# Pairs Trading on International ETFs

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**Abstract**

Pairs trading is a popular, market-neutral trading strategy among finance practitioners that has been recently evaluated in a number of papers. Since it is a successful trading strategy, allowing for multiple implementations of solid underlying ideas, it is interesting to further explore the underlying factors for its success. In this paper we do so using a large family of international exchange traded funds (ETFs), a recent instrument of choice among professionals. Using ETFs from across the world we examine the performance of the pairs trading strategy and the various potential sources of its profitability. Our results show that pair trading is a profitable strategy in the context of international ETFs. There is a clear difference between the long and short component of the pairs, maybe in contrast to the common perception on the profitability of long trades. Finally, we explore the sources of the strategy's total profitability and find that it can be explained by a number of fundamentals, the most important being the earnings per share, the dividend yield and the unemployment rate.

***Keywords:*** *convergence/divergence of prices, exchange traded funds, ETF, Fama-French, international asset pricing, long and short strategies, market neutral strategies, mean reversion.*

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# 1. Introduction

Investors and finance professionals are always on the lookout for successful trading strategies that account for different aspects and assumptions about the markets. A family of strategies, that are relatively aggressive, is the one that uses assumptions and models about market timing: the ability to provide accurate signals of when to enter/exit the market and which way (long or short) to invest.

However, market timing can also be casted in the context of market neutral strategies, where both a long and a short position are taken based on a timing signal. An example of such a strategy, much used in the industry but having received little attention in academia, is pairs trading. This particular strategy uses a number of underlying assumptions about the path that asset prices take; the most important ones are those of co-movement and mean reversion: prices of selected assets tend to move together and when they diverge this presents an investment opportunity that is exploited by taking a market neutral position. In a recent paper Gatev et al. (2006) report that the origins of pairs trading probably lies in the mid 1980s when Nunzio Tartaglia developed a high-end trading platform to implement it. In the early 1990s pairs trading strategy flourished as it was used by many individual and institutional investors, mostly hedge funds, in their attempt to reduce market exposure[1]. The pairs trading strategy exploits this with a number of statistical tools, such as the concept of distance and of convergence/divergence of prices based on this distance. In this paper we examine in detail the performance of pairs trading using a large family of international exchange traded funds (ETFs), a liquid instrument of choice among professionals. Besides making a few methodological innovations in the application of the strategy we examine in sufficient detail the probable underlying causes of the profitability of the strategy and its variations.

Gatev, Goetzmann and Rouwenhorst (2006, hereafter GGR) and Engleberg, Gao and Jagannathan (2008, hereafter EGJ) are the most authoritative recent studies and replicate the "original" pairs trading methodology, as discussed above. We have certain methodological deviations from their approach, which we describe. The EGJ paper works some of the implications of pairs trading profitability, especially in examining the factors that may be responsible for the success of the method. These two papers provide a rather thorough treatment of pairs trading for the US securities markets and this

[1] According to Thomson Financial database (2010), pair trading covers around 27% of the total hedge funds strategies.

distinguishes their works from ours where we concentrate, for the first time in this literature, on international ETFs[2].

There is a limited number of, neutral and non-neutral, strategies that use pairs and distances for formulating combinations of long/short positions. Jurek and Yang (2007) use the "Siamese twin formula" where a 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 one. Here the fundamentals of a security take the place of price divergence. Nath (2003) applied an approach based on the (static) empirical distribution of returns. Now a record of the distance of pairs of different securities is being kept and a trade opens a trade when the difference exceeds the 15% percentile. At the same time positions that were already open are liquidated when the distance falls below the 5% percentile. There is also the literature that uses results on mean reversions but the strategies on this literature do not necessarily use pairs or are market neutral to be directly comparable to pairs trading.

While we cannot account for all the variations of this strategy that have been applied by practitioners, there have been two recent studies that examine some of the mechanics of implementation of pairs trading in some detail. By focusing on the way that one enters into a trade, it appears that is more important to have a solid understanding of why and when to exit a trade. Since pairs trading requires to monitor convergence/divergence of prices one can have the situation that one stays into a trade "too long". According to GGR (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 EGJ (2008) is called "cream-skimming strategy" and limits the trade only to the first 10 days after a trade is initiated. One of the contributions of our paper is that it examines in detail the profitability implications of different forms of exiting from a trade. Related to this issue is the issue of number of eligible pairs to trade, as pairs are ranked and then one has to make a decision of which pairs will he/she be considering for monitoring and actually trading.

