rotation between S&P500 and Financials ETFs the volatility ratio incorporates the most accurate sign prediction with 57%. The dynamic switching rotation strategy exhibits a correct sign prediction slightly above the average of with 51%. Above the average correct predictions represented by the naïve model and difference of volatilities. ARIMA is the laggard with 50% correct sign predictions.

Panel C, reveals the interaction between S&P500 and Nasdaq 100, our dynamic switching rotation strategy according with the naïve model presents the best correct sign predictions with 0.51. The results indicate that dynamics of our model for the respective trading strategy is driven only by the lagged volatility, with excess return and cross terms to be insignificant. ARIMA model performed the lowest correct sign predictions with 0.46. Correct sign predictions based on Monday observations exhibits by the naïve model, rotation strategy and volatility ratio. ARIMA model is the laggard for the three pairs. The standard errors between models across the same pairs are equal.

Table 17, represents the correct sign prediction according to Wednesday. On the decomposition of the pair between S&P500 and the Oil sector the correct sing predictions ranges significant above the average where ARIMA model performs the best prediction forecasts with 55%. On the contrary, the formation of the strategies between S&P500 and Financials (panel B), the results are reverting and ARIMA presents the lowest robustness on sign prediction with 48%. Naïve model quantitative outcome is equal to 58%, difference of volatility (57%) and volatility ratio (55%) and corresponds to the leader strategies in means of correct sign predictions. On the implementation of the strategies between S&P500 and Nasdaq 100 (panel C) arises a tendency of correct predictions to remain below the average across the models, nevertheless the only distinction arises from the naïve model which quantitatively exhibits a sample mean of 51%.

Table 18, represents the proportion of correct sign prediction of the excess based on estimations for the last business day of the week. Incorporating S&P500 and Oil sector results exhibit a heterogenic landscape. Volatility ratio achieves a correct prediction of 58% the same as difference of volatilities. On the contrary, ARIMA model fail to retrieve the dynamics and predict accuracy in means of sign presents the lowest level with 48%. The estimations based on rotation trading between S&P500 and Financial sector are characterising by three high sign methodologies, the naïve model, difference of volatility and volatility ratio with correct sign predictions 59%, 58% and 59% respectively. ARIMA fails to surpass the average. On the trading between S&P500 and Nasdaq 100 the results remains below the average across the models and the higher outcome is confirmed by rotation strategy exhibits the superior correct prediction which correspond to a sample mean 50%.

Our results are generally aligned with Pesaran and Timmermann (1995) where for the horizon of 1960 with 1992 their predictions achieve a proportion of the sign of the correct excess returns at least 58%. On a different perspective, Lam and Li (2004) argued that a correct prediction probability should around 60%, so as taking under consideration transaction costs c=0.001, the strategies to reveal economic significance. The comparison between the three different days emerge the following assumptions: ARIMA models in the majority of the pairs presents low accuracy in means of sign prediction. Volatility driven models obtain higher performance than rotation strategy or versus a combined model of market and volatility timing. Inside the three pairs, implementation of S&P500 and Nasdaq 100 reveals the lowest accurate sign predictions both for volatility and market timing models. Taking under consideration that two underlying ETFs exhibit the lowest potential wealth, we can conclude that low incremental of potential opportunities increases the possibilities for correct sign prediction. The aforementioned assumption is supported by the other two pairs where the volatile Oil sector and Financials ETFs creates more accurate sign predictions. Substantially higher proportion of correct signs achieved by all the rolling forecasts over the trading set of S&P500 and Financial sector based on the last day of the week.

Regarding the proportion level of volatility, we analyze further in the next section. However, Pesaran and Timmermann (1995) confirmed that among their subsamples the highest proportion of correct signs predictions achieve in the subsample in the period of 1970s where the US market was volatile comparing with the alternative subperiods 1960, 1980 and 1988. Apparently, they argued that proportion of correctly predicted signs contains valuable information.

6.4. Volatility as a Profit Generator: A sensitivity analysis

In this section, we are trying to measure the impact of different levels of volatility in predictive robust signs and if any positive affect on the performance of trading strategies. Many hedge fund managers argues that in high volatile environment statistical based funds performs better than in opposite market conditions. In this section, we are trying to investigate this behaviour and to answer to the following question. Does different levels of volatility generates correct sign predictions? Does high volatility creates robust sign predictions? The economic interpretation of our concern emerges by Pesaran and Timmerman (1995) research where argued that high volatility periods in the markets concludes to superior predictability of excess returns. A merely interpretation to this behaviour names the relations between predictability of excess returns and time-varying risk premium. They justify thus behaviour under the hypothesis that on downturn markets (highly volatile markets) investors are satisfied with lower returns than in periods of bear markets.[49] Diebold et al (1988) argued that forecasting estimates varies depending on the current level of volatility. Copeland and Copeland (1999) incorporated different levels of volatility using the most widespread index "VIX" and strongly proved that in high volatility environments investors are conservative (invest in large caps and value stocks) and revert their behaviour in uptrend environments (invest in small cap and growth equities).

Pesaran and Timmerman (1995) argued about the difficulty to illustrate the evidence that switching strategies outperform the market in high volatile periods. On that concept, the economic interpretation when capital markets are dominated by volatility clustering, names the diminishing of the proportion of the returns and the reverse behaviour on an upmarket environment. They testify the strengthen of their evidence in the case of a risk averse investor. In addition, they denoted that "*price of risk is time-varying so that there is no constant, proportional relationship between the first and second conditional moments of stock returns*".

We classified the evidence into three hypotheses in order to decompose one by one the effect of volatility into correct sign prediction. On that concept, we investigate if volatility bounce helps to improve forecasting performance. We conducted Pearson's[50] Chi-squared test for the estimation of the results. Pearson test has distinctive merit versus to alternative chi-square distributions since conducts a distinction between the test statistic and the underlying distribution. Tables 19, 20, 21 represent the results for the three days of the week as we have refer separately up to now. Table 19, arises some interesting results on the pairwise trading between

[49] Their conclusion based on two separate periods 1962, 1974 where the increased market volatility conclude to increased forecastability in means of goodness of the forecasts

[50] Pearson's Chi-square ($\chi 2$) test is the best-known of several chi-square tests, statistical procedures whose results are evaluated by reference to the chi-square distribution. The test considers a null hypothesis that the frequency distribution of certain events observed in a sample is consistent under the functional distribution. The events must be mutually exclusive.

S&P500 and Financial Sector. Panel B, disclosures the significance relation of S&P500 volatility and correct sign predictions for the naïve model. The results are identical on Panel C, where both the trading on S&P500 and Financial Sector are motivated by the correct sign predictions.

Table 20, exhibits the empirical evidence based on trading implemented on Wednesday. In Panel B, naïve model tends to be driven by level of volatility when rotation trading implemented between S&P500 and Nasdaq 100. The conditional relation is confirmed when we rotate between S&P500 and Financial Sector but constrain on S&P500 predictions. On Panel C, the results are reverted and the switching trading between S&P500 and Oil seems to be dependent solely on S&P500.

Table 21 considers the relation between volatility and correct predictions based on Friday. Panel B reveals that trading based on naïve model is conditional to the level of volatility. On panel C, main model evidence fall down to reveal any conditionality between volatility and predictions. Our empirical examination fails to illustrates a clear dependence between returns are different levels of volatility.

6.5. Decomposition of Trading Activity: The Time and Price Effect

The theoretical motivation for the empirical investigation names the scope to capture the direction of price dynamics and can be summed up to the following questions. If the prices moved on the last trade which is the probability to trade again? Is there any systematic pattern that moves the prices? Which is the size of directions of changes? However, the most important motivation arise from Dufour and Engle (1999) publication that argued that trades include and convey information. In addition, they strongly supported that for the existence of a substantial positive correlation between time duration and increase in the number of transactions, nevertheless, the price impact of the trades and the price of reversion is primary based on information.