As in the previous two papers who worked on pairs trading, we examine also in some detail the economic and other market factors that may explain profitability in pairs

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[2] ETFs are very popular in the implementation of trading strategies among the practitioners, to testify so according to ETF landscape global handbook providing by Blackrock,, at the beginning of June 2010 the global ETF industry had 2,218 ETFs with 4,478 listings, assets of $1,0441.1bn from 131 providers on 42 exchanges around the world.

trading. In this paper, we attempt to provide an answer, checking one by one the pairs, on the source of profitability, under the question of: "What are the main factors that cause the prices of pairs to diverge and how that affects subsequent convergence?" and "Could we explain statistical strategies under any fundamental factors?" The significant difference in this exercise, compared to previous studies, is that we use a family of international assets and that, apart from the "traditional" set of variables (market and idiosyncratic factors) that that are usually used in assessing the causes of strategy profitability, we include macroeconomic factors for the first time in such an analysis.

Finally, to face the potential problem of diminished profitability, because of "hedge fund overcrowding", we make a modification of the trading algorithm from the sum of squares to absolute deviations; this leads to a more robust measure to capture smaller divergences, increasing the number of trades and as a result lead to higher profitability.

The rest of the paper is organized as follows. In section 2 we discuss issues of arbitrage, liquidity and short sales constraints, as they relate to the pairs trading strategy. In section 3 we detail our data and statistics related to our sample of ETFs. In section 4 we present our methodology with the proposed modifications while in section 5 we discuss our results for the performance of pairs trading. In section 6 we present results that relate this performance to various economic factors and in section 7 we offer some concluding remarks.

## 2. Arbitrage, liquidity and short sale constraints

Trading strategies are implicitly grounded on the presence of a (possibly time-varying) arbitrage mechanism that could create profitable trading opportunities. Pairs trading assumes that such opportunities arises either when there is "extreme" divergence between pairs of assets within a larger family. Whether arbitrage opportunities exist is, of course, a matter of continuous investigation.

According to Shleifer and Vishny (1997) an arbitrage mechanism becomes ineffective when all arbitrageurs are fully invested and the profits have to be shared to a pool of participants. From such a pool of investors only a small incremental group of "specialists" could identify promptly abnormal returns and can utilize them. When the majority of investors realize these abnormalities, superior profits will diminish and investors will go long onto overpriced assets. It therefore becomes paramount to know when to enter a trade and when to exit from it, even when arbitrage opportunities exist and are acknowledged by investors. Risk aversion is a prime factor to be considered when taking trading positions. Empirical evidence shows that periods of high market volatility are considered significant by professionals in placing their trades: they tend to avoid extremely volatile arbitrage positions, even those positions which (ex post) are seen to terminate in excess returns. Thus, a high volatility environment will force investors to increase their redemptions and fund managers to exit the market, possibly with increased probability of having a loss. Extreme circumstances (such as the divergence that is used in pairs trading) do not reflect a direct consequence of fundamentals and macroeconomic risks but may simply reflect the arbitrageurs risk aversion. This is an important point to remember later when we discuss the factors of pairs trading profitability.

Jurek and Yang (2006) confirm Shleifer and Vishny's (1997) work, where arbitrageurs are reluctant to increase their allocation in a high volatility environment even when a mispricing opportunity has been detected. There is a trade-off between horizon and divergence risk, where after a crucial cut-off point any mispricing, even in the case of expanding divergence, leads to a smaller exposure to market positions. They argued that this trade-off creates a time-varying boundary, where outside the bounds even when the opportunity map increases rational arbitrageurs will diminish their exposure.

Kondor (2008) confirmed the vital role of arbitrage in the success of a trading strategy under three perspectives: (1) competition among investors leads the prices out of their long run "equilibrium" and the predictability of the direction of change diminishes (2) such competition can lead to substantial losses in the majority of cases when an extremely short horizon is considered (3) the absence of arbitrage from the market helps prices to converge to their "equilibrium".

Jacob and Levy (2003), on the question of optimal time to exit, argued that statistical arbitrage opportunities and accurate forecasting of the time series of price or return spreads should be considered as the unique factor which affects profitability of a pair trading strategy.