A number of studies have argued about the causality on the density of trading activity. Campbell, Lo, and MacKinlay (1997), Hasbrouck (1999) argued that price reversals are generated by bid-ask bounce, while on second level analysis this behaviour is generated by market makers activity- buying higher and sell at lower prices-. On the contrary, Rudberg and Shephard (2002) stated that price change is uncorrelated with market makers consecutive activity and price changes are driven by large volumes, nevertheless incremental changes are short lived. Diamond and Verrecchia (1987) confirmed the hypothesis that traders will act any moments of the trading day, when there is an event or news, on both directions (either positive or negative news). On the same context, long duration trades are consequently impact of no news. Easley and O' Hara (1992) strict the above results that informed traders react only when there are news.

In Tables 7-14, we report the estimated activity, duration and direction process utilizing as the critical information criterion, the number of transactions during the three different days of the week. We conduct the decomposition of the trading distribution to the following specifications: Naïve model, ARIMA model, Rotation methodology and finally the two volatilities specifications – differences of volatilities and ratio of volatilities -. The decomposition contains the recording of each transaction, when it is opened a trade, the total number of transactions, the mean trading time, and transition probabilities from trade to no trade and the reversal movement. Besides in every state we recorded the minimum and maximum duration.

Table 7, represents one-by-one the trading models with respect on Monday based on pair trading, S&P500 and Oil sector. The quantitative effect of number of trades varies across the models. More precisely, naïve model traded 207 times, rotation strategy 162, while differences of volatility and volatility ratio can be considered as a buy and hold strategy since they react only once. The decomposition on transition probabilities on the standard rotation trading reveals an intensive activity during the trading horizon. Trade to trade state exhibits transition probability 0.76. The second state refers to no trade to trade with probability equals to 0.56. Naïve model tends to keep stable on states and it is confirmed by the transition probabilities where no trade to no trade and trade to trade represent a probability of 0.84 and 0.98 respectively. The results tend to be significant as test of independence confirms apart the unique exception of ARIMA model where p-value equals to 0.28.

Table 8, represents the trading activity between S&P500 and Financial Sector. According to the estimations ARIMA model and rotation strategy conducted the most transactions, on the contrary, Naïve model and volatility ratio transacted the least. Transition probabilities confirm our hypothesis. Although, transition probabilities referring to naïve model, differences of volatility and volatility ratio shows that during the implementation there was a monotonic transition between trading and no trading. Precisely, naïve model trade to no trade probability is almost 1, and trade to trade is 0.92. The results are identical for the two remaining models.

Table 9, represents the trading activity between S&P500 and Nasdaq 100. Volatility driven models (Difference and ratio) activated the smallest amount of trades, 5 and 2 respectively. According to transition probabilities, Naïve model and two volatilities models (difference and ratio) reveals a lucid and stable trend when abstain from the trade sign is followed by retain the stay out of the trade. Identical state remains for the naïve model and differences of volatility when they consecutive trading activity appears to be the most appealing outcome.

Table 10, represents the trading activity between S&P500 and Oil Sector based on Wednesday. From the perspective of number of transactions conditional volatility models (differences and volatility) reacts only for a single trade. On the contrary, naïve model exhibits 233 transactions. No trade to trade stands for 0.83 and trade to trade 0.98. These findings provide the evidence that the sign of the last active trade has a sustained effect in trading time. The sign of the last active trade has a sustained effect on the probability of the next sign movement, so if the last price movement were up then there is a slightly higher probability of a sign reversal than a non-reversal sign.

Table 11, represents the trading activity between S&P500 and Financial Sector for Wednesday. The models seem to reveal a straightforward behaviour to remain in no trade region when they are out of a trade. Although, the behaviour changes when they are on trade since the probabilities show that a transition to enter a trade or to stay aside is almost the same, with a bias to no trade. Naïve model although transact the most, considered a maximum no trade horizon of 98 weeks, which means that there was a period with weak forecast innovations.

Table 12, represents the trading activity between S&P500 and Nasdaq 100 for Wednesday. Conditional volatility transacts the least. The alternative specification models are intensive to trade when they are already in trade and they are intensive to stay aside if the previous sign generator reveals no trade.

Table 13, represents the trading activity between S&P500 and Oil Sector for Friday. Our strategy rotates 158 times. However, our model fails to capture a clear trend as it can be withdrawn form the transition probabilities, since the probabilities exhibit the same intensity between the 4 states. A distinguish pattern reveals that naïve model exhibits a maximum duration trade of 181 weeks, which undoubtedly take place into a concrete period of trading horizon.

Table 14, represents the trading activity between S&P500 and Financial Sector for Friday. ARIMA exhibits the higher activity (148) among the specializations. A clear trend between the two states of no trade to trade and trade to trade is distinguished by the rotation strategy.

Table 15, represents the trading activity between S&P500 and Nasdaq 100 for Friday. Naïve model even though changes the trade between the two assets many times (130) transactions, followed a specific pattern to stay off the trade when the previous sign was no trade and to keep trading when the last sign reveals trade.

In this section, we emphasized on the decomposition of the sequential of trading activity based both on single asset rotation strategies and the alternative model specifications. The decomposition of the trading activity reveals some dramatic evidence. Rotation trading between S&P500 and Oil sector and between S&P500 and Nasdaq 100, two different conceptually models, naïve and ARIMA exhibit the most intensive trading activity which reveals that historical returns and variation conveys adequate information. The estimated activity under the predictions based on S&P500 and Financial Sector, reveals that trading strategies based on naïve model transacts at a reduced amount than volatility models and reveals the significance of volatility into trading intensity. The variable that related to the current directions of our activity models appears to be the variance.

Regarding the trading activity during different days of the week, final results confirmed French (1980) conclusion that distribution of trading activity is not affected by specific days of the week.

The decomposition of the sequentially price movements of trade-by-trade action indicate that estimated activity and direction process using contemporaneous durations. For the trading models current durations exhibits a significant positive shock on activity which emerges by the feedback of the analysis of trading time. Probably the most triggering result arise with conditional volatility models generate the least transactions with a clear pattern between switch from long to neutral and the reversal. Conditional volatility model exhibits the least trades and as Easley and O' Hara (1992) argued that long duration trades are linked with the eclipse of news. On a different perspective, Lam and Li (2004) argued that optimal market timing strategy outcome, without transaction costs, appear to be sensitive to the reconsideration of frequency.

7. Economic Significance of Volatility and Market Timing and the Concluding remarks

This chapter denoted the evidence of the literature on the predictability behaviour of expected returns in a time varying framework. The main contribution names the forecast approach applied relative to the existing models in the treatment of the expected returns and variations and the relative interaction in a time-varying framework. We considered a number of ex ante predictors which applied for the first time in order to appraise the economic significance of variability and expected returns. The overreactions between expected returns and variations are applied on the concept of dynamic trading strategies. Market timing trading rules are under investigation in the theoretical framework and by the insiders or financial markets.

This extensive interest has one main causality argument. They are financial series that contains information and abnormal returns which the optimal trading model can be generated substantial profits and we exploited the potential of creating a new methodology of trading based on time varying volatility modelling. The methodological mechanism applied in the context of a novel investment tool in financial markets, Exchange Trades Funds and explored the degree of their predictability behaviour into separate horizons for each rotation strategy starting at 1993 and terminates at April of 2008.

Empirical evidence proved the existence of variations across the performances of single asset rotating portfolios and confirmed the significance of the proportion of volatility to the realized correct sign predictions. In this context, it is noteworthy to refer that in periods that financial markets dominated by high volatility are dominated by higher than normal predictability of excess returns. The above conclusion can easily extrapolated by the significance of sign prediction accuracy. The implementation of prediction accuracy and tests of forecasting encompassing into the different econometric specification allow investigating behind for the adequacy of the specifications.

The results documented appear to be sensitive in the selection of the trading specification which confirms the motivation of this research about the cross interactions between time varying expected returns and variation. Comparing the performance of the rotation portfolios based on forecasts using different model selection criteria, rotation trading is performing the highest final wealth as a result of the interaction between expected returns and variation. Applying our methodology under different days of the week, I merely confirm the literature in means of the performance, with our rotation trading to exhibits the most statically and economic significant excess returns on Monday.

Summary of Chapter 3

In this chapter, I examined the economic and statistical significance of conditional expected returns and volatility on the creation of trading methodology based on rotation strategies. Although, there is a huge literature incorporating forecasting specifications to the creation of trading strategies, however, there is a lack of examining time varying expected returns and the respective variation and conditional their co movements into profitable trading strategies. We employ estimations based of forecasting methodology to create profitable rotation strategies. Rotation trading strategies methodology names the rotation between two risky assets. Estimations robustness conducted to the evaluating of our methodology. The majority of studies have studied stocks behaviour, however, we incorporated ETFs to explore a dynamic trading strategy. While much research has provided attention to the relative merits of equities research which applied ETFs as the basic investment tool to build up trading strategies is extremely limited. The research now its novel and no one has used econometric modelling to built up trading strategies on ETFs.

In this chapter, we present an analysis of rotation strategies that rely on time series patterns. We implement the empirical examination of the two of the driving factors in asset management theory, volatility and market timing. Both examinations are considered under linear forecasting methodology. I found that the important determinant of the profitability of rotation strategies is volatility timing. The dispersion in mean returns exposes weak behaviour versus to dispersion of variance. The selection of the specification appear to be sensitive in the selection of the trading specification which confirms our initial conception of the cross interaction between time varying expected returns and variation. Comparing the performance of the rotation portfolios based on forecasts using different model selection criteria, our rotation trading is performing the highest final wealth, when there is not a clear domination between expected return and variation. Applying our methodology under different days of the week, I merely confirm the literature in means of the performance, with rotation trading to exhibits the most statically and economic significant excess returns on Monday.

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Tables and Figures

Table 1

Performance Measures of the Rotation Strategies Relative to Volatility Timing

The table illustrates evaluation of volatility and market timing under 5 different models. The results correspond to the following separate model: Naive, ARIMA and Rotation strategy for the three pairs that we implement the strategy. The results of the table correspond to Monday. The horizon for the estimations for the first pair S&P500 vs. OIL extends from 7 February 2001 until 4 April 2008. For the second pair S&P500 vs. Financial Sector horizon extends from 22 December 1998 till 4 of April 2008. Lastly, the S&P500 and Nasdaq are estimated since 10 March 1999 till 4 April 2008. The estimation period is 104 weeks and the results correspond to out of sample one step ahead forecasts.

Panel A: S&P500 vs. OIL

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	OIL	Equally Weighted
End wealth	2.069	1.589	2.147	2.147	1.996	1.387	2.147	1.767
Average Return	0.005	0.003	0.005	0.005	0.004	0.002	0.005	0.003
Standard Deviation	0.039	0.028	0.039	0.039	0.035	0.018	0.039	0.025
Sharpe Ratio	0.119	0.090	0.126	0.126	0.122	0.091	0.126	0.133
Minimum Realized Return	-0.108	-0.101	-0.108	-0.108	-0.108	-0.055	-0.108	-0.076

Panel B: S&P500 vs. FINANCIAL SECTOR

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	Financial Sector	Equally Weighted
End wealth	1.888	1.702	2.029	2.175	2.228	1.145	1.899	1.522
Average Return	0.003	0.002	0.003	0.004	0.004	0.000	0.003	0.002
Standard Deviation	0.035	0.031	0.035	0.035	0.032	0.025	0.035	0.027
Sharpe Ratio	0.077	0.069	0.089	0.103	0.115	0.018	0.078	0.059
Minimum Realized Return	-0.147	-0.137	-0.147	-0.147	-0.137	-0.116	-0.147	-0.127

Panel C: S&P500 vs. NASDAQ 100

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	Nasdaq 100	Equally Weighted
End wealth	1.032	0.856	0.912	0.967	1.282	1.045	0.948	0.997
Average Return	0.000	-0.0004	-0.0003	-0.0001	0.0009	0.0001	-0.0002	0.0000
Standard Deviation	0.027	0.032	0.037	0.037	0.030	0.024	0.037	0.030
Sharpe Ratio	0.004	-0.014	-0.007	-0.003	0.029	0.006	-0.004	0.000
Minimum Realized Return	-0.116	-0.116	-0.143	-0.143	-0.116	-0.116	-0.143	-0.108

Table 2

Performance Measures of the Rotation Strategies Relative to Volatility Timing

The table illustrates evaluation of volatility and market timing under 5 different models. The results correspond to each separate model: Naive, ARIMA and Rotation strategy for the three pairs that we implement the strategy. The results of the table correspond to Wednesday. The horizon for the estimations for the first pair S&P500 vs. OIL extends from 7 February 2001 until 4 April 2008. For the second pair S&P500 vs. Financial Sector horizon extends from 22 December 1998 till 4 of April 2008. Lastly, the S&P500 and Nasdaq are estimated since 10 March 1999 till 4 April 2008. The estimation period is 104 weeks and the results correspond to out of sample one step ahead forecasts.

Panel A: S&P500 vs. OIL

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	OIL	Equally Weighted
End wealth	2.323	2.464	2.234	2.234	1.829	1.523	2.234	1.878
Average Return	0.005	0.006	0.005	0.005	0.003	0.002	0.005	0.003
Standard Deviation	0.035	0.028	0.036	0.036	0.031	0.017	0.036	0.023
Sharpe Ratio	0.144	0.197	0.129	0.129	0.102	0.118	0.129	0.145
Minimum Realized Return	-0.117	-0.086	-0.117	-0.117	-0.117	-0.060	-0.117	-0.080

Panel B: S&P500 vs. FINANCIAL SECTOR

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	Financial Sector	Equally Weighted
End wealth	1.871	1.638	1.822	1.611	1.709	1.025	1.831	1.428
Average Return	0.002	0.002	0.002	0.002	0.002	0.000	0.002	0.001
Standard Deviation	0.031	0.027	0.031	0.031	0.029	0.023	0.031	0.024
Sharpe Ratio	0.075	0.062	0.072	0.052	0.066	0.003	0.071	0.048
Minimum Realized Return	-0.112	-0.109	-0.112	-0.112	-0.112	-0.109	-0.112	-0.110

Panel C: S&P500 vs. NASDAQ 100

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	Nasdaq 100	Equally Weighted
End wealth	1.102	0.989	1.031	1.041	0.973	1.150	1.039	1.095
Average Return	0.0003	-0.00003	0.0001	0.0001	-0.0001	0.0004	0.0001	0.0003
Standard Deviation	0.024	0.031	0.037	0.037	0.029	0.022	0.037	0.028
Sharpe Ratio	0.012	-0.001	0.002	0.003	-0.003	0.019	0.003	0.009
Minimum Realized Return	-0.109	-0.165	-0.165	-0.165	-0.165	-0.109	-0.165	-0.137

Table 3

Performance Measures of the Rotation Strategies Relative to Volatility Timing

The table illustrates evaluation of volatility and market timing under 5 different models. The results correspond to each separate model: Naive, ARIMA and Rotation strategy for the three pairs that we implement the strategy. The results of the table correspond to Friday. The horizon for the estimations for the first pair S&P500 vs. OIL extends from 7 February 2001 until 4 April 2008. For the second pair S&P500 vs. Financial Sector horizon extends from 22 December 1998 till 4 of April 2008. Lastly, the S&P500 and Nasdaq are estimated since 10 March 1999 till 4 April 2008. The estimation period is 104 weeks and the results correspond to out of sample one step ahead forecasts.