Do et al (2006), Jurek et al. (2006) and Kondor (2008) all also discussed the issue of the "convergence time", i.e. the time to exit in pairs trading-like strategies. All agree that the decision of when to exit is among important factors that affect a strategies performance.

Based on this we are lead to investigate several different timing intervals and to cross-compare results on the decision of when to exit a trade from a pairs trading strategy in an attempt to shed some light on whether there is an "optimal trading horizon".

Beyond these issues there are two other ones that greatly affect the implementation and profitability of any trading strategy: liquidity and trading constraints, especially short selling. There are studies that provide evidence that mean-reversals, both on a short and long run, are driven by the level of liquidity, see Conrad, Hemmed and Niden (1994), and Cooper (1999). Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996) and Brennan, Chordia, and Subrahmanyam (1998) argued that illiquid stocks give on average higher returns. Amihud (2002) and Jones (2001) model liquidity as an endogenous variable and show that there is a link between market liquidity and expected market returns. EWJ (2008), on the other hand, provide evidence that liquidity factors have limited power to explain pairs trading profits and this power further decline further as we shorten the time-to-exit from a trade. 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, showing 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 and Ready (1997), under a different perspective, showed 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. However, EGJ (2008) on their pairs trading implementation argued that short-sale constraints are not correlated with the risk and return of pair trading. In our analysis we find that short selling might be important in that it appears as a strong driving force of pairs trading profitability in the group of ETFs that we consider.

## 3. Data

Our empirical analysis focuses on 22 international, passive ETFs. The ETFs come from both developed and developing economics. Our dataset's primary listing is the American Stock Exchange[3] 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[4] (EZU), MSCI UK(EWU), MSCI BRAZIL (EWZ), MSCI TAIWAN (EWT) and S&P500 (SPY), the biggest ETF worldwide[5].

The majority of the ETF records starts on April, 01 1996[6]. Exceptions are MSCI S. Korea, that started on 10/05/2000, MSCI Taiwan that started on 20/06/2000 and MSCI EMU that started on 25/07/2000. All ETF data end on 11/03/2009. Our analysis is based on daily observations including open, high, low and closing (dividend adjusted[7]) prices for each ETF series. All of the ETFs we use have futures contracts and some of them also have options[8]. Almost all of them can be traded, over the counter, to electronic platforms (ECN) at the AMEX trading hours.

An important part of our analysis, which has not been considered in the previous papers, is to examine whether there is differential behaviour of pairs trading in developed against developing economies. For this we split the ETFs into two respective groups and perform a separate analysis on both. We also use segmentation for our ETFs, based on

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3 The majority of the ETFs are provided by Barclays Global Investors - (Ishares).

4 EMU corresponds to the performance of publicly traded securities in the European Monetary Union markets.

5 We focus only to the aforementioned ETFs under the following criterion: We have selected all the international ETFs that have been launched before the 30/07/2000, which was our cut off date in order to have a sufficient number of observations. The included ETFs are a subsample of the broader group of international ETFs. International ETFs are a popular group among the practitioners (with high trading volumes and large market capitalization) since they embed distinctive properties in the implementation (event its beyond the scope of this paper its much more cheaper and easier to invest into Taiwan through ETF than directly to the local stock exchange). Among others Pennathur (2002) compared the performance of international ETFs with closed end funds of the objective country in means of diversification benefit, since country funds are determined in the US and NAVs in the home country. Engle et al (2002) compared domestic against international ETFs in means of premiums/discounts, for 4 separate horizons, during a day, end of the day, minute by minute and intraday.

6 It's the first time that we apply pair trading including the period of the great credit crunch.

7 Dividends may be responsible for the divergence of the prices.

8 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.

market capitalisation. This split allows examining the potential effects of liquidity on the pairs trading strategy in cross-comparison with the level of financial development of the underlying market.

In addition to our full sample results we divided our sample into four different sub-periods. The first sub-period covers April 1st 1996 to December 31st of 1999. The second sub-period starts on January 1st 2000 and goes until December 31st of 2002. The third sub-period covers the period from January 1st 2003 until the end of 2005, and the last period is extended from January 1st of 2006 till the end of our dataset. The idea behind these sample splits is to examine if there are any patterns that lead the strategy only on specific periods and to check the relation of pairs trading to different conditions of capital markets. Furthermore, note that the first sub-period corresponds to a bull market while the second sub-period corresponds to a bear market. The third sub-period is related to a "recovery" period for the markets while the last sub-period covers both the rally of recent years and part of the start of the recent crisis.