Panel A: S&P500 vs. OIL

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	OIL	Equally Weighted
End wealth	2.167	2.400	2.153	2.188	1.957	1.496	2.188	1.842
Average Return	0.005	0.005	0.005	0.005	0.004	0.002	0.005	0.003
Standard Deviation	0.036	0.028	0.037	0.037	0.032	0.018	0.037	0.023
Sharpe Ratio	0.128	0.197	0.122	0.125	0.116	0.110	0.125	0.140
Minimum Realized Return	-0.122	-0.106	-0.122	-0.122	-0.122	-0.059	-0.122	-0.083

Panel B: S&P500 vs. FINANCIAL SECTOR

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	Financial Sector	Equally Weighted
End wealth	1.829	1.425	2.049	1.996	1.491	1.015	1.880	1.448
Average Return	0.002	0.001	0.003	0.003	0.001	0.000	0.002	0.001
Standard Deviation	0.031	0.027	0.031	0.031	0.029	0.022	0.031	0.024
Sharpe Ratio	0.073	0.044	0.093	0.088	0.047	0.002	0.077	0.051
Minimum Realized Return	-0.138	-0.111	-0.111	-0.111	-0.111	-0.111	-0.138	-0.124

Panel C: S&P500 vs. NASDAQ 100

	Naïve	ARIMA	Differ. of Volatility	Volatility Ratio	Rot. Strategy	S&P500	Nasdaq 100	Equally Weighted
End wealth	1.092	1.206	1.166	1.193	1.340	1.189	1.234	1.211
Average Return	0.0003	0.0006	0.0005	0.0005	0.0010	0.0005	0.0007	0.0006
Standard Deviation	0.024	0.033	0.038	0.038	0.026	0.022	0.038	0.029
Sharpe Ratio	0.011	0.018	0.012	0.014	0.038	0.024	0.017	0.021
Minimum Realized Return	-0.111	-0.179	-0.179	-0.179	-0.111	-0.111	-0.179	-0.145

Table 4

Statistics for Forecasts Errors Evaluation of Volatility Timing

The table illustrates evaluation of forecast accuracy under three different measurements (ME, MSE and MAE). The results correspond to each separate model: Naive, ARIMA, Rotation strategy and for the three pairs S&P500 - OIL, S&P500-FINANCIALS, S&P500-NASDAQ that we implement the strategy. The results of the table correspond to Monday. The horizon for the estimations for the first pair SP500 vs. OIL extends from 7 February 2001 until 4 April 2008. For the second pair S&P500 vs. Financial Sector horizon extends from 22 December 1998 till 4 of April 2008. Lastly, the S&P500 and Nasdaq are estimated since 10 March 1999 till 4 April 2008.

	Naïve	ARIMA	Rot. Strategy
Panel A: S&P500 vs. OIL			
Mean Error (ME)	-0.0005	-0.0032	-0.0005
Mean Squared Error (MSE)	0.0013	0.0013	0.0014
Mean Absolute Error (MAE)	0.0282	0.0285	0.0291
Panel B: S&P500 vs. FINANCIAL SECTOR			
Mean Error (ME)	0.0000	-0.0021	0.0006
Mean Squared Error (MSE)	0.0008	0.0008	0.0009
Mean Absolute Error (MAE)	0.0219	0.0218	0.0234
Panel C: S&P500 vs. NASDAQ			
Mean Error (ME)	-0.0012	0.0005	-0.0009
Mean Squared Error (MSE)	0.0004	0.0004	0.0005
Mean Absolute Error (MAE)	0.0150	0.0152	0.0163

Table 5

Statistics for Forecasts Errors Evaluation of Volatility Timing

The table illustrates evaluation of forecast accuracy under three different measurements (ME, MSE and MAE). The results correspond to each separate model: Naive, ARIMA, Rotation strategy and for the three pairs S&P500 - OIL, S&P500-FINANCIALS, S&P500-NASDAQ that we implement the strategy. The results of the table correspond to Wednesday. The horizon for the estimations for the first pair SP500 vs. OIL extends from 7 February 2001 until 4 April 2008. For the second pair S&P500 vs. Financial Sector horizon extends from 22 December 1998 till 4 of April 2008. Lastly, the S&P500 and Nasdaq are estimated since 10 March 1999 till 4 April 2008.

Panel A: S&P500 vs. OIL			
	Naïve	ARIMA	Rot. Strategy
Mean Error (ME)	-0.0003	-0.0031	-0.0009
Mean Squared Error (MSE)	0.0011	0.0011	0.0012
Mean Absolute Error (MAE)	0.0264	0.0265	0.0278
Panel B: S&P500 vs. FINANCIAL SECTOR			
Mean Error (ME)	0.0000	-0.0023	0.0021
Mean Squared Error (MSE)	0.0006	0.0006	0.0139
Mean Absolute Error (MAE)	0.0200	0.0202	0.0286
Panel C: S&P500 vs. NASDAQ			
Mean Error (ME)	-0.0011	0.0004	-0.0015
Mean Squared Error (MSE)	0.0005	0.0005	0.0005
Mean Absolute Error (MAE)	0.0147	0.0148	0.0160

Table 6

Statistics for Forecasts Errors Evaluation of Volatility Timing

The table illustrates evaluation of forecast accuracy under three different measurements (ME, MSE and MAE). The results correspond to each separate model: Naive, ARIMA, Rotation strategy and for the three pairs S&P500 - OIL, S&P500-FINANCIALS, S&P500-NASDAQ that we implement the strategy. The results of the table correspond to Friday. The horizon for the estimations for the first pair SP500 vs. OIL extends from 7 February 2001 until 4 April 2008. For the second pair S&P500 vs. Financial Sector horizon extends from 22 December 1998 till 4 of April 2008. Lastly, the S&P500 and Nasdaq are estimated since 10 March 1999 till 4 April 2008.

Panel A: S&P500 vs. OIL			
	Naïve	ARIMA	Rot. Strategy
Mean Error (ME)	-0.0002	-0.0030	-0.0011
Mean Squared Error (MSE)	0.0012	0.0011	0.0012
Mean Absolute Error (MAE)	0.0276	0.0280	0.0280
Panel B: S&P500 vs. FINANCIAL SECTOR			
Mean Error (ME)	-0.0002	-0.0026	0.0001
Mean Squared Error (MSE)	0.0007	0.0007	0.0007
Mean Absolute Error (MAE)	0.0203	0.0205	0.0218
Panel C: S&P500 vs. NASDAQ			
Mean Error (ME)	-0.0015	0.0000	-0.0031
Mean Squared Error (MSE)	0.0005	0.0005	0.0007
Mean Absolute Error (MAE)	0.0157	0.0155	0.0172

Table 7

Ex-Post Decomposition based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses the mean, trading, no trading, minimum and maximum duration of those positions as well the transition probabilities. The table represents the pair S&P500 versus Oil. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Monday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	207	125	162	1.0	1.0
Mean trading time	0.892	0.539	0.698	0.004	0.004
No Trade To No Trade	0.840	0.425	0.443	1.000	0.000
No Trade To Trade	0.160	0.575	0.557	0.000	0.000
Trade To No Trade	0.019	0.496	0.242	1.000	0.000
Trade To Trade	0.981	0.504	0.758	0.000	0.000
Mean Duration No Trade	6.250	1.721	1.795	0.000	0.000
Max Duration No Trade	16.000	7.000	8.000	0.000	0.000
Mean Duration Trade	10.000	2.016	4.128	0.000	0.000
Max Duration Trade	20.000	5.000	31.000	0.000	0.000
p-value for Independent Test	0.000	0.277	0.003	0.000	0.000

Table 8

Ex-Post Decomposition based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses the mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Financials. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Monday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	37	163	229	53	37
Mean trading time	0.112	0.492	0.692	0.160	0.112
No Trade To No Trade	0.993	0.506	0.324	0.928	0.969
No Trade To Trade	0.007	0.494	0.676	0.072	0.031
Trade To No Trade	0.081	0.512	0.303	0.396	0.270
Trade To Trade	0.919	0.488	0.697	0.604	0.730
Mean Duration No Trade	48.0	2.024	1.478	4.600	12.000
Max Duration No Trade	66.0	6.000	6.000	35.000	47.000
Mean Duration Trade	12.3	1.928	3.290	2.524	3.700
Max Duration Trade	35.0	9.000	39.000	18	21
p-value for Independent Test	0.0	0.908	0.705	0.00	0.00

Table 9

Ex-Post Decomposition based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses the mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Nasdaq. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Monday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	121	157	179	5	2
Mean trading time	0.376	0.488	0.556	0.016	0.006
No Trade To No Trade	0.935	0.524	0.563	0.997	0.997
No Trade To Trade	0.065	0.476	0.437	0.003	0.003
Trade To No Trade	0.108	0.503	0.352	0.250	1.000
Trade To Trade	0.892	0.497	0.648	0.750	0.000
Mean Duration No Trade	15.46	2.08	2.29	317.00	291.00
Max Duration No Trade	113.00	8.0	15.00	317.00	291.00
Mean Duration Trade	9.23	1.987	2.84	1.00	1.00
Max Duration Trade	61.00	6.0	21.00	1.00	1.00
p-value for Independent Test	0.00	0.704	0.00	0.00	0.91

Table 10

Ex-Post Analysis based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses the mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Oil. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Wednesday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	233	144	149	1	1
Mean trading time	0.886	0.548	0.567	0.004	0.004
No Trade To No Trade	0.833	0.462	0.434	1.000	0.000
No Trade To Trade	0.167	0.538	0.566	0.000	0.000
Trade To No Trade	0.022	0.448	0.436	1.000	0.000
Trade To Trade	0.978	0.552	0.564	0.000	0.000
Mean Duration No Trade	6	1.86	1.75	0.000	0.000
Max Duration No Trade	19	6.00	10.00	0.000	0.000
Mean Duration Trade	8	2.23	2.29	0.000	0.000
Max Duration Trade	20	8.00	14.00	0.000	0.000
p-value for Independent Test	0	0.81	0.97	0.000	0.000

Table 11

Ex-Post Decomposition based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses into mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Financials. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Wednesday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	37	163	141	44	32
Mean trading time	0.099	0.436	0.377	0.118	0.086
No Trade To No Trade	0.982	0.586	0.685	0.930	0.944
No Trade To Trade	0.018	0.414	0.315	0.070	0.056
Trade To No Trade	0.189	0.540	0.525	0.545	0.625
Trade To Trade	0.811	0.460	0.475	0.455	0.375
Mean Duration No Trade	18.500	2.402	3.110	6.304	8.211
Max Duration No Trade	98.000	10.000	34.000	34.000	47.000
Mean Duration Trade	5.286	1.852	1.905	1.833	1.600
Max Duration Trade	18.000	6.000	5.000	6.000	5.000
p-value for Independent Test	0.000	0.376	0.002	0.000	0.000

Table 12
Ex-Post Decomposition based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses the mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Nasdaq. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Wednesday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	143	175	199	6	2
Mean trading time	0.394	0.482	0.548	0.017	0.006
No Trade To No Trade	0.932	0.553	0.591	0.989	0.997
No Trade To Trade	0.068	0.447	0.409	0.011	0.003
Trade To No Trade	0.106	0.483	0.338	0.80	1.00
Trade To Trade	0.894	0.517	0.662	0.20	0.00
Mean Duration No Trade	14.667	2.238	2.448	89.250	328
Max Duration No Trade	125	7	12	347	328
Mean Duration Trade	9.067	2.071	2.940	1.250	1
Max Duration Trade	65	7	31	2	1
p-value for Independent Test	0.000	0.180	0.000	0.049	0.916

Table 13
Ex-Post Analysis based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses the mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Oil. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Friday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	225	136	158	2	1
Mean trading time	0.879	0.531	0.617	0.008	0.004
No Trade To No Trade	0.839	0.513	0.408	0.996	1.000
No Trade To Trade	0.161	0.487	0.592	0.004	0.000
Trade To No Trade	0.022	0.434	0.369	1.000	1.000
Trade To Trade	0.978	0.566	0.631	0.000	0.000
Mean Duration No Trade	6.200	2.052	1.690	254.000	0.000
Max Duration No Trade	19.000	10.000	9.000	254.000	0.000
Mean Duration Trade	43.600	2.305	2.655	1.000	0.000
Max Duration Trade	181.000	9.000	10.000	1.000	0.000
p-value for Independent Test	0.000	0.208	0.537	0.929	0.000

Table 14

Ex-Post Decomposition based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses the mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Financials. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Friday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	37	148	246	60	62
Mean trading time	0.102	0.409	0.680	0.166	0.171
No Trade To No Trade	0.988	0.612	0.371	0.924	0.926
No Trade To Trade	0.012	0.388	0.629	0.076	0.074
Trade To No Trade	0.135	0.565	0.298	0.400	0.371
Trade To Trade	0.865	0.435	0.702	0.600	0.629
Mean Duration No Trade	26.500	2.578	1.589	4.174	5.182
Max Duration No Trade	97.000	8.000	6.000	19.000	20.000
Mean Duration Trade	7.400	1.771	3.329	2.500	2.696
Max Duration Trade	13.000	7.000	20.000	12.000	14.000
p-value for Independent Test	0.000	0.367	0.170	0.000	0.000

Table 15

Ex-Post Decomposition based on Trading Activity

We represent a decomposition of the distribution of trades recorded trade-by trade. Our decomposition analyses into the mean, trading, no trading, the minimum and maximum duration of those positions. The table represents the pair S&P500 versus Nasdaq. The estimations referring to 5 models Naive model, ARIMA, our Rotation strategy and two time varying volatility strategies (differences of volatility and volatility ratio). P-value correspond to test for independence. Results correspond to Friday.

	Naïve	ARIMA	Rot. Strategy	Difference of Volatility	Volatility Ratio
Number of trades	130	175	133	14	5
Mean trading time	0.368	0.496	0.377	0.040	0.014
No Trade To No Trade	0.919	0.542	0.680	0.988	0.991
No Trade To Trade	0.081	0.458	0.320	0.012	0.009
Trade To No Trade	0.140	0.469	0.534	0.308	0.80
Trade To Trade	0.860	0.531	0.466	0.692	0.20
Mean Duration No Trade	12.389	2.185	3.129	84.750	115.333
Max Duration No Trade	121.00	12.00	21.00	320.00	320.00
Mean Duration Trade	7.000	2.134	1.873	2.000	1.250
Max Duration Trade	49.000	9.000	10.000	4.000	2.000
p-value for Independent Test	0.000	0.166	0.006	0.000	0.038

Table 16

Non-parametric Statistic of Volatility and Market Timing of Correctly Signs Predictions of Excess Returns

We estimate the percentage that the different model selection - Naive model, ARIMA, Rotation strategy and the two time varying volatility strategies (differences of volatility and volatility ratio- was correct in their prediction and then we test whether it is significantly different from 50%. The table represents our three pairs S&P500 versus Oil, Nasdaq and Financials. In the estimation of our results we applied bootstrap technique simulated by 400 iterations and 20 lags backwards. Results correspond to Monday.

	Naïve	ARIMA	Difference of Volatility	Volatility Ratio	Rot. Strategy
Panel A: S&P500 vs. OIL					
Sample Mean	0.559	0.489	0.552	0.551	0.545
Standard Errors	0.026	0.035	0.026	0.027	0.026
Panel B: S&P500 vs. FINANCIAL SECTOR					
Sample Mean	0.548	0.501	0.547	0.570	0.513
Standard Errors	0.018	0.031	0.017	0.019	0.024
Panel C: S&P500 vs. NASDAQ 100					
Sample Mean	0.521	0.464	0.493	0.510	0.518
Standard Errors	0.026	0.024	0.026	0.024	0.025

Table 17

Non-parametric Statistic of Volatility and Market Timing OF Correctly Signs Predictions of Excess Returns

We estimate the percentage that the different model selection - Naive model, ARIMA, Rotation strategy and the two time varying volatility strategies (differences of volatility and volatility ratio-was correct in their prediction and then we test whether it is significantly different from 50%. The table represents our three pairs S&P500 versus Oil, Nasdaq and Financials. In the estimation of our results we applied bootstrap technique simulated by 400 iterations and 20 lags backwards. Results correspond to Wednesday.

	Naïve	ARIMA	Difference of Volatility	Volatility Ratio	Rot. Strategy
Panel A: S&P500 vs. OIL					
Sample Mean	0.532	0.540	0.535	0.535	0.523
Standard Errors	0.027	0.026	0.025	0.026	0.021
Panel B: S&P500 vs. FINANCIAL SECTOR					
Sample Mean	0.575	0.484	0.567	0.550	0.538
Standard Errors	0.026	0.023	0.023	0.028	0.032
Panel C: S&P500 vs. NASDAQ 100					
Sample Mean	0.506	0.486	0.480	0.479	0.478
Standard Errors	0.024	0.025	0.024	0.024	0.026

Table 18

Non-parametric Statistic of Volatility and Market Timing OF Correctly Signs Predictions of Excess Returns

We estimate the percentage that the different model selection - Naive model, ARIMA, Rotation strategy and the two time varying volatility strategies (differences of volatility and volatility ratio- was correct in their prediction and then we test whether it is significantly different from 50%. The table represents our three pairs S&P500 versus Oil, Nasdaq and Financials. In the estimation of our results we applied bootstrap technique simulated by 400 iterations and 20lags backwards. Results correspond to Friday.