Finally, two short comments on the suitability of our chosen dataset. First, the MSCI indices are free of survivor bias and are a very robust proxy of market performance for each country. In addition, when using such indices there is practically no bankruptcy risk, a factor that was discussed in GGR (2006) in connection with pairs trading performance. A characteristic example arises by the properties of "twin" stocks. A negative announcement on the first stock will have identical influence on both stocks but on different direction (positive for one and negative for the other): pairs trading between such "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.

## 4. Methodology

In this section we describe the empirical methodology for implementing pairs trading. We start off with some preliminaries and terminology. To apply the methodology we have to first make a selection of pairs. This has to be done on a specific (rolling) time segment called the "formation period". During the formation period a specific rule is applied to find which pairs are eligible for trading. Then we have the actual trading period, whose length has to also be pre-selected as was done for the length of the formation period. During the trading period another rule is applied to monitor whether a trade should be terminated; all trades are exited at the end of the trading period. Then another formation period is considered and so on. Note that trading periods do not overlap while there is a partial overlap to the formation periods. To avoid the pitfalls of (excess) data mining we fix the formation period to 120 trading days throughout our analysis and experiment with different lengths for the trading period. Our approach relies on a shorter formation period when compared with GGR (2006) and EWJ (2008) but we have the advantage of non-overlapping trading periods. During the formation period we apply a rule similar, but not identical, to the one used in GGR (2006) and EWJ (2008). Our approach is as follows.

During the 120 days of each formation period we record the price of all ETFs in the group we are using. From these prices we compute normalized cumulative price indices which are comparable across the ETFs in the group. Divergence is based on these indices that are given as:

$$P_t^a = \prod_{j=t+1}^{t+i} (1 + r_t^a), \qquad \text{for } t = 1, 2, \ldots, 120 \tag{1}$$

where $r_t^a = \left(\frac{P_t}{P_{t-1}}\right) - 1$ is the simple return of the *a*th ETF and the index *i* runs as a sequence of the form  to create the partially overlapping rolling formation periods (note that these exclude the 20-day trading period) and similarly for other lengths of the trading period. Next, for each formation period we compute the average absolute distance among all pairs in the group we are considering as:

$$\Delta_{ab} = \frac{1}{120} \sum_{t=i+1}^{120+i} \left| P_t^a - P_t^b \right|, \qquad \text{for all pairs } a, b \tag{2}$$

and we rank the distances from largest to smallest to identify trading opportunities, where these distances are larger than a pre-specified threshold. The use of absolute distances allows us to have more of trading opportunities and, as usual when compared to a sum-of-squares measure, is more robust to sudden large discrepancies that quickly disappear. It is interesting to note that the use of the absolute value instead of the square in computing distances, as in the previous papers, changes the way we use the threshold $c$ for getting into and out of a trade (see below). However, it is well known that there is a relationship between the mean absolute deviation and the variance in many distributions so that the two approaches are statistically equivalent (although they may differ in trading performance). As an example, for the normal distribution the relationship between the mean absolute deviation MAD and the standard deviation SD is given by MAD = 0.798 SD. Similar results hold for other distributions. Note that the MAD in the above example is smaller than the corresponding value of the SD, that is computed using the sum of squares.

Suppose now that we consider the top $L$ pairs, i.e. the pairs that have the $L$ largest $\Delta_{ab}$ values during the formation period. For each of the 20 days of the trading period we compute the 120-day normalized cumulative price indices and compare them to a fraction of the $\Delta_{ab}$ formation value for each pair; if the absolute difference of the price indices is greater than this fraction then a trade is initiated as:

$$T_{t+s}^{ab} = \begin{cases} 1, & \text{if } \left|R_{t+s}^{a} - R_{t+s}^{b}\right| > c\Delta_{ab} \\ 0, & \text{otherwise} \end{cases}, \text{for } s = 1,2,\dots,20 \tag{3}$$