	Naïve	ARIMA	Difference of Volatility	Volatility Ratio	Rot. Strategy
Panel A: S&P500 vs. OIL					
Sample Mean	0.568	0.528	0.578	0.581	0.519
Standard Errors	0.027	0.027	0.024	0.024	0.033
Panel B: S&P500 vs. FINANCIAL SECTOR					
Sample Mean	0.588	0.487	0.581	0.585	0.520
Standard Errors	0.022	0.025	0.028	0.026	0.022
Panel C: S&P500 vs. NASDAQ 100					
Sample Mean	0.500	0.460	0.492	0.496	0.500
Standard Errors	0.025	0.034	0.026	0.028	0.026

Table 19

Non-parametric Statistic of Estimation of different Levels of Volatility in the Prediction of Excess Returns

We estimate according to Pearsons chi-square statistic the hypothesis if different levels of volatilities affects the returns and the predictions. Panels A and B refer to naïve model and Panel C to rotation strategy. The results corresponds to Monday. The corresponding p-values are reported in nominal form.

Panel A: *Higher Return and Higher Volatility*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	0.067	0.130	0.001
	1.000	0.839	1.000

Panel B: *Higher Return, Higher Volatility and Correct Predictions*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	1.228	1.483	20.158
	0.309	0.269	0.000
Nasdaq 100		1.406	
		0.285	
Financial Sector			0.844
			0.376
Oil Sector	0.684		
	0.671		

Panel C: *Higher Return, Higher Volatility and Correct Predictions*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	1.601	0.136	1.364
	0.228	0.815	0.261
Nasdaq 100		0.110	
		0.821	
Financial Sector			3.225
			0.083
Oil Sector	1.360		
	0.417		

Table 20

Non-parametric Statistic of Estimation of different Levels of Volatility in the Prediction of Excess Returns

We estimate according to Pearsons chi-square statistic the hypothesis if different levels of volatilities affects the returns and the predictions. Panels A and B refer to naïve model and Panel C to rotation strategy. The results corresponds to Wednesday. The corresponding p-values are reported in nominal form.

Panel A: *Higher Return and Higher Volatility*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	0.307	1.574	0.000
	0.791	0.232	1.00

Panel B: *Higher Return, Higher Volatility and Correct Predictions*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	3.324	3.942	14.652
	0.123	0.050	0.000
Nasdaq 100		6.420	
		0.019	
Financial Sector			0.157
			0.708
Oil Sector	0.020		
	1.000		

Panel C: Higher Return, Higher Volatility and Correct Predictions

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	3.999	0.375	0.003
	0.059	0.655	1.000
Nasdaq 100		0.063	
		0.819	
Financial Sector			1.070
			0.303
Oil Sector	0.904		
	0.517		

Table 21

Non-parametric Statistic of Estimation of different Levels of Volatility in the Prediction of Excess Returns

We estimate according to Pearsons chi-square statistic the hypothesis if different levels of volatilities affects the returns and the predictions. Panels A and B refer to naïve model and Panel C to rotation strategy. The results corresponds to Friday. The corresponding p-values are reported in nominal form.

Panel A: *Higher Return and Higher Volatility*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	3.201	0.013	1.510
	0.136	1.000	0.240

Panel B: *Higher Return, Higher Volatility and Correct Predictions*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	18.909	2.854	17.366
	0.002	0.093	0.000
Nasdaq 100		3.350	
		0.077	
Financial Sector			3.181
			0.084
Oil Sector	3.451		
	0.077		

Panel C: *Higher Return, Higher Volatility and Correct Predictions*

Pairs	**S&P500 - OIL**	**S&P500 - Nasdaq 100**	**S&P500-Financial Sector**
S&P500	0.756	0.673	2.265
	0.431	0.527	0.172
Nasdaq 100		0.060	
		1.000	
Financial Sector			2.241
			0.138
Oil Sector	0.611		
	0.539		

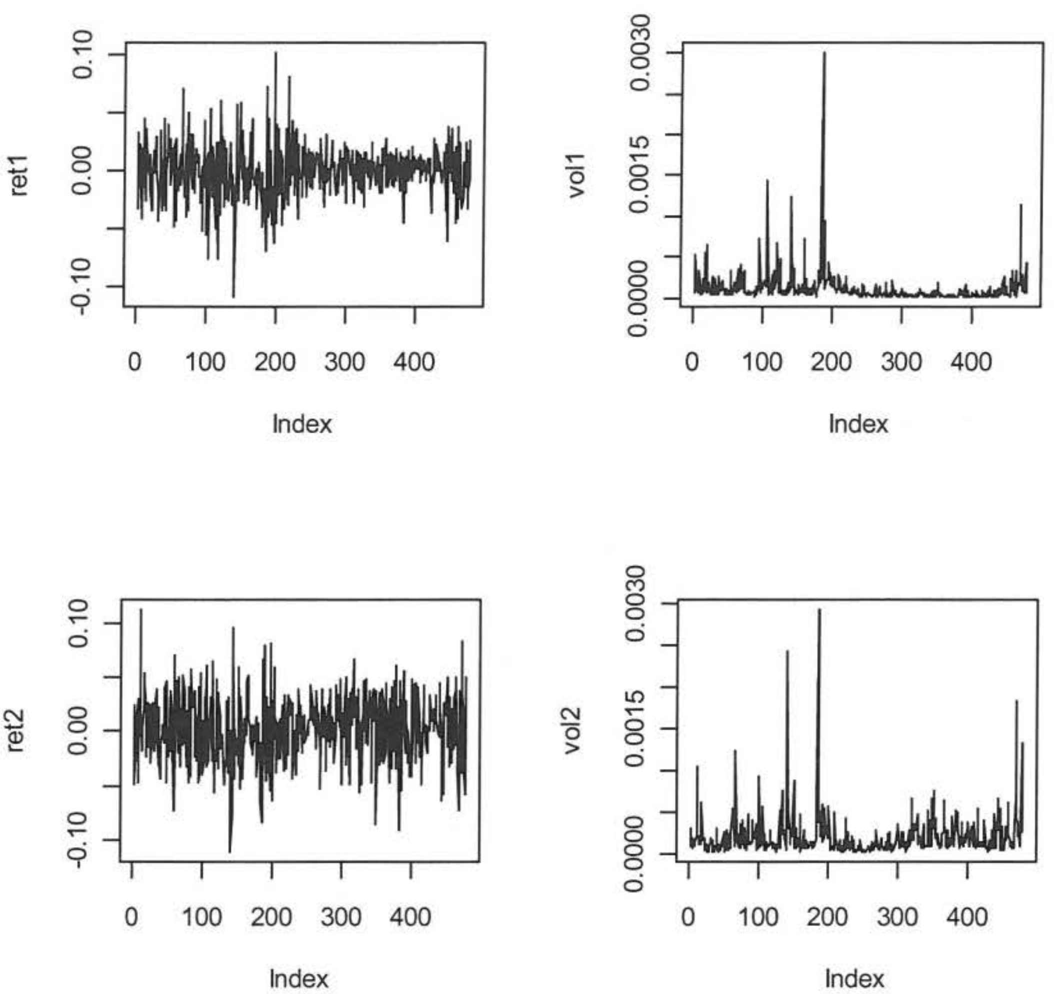

Figure 1: The figure plots mean return and volatility for the two assets. Ret_1 represents the mean return for S&P500 and vol_1 the volatility of S&P500 for the trading period. Respectively, Ret_2 represents the mean return for Oil Sector and vol_2 volatility of Oil Sector. The estimations are conducted on Wednesday. The sample horizon extends from March, 2001 to April, 2008.

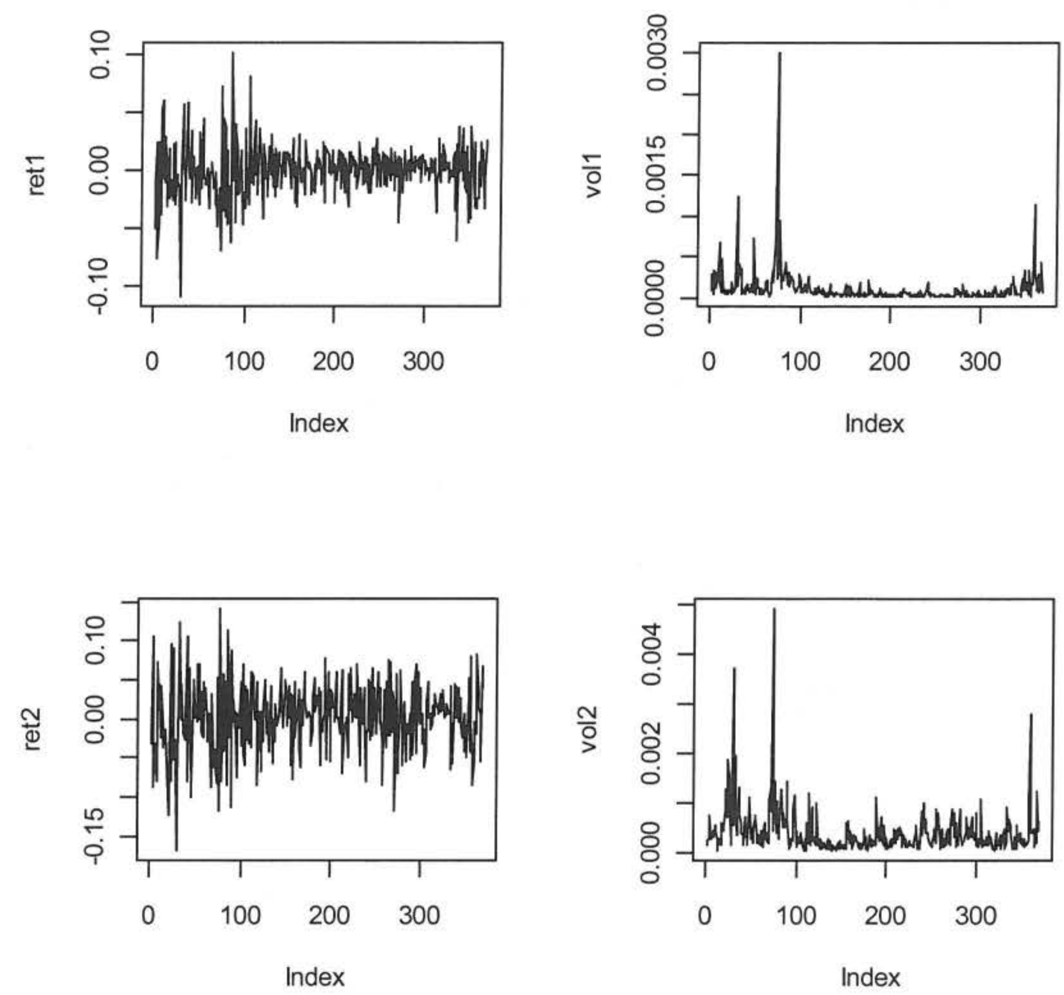

Figure 2: The figure plots mean return and volatility for the two assets. Ret_1 represents the mean return for S&P500 and vol_1 the volatility of S&P500 for the trading period. Respectively, Ret_2 represents the mean return for Financial Sector and vol_2 volatility of Financial Sector. The estimations are conducted on Wednesday. The sample horizon extends from December, 1998 to April, 2008.

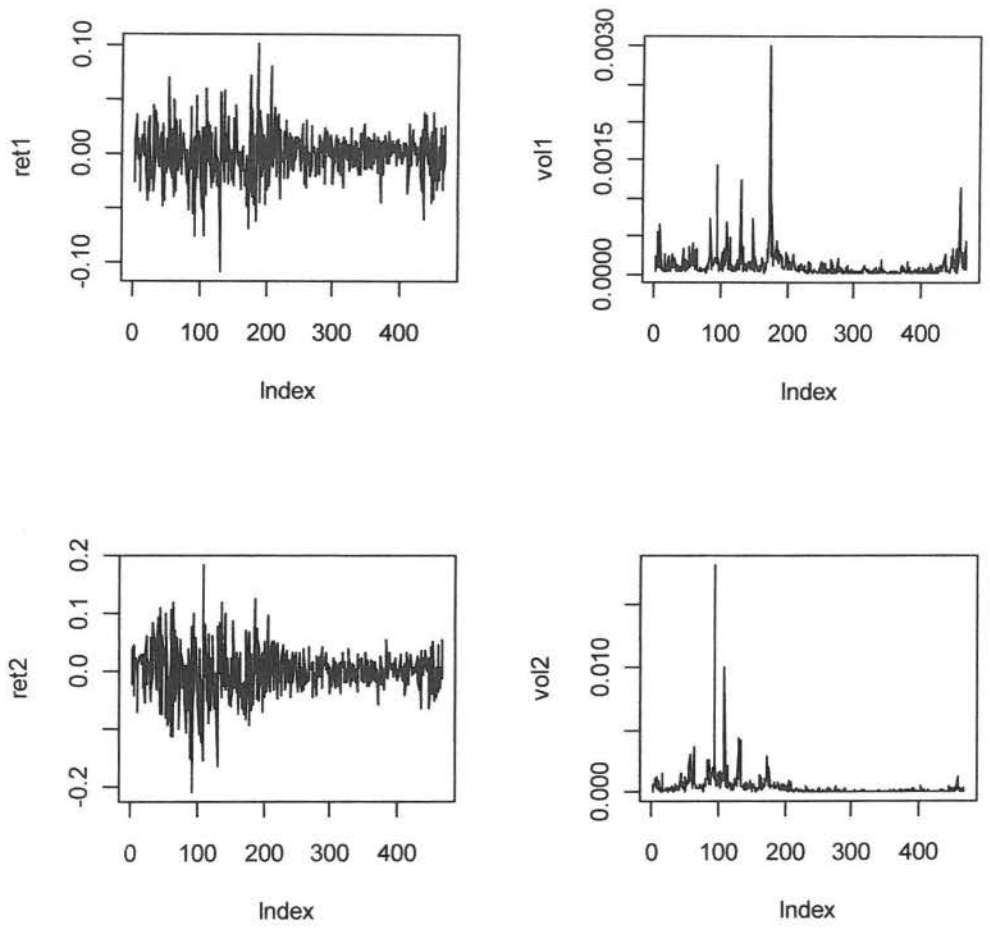

Figure 3: The figure plots mean return and volatility for the two assets. Ret_1 represents the mean return for S&P500 and vol_1 the volatility of S&P500 for the trading period. Respectively, Ret_2 represents the mean return for Nasdaq 100 and vol_2 volatility of Nasdaq 100. The estimations are conducted on Wednesday. The sample horizon extends from March, 1999 to April, 2008.

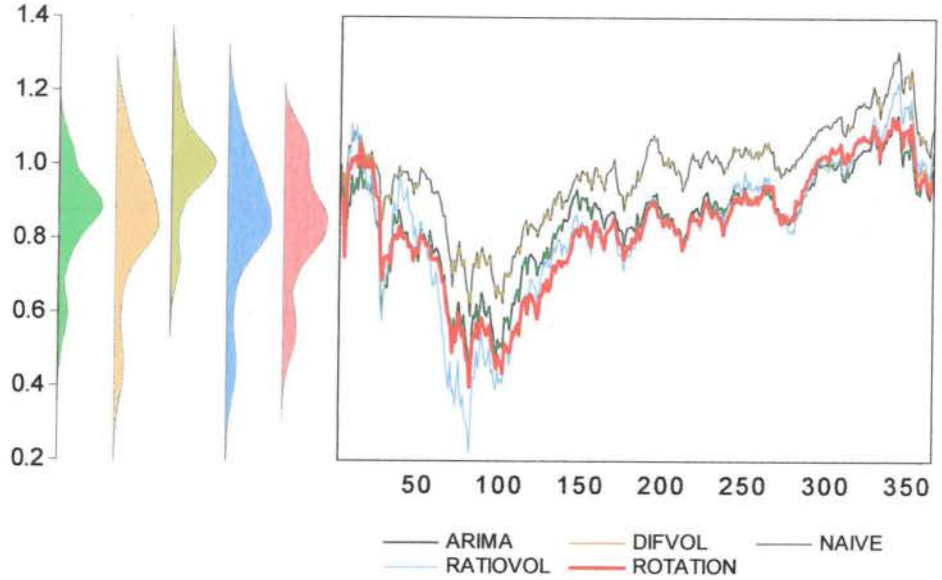

Figure 4: The figure plots terminal wealth of our rotation trading with 4 specifications. Rotation strategy has been conducted between S&P500 and Oil Sector. The estimations are based on weekly horizon and for the specific day of Wednesday. The alternative specifications are an Arima model, Naïve model, Ratio of Volatilities, Differences of Volatility. The initial wealth equals to $1. The left side of the figure plot Kernel Density.