for some constant $c$ (we experiment with $c$ = 0.5, 1 and 2.) When a position is initialized we go long in the asset with the lowest price index and short in the asset with the highest one, say if $R_{t+s}^{a} > R_{t+s}^{b}$ then we go long on $R_{t+s}^{b}$ and short on $R_{t+s}^{a}$. Then, we check that each day in the trading period the same sign is maintained otherwise the trade is terminated and the associated return of the trade is computed and stored. We thus have:

$$\text{if } T_{t+s}^{ab} = 1 \wedge sgn\left(R_{t+s+1}^{a} - R_{t+s+1}^{b}\right) = sgn\left(R_{t+s}^{a} - R_{t+s}^{b}\right) \text{ then } T_{t+s+1}^{ab} = 1, \tag{4}$$

$$\text{else } T_{t+s+1}^{ab} = -1$$

The above procedure is repeated for all $L$ pairs and the strategy's return is then computed. Since we have both a long and a short position across $L$ pairs we need to find the return for each long/short position and the total return across all $L$ positions. First, we compute the return for a single pair as:

$$R_{t+s}^{ab} = R_{t+s}^{ab,Long} - R_{t+s}^{ab,short} \tag{5}$$

and then we compute the return for the "portfolio" of $L$ pairs as a weighted sum of the form:

$$R^{P}_{t+s} = \sum_{\forall a,b} W^{ab}_{t+s} R^{ab}_{t+s} \tag{6}$$

where the weights are computed based on the previously accumulated wealth as in:

$$W^{ab}_{t+s} = \frac{\omega^{ab}_{t+s}}{\sum_{\forall a,b} \omega^{ab}_{t+s}} \text{ and } \omega^{ab}_{t+s} = \left(1 + R^{ab}_{t-1+s}\right) \times \cdots \times \left(1 + R^{ab}_{t-20+s}\right)$$

The above describe our basic methodology for pairs trading. An important issue that we do not put into equation format is whether a trade is executed on the signal day or the following day (a one-day delay); we experiment with both scenarios as do GGR (2006) and EWJ (2008). Other variations and robustness checks are presented and discussed in the results section that follows.

## 5. Empirical results

### 5.1. Choice of trading horizon

The pairs trading methodology relies on certain user-defined conditions, such as the choice of $c$ and the choice of the trading horizon. We therefore start our discussion with empirical results on the choice of a 20-day trading horizon. In Figure 1 we present the mean return of the pairs trading strategy for three different values of $c$ and a sequence of trading horizons $k$=1, 2, 3, 4, 5, 10, 20, ... , 120 days for $L$=5 (using the first five pairs). Within the maximum horizon of 120 business days, the optimal trading period roughly corresponds to 20 days, irrespective of the choice of $c$. We can see a rather clear peak at the 20-day trading horizon. While it is possible to let the pairs trading strategy run until the price indices have converged we can clearly see that there is an increasing risk associated with this approach.

### 5.2. Properties of trading

Using the 20-day horizon we next compute some summary measures for the actual trading activity and report them in Table 1. In Panel A of the table we report some statistics on the time and duration of pairs trading across different values of $L$. The interesting results are that (a) there is, on average, one-round trip per pair across all $L$ combinations and (b) almost all pairs open for trading with the 20-day horizon. However, not all pairs convergence and the trade is terminated within the 20-days. As we can see from Panel B of Table 1 to have about 50% of the pairs to converge we require a trading horizon of about 40 days. This is an interesting result of practical significance that can partially explain the success of the pairs trading method: if one waits long enough for all the trades to converge will essentially gain nothing from this strategy; there appears to be an issue of underlying "timing" at work here, a horizon after which you will not be making much of a profit. Taking any profits that may arise using the signals of the strategy appears to be a suitable way to go.

### 5.3. Stochastic dominance

There is considerable literature that uses the notion of "stochastic dominance" in evaluating the performance of strategies and the ranking of assets (e.g. mutual funds) and types of portfolios. Here we use the methodology proposed by Cho et al. (2007) for a quick (but comprehensive) way to assess the overall performance of the pairs trading strategy we implemented.[9] In an early paper, 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*". Fong et al (2005) find evidence for international momentum strategies. They strongly argue that the non-parametric nature of stochastic dominance tests allows clearly deciding between profits and losses and the knowledge of the utility function is adequate for the investors to decide, without to be aware of the distribution of the returns. Post (2003) compared the power of stochastic dominance efficiency into a portfolio. In his 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).