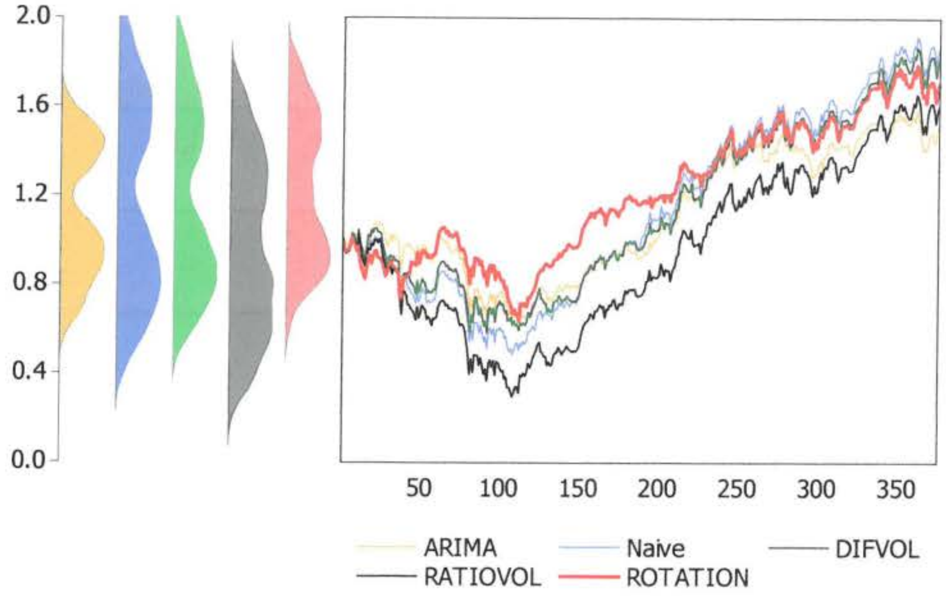

Figure 5: The figure plots terminal wealth of our rotation trading with 4 specifications. Rotation strategy has been conducted between S&P500 and Financial Sector. The estimations are based on weekly horizon and for the specific day of Wednesday. The alternative specifications are an Arima model, Naïve model, Ratio of Volatilities, Differences of Volatility. The initial wealth equals to $1. The left side of the figure plot Kernel Density.

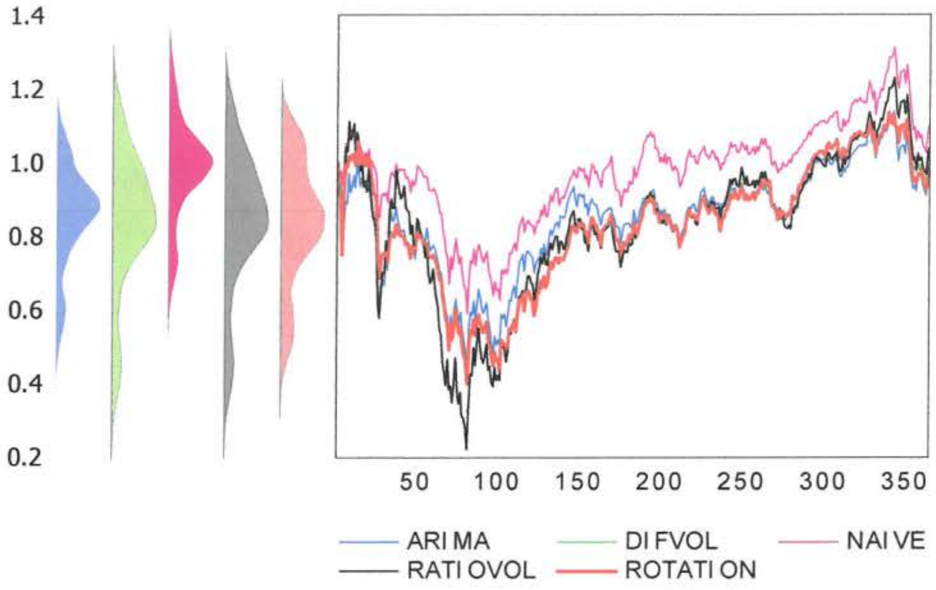

Figure 6: The figure plots terminal wealth of our rotation trading with 4 specifications. Rotation strategy has been conducted between S&P500 and Nasdaq 100. The estimations are based on weekly horizon and for the specific day of Wednesday. The alternative specifications are an Arima model, Naïve model, Ratio of Volatilities, Differences of Volatility. The initial wealth equals to \$1. The left side of the figure plot Kernel Density.

Chapter 4: Economic Implications and Conclusion

The overall contribution of my thesis represents an in-depth analysis to two different major perspectives of asset allocation strategies with the distinctive investment tool of Exchange Traded Funds. I analyze two strategies that are diametrically opposed in philosophy and implementation: market neutral strategies that rely on price reversals and (non-neutral) market timing strategies that rely on sign forecastability.

(a) Market neutral trading strategy and

(b) Market timing outright net market exposure

The market environment defines the decision between the mode of the implementation of each trading strategy. Market neutral and market timing strategies are in competition as the means of investor's interest. In my analysis, market neutral trading strategies were found to have solid performance on "shorting the market". A market neutral strategy hedges against market downturns especially or in other words hedges against market timing. Extreme volatility leads investors to market neutral strategies while on the other hand market timing requires extreme volatility to achieve optimized forecasts. The primary aim of a market neutral strategy is to reduce volatility and risk and deliver positive returns. According to the empirical evidence, the best market neutral strategy achieved a weekly mean return of 0.08% while simultaneously a market timing strategy achieved a weekly mean return of 0.4%.

Furthermore, the best market neutral strategy achieved a weekly standard deviation of 1.9% and market timing strategy achieved 3.5%, almost the double risk.

The implementation of two diametrically different trading strategies confirms the conjecture that the important determinant of profitability is return volatility and time horizon. The construction of a profitable trading strategy requires the existence of a dynamic multifunctional mechanism, where each individual stage is crucial to the success of the trading strategy.

As shown extensively through out the analysis there is always at least one trading strategy either in pair trading or in rotation that outperforms the market as measured by the constituents of the pairs involved in the trade or the rotation benchmark.

The analysis presented in this thesis has a multifold of economic implications, the most important of which is related to the notion of market efficiency. Market efficiency is not associated with profits generated by market timing, as timing an efficient market should be practically impossible. Nevertheless, my results support a vast literature on profitable market timing strategies and indicate that asset allocation strategies that exploit any potential market inefficiencies do exist and are significantly profitable. This is important for any rational investor whose willingness to enter the market is directly related to the potential profits that he/she might generate by active trading.

Then, there are the issues of volatility and return predictability which are related to the profitability of the trading strategies. My results support past literature on the topic on the importance of volatility predictability, particularly in the context of the active, non-neutral rotation strategy. Return predictability is manifested both at the strategy level and the model forecasting level and their combination provides solid economic performance for the two strategies that are being examined in this thesis.

The results presented herein are related to the important methodological and practical issue of asset allocation. Active trading strategies require careful consideration, formulation and backtesting but nevertheless appear to be successful in capturing market movements that can generate significant profits, over and above those generated by a buy-and-hold strategy. In addition, these strategies are direct competitors to portfolio-based strategies that are widely used in both academic studies and by market practitioners.

Finally, my thesis contributes in examining the potential underlying economic causes behind the manifested profitability of the trading strategies I analyzed. In the end it is always the state of the economy that does matter for explaining profits over the long-run: this is important as it strongly suggests that healthy economies are related to healthy markets and thus to potential for profitability.