We will not digress into many details of the methodological and computational aspects of the tests we performed, as they are given in the Cho et al. (2007) paper, but proceed directly to the hypotheses of interest and the results.[10] The null hypothesis is that a particular strategy is dominated by the benchmark. Here this is formulated (along with the alternative) as:

[9] We make no attempt to review the large literature on stochastic dominance here. The paper by Cho et al. (2007) contains many references up to that date.

[10] Details on the methodology and computational details are available on request.

**$H_o$:** pairs profitability stochastically dominated by S&P500 profitability

**$H_1$:** pairs profitability stochastically dominates S&P500 profitability

Table 2, has the results according to first through third order stochastic dominance. These concepts are basically saying that the average utility (of unknown form) of the returns is higher for the better strategy and that the cumulative distribution function of the better strategy's returns is everywhere lower than the distribution function of the competing strategy (i.e., there is lower cumulative probability of smaller returns, for any given return value, for the better strategy). For all the cases examined, the *p*-values reject the null hypothesis showing that pair trading returns dominate the distribution of S&P500 returns. Under utility function/decision making framework, a rational investor who chooses to invest on a net exposure to the market will prefer to invest in pair trading strategy rather than to the buy and hold strategy on S&P500.

### 5.4. Omega Function

Another approach for a non-parametric, "total" performance measure is that based on the (so-called) omega function or omega ratio developed by Keating and Shadwick (2002) and further detailed and explained in Kazemi et al. (2004). This is a statistic that is based on the use of the distribution function of returns and it compares the cumulative probabilities between two sections of the distribution function. As re-iterated in Bertrand and Prigent (2010) the omega ratio is defined as "the probability weighted ratio of gains to losses relative to a return threshold". The formula for the omega ratio is given by:

$$\Omega(L) = \int_L^b [1 - F(r)]\,dr \Big/ \int_a^L F(r)\,dr \qquad (7)$$

where $F(r)$ is the cumulative distribution of the return defined in the interval $(a,b)$ and $L$ is the is the return threshold (we use $L = 0$ in our analysis). Anything above the threshold is considered a gain and anything below it a loss. From this definition we can see that a larger omega ratio is preferable to a smaller one. There is a nice interpretation, provided by Kazemi et al. (2004), as the ratio of expectations of gains above the threshold to expectations of losses below the threshold.

Figure 5, exhibits the results of omega ratio under the segmentation between positive returns. The results represent the best 5 eligible pairs for the main pairs trading strategy in relative comparison with the long and short components, the S&P500 and an equally weighted portfolio (the latter constructed by the long and short components). The results here are not favourable to the pairs trading strategy since they exhibit that the upside mean is limited for pair trading, however, one should note that the S&P500 and an equally weighted portfolio exhibit a steepest curve about zero returns.

### 5.5. Profitability of pairs trading: baseline results

Pairs' trading is, in general, a profitable strategy as can be seen from the broad summary measures of the previous sections. The extent of the profitability results that we obtain of course varies, depending on the number of pairs $L$ used, the groupings based on market origin or capitalization and sub-samples in time. But it will be seen that the profitability results are robust across all these categories.

Before discussing the results let us overview the exact methodological parameters on which they are based. The back testing starts on September, 23 1996 with the first 19 available ETFs. At June, 20 2000 we add the latest ETF. The number of pairs used in constructing the portfolio returns are set to $L = 2, 5, 10$ and 20. The formation period is 120 and the trading period is 20 days; results based on a 60-day trading period are also available but not discussed here. The threshold parameter is set to $c = 0.5$ throughout. Finally, a trade is initiated at the closing prices of the day *after* a signal is given (one-day waiting) and, for comparison, we also provide results when a trade is initiated at the closing prices of the signal ("event" in the tables) day.

Table 3 presents the baseline results of our application of pairs trading. Panel A has the results based on the event day and Panel B has the results with one-day waiting. We present various summary measures and we discuss them in turn. Terminal wealth of the portfolio is affected by the size of $L$: using half or more of our universe of pairs results in deterioration of performance based on terminal wealth, especially when one uses the (more realistic) one-day waiting approach. Therefore, a smaller size of pairs, in our case that of about 10% to 25%, appears to be best suited for the strategy at hand. Note that terminal wealth is cut in half or more when the one-day waiting approach is used although the other performance measures appear to be quite similar. The strategy's skewness is always positive, a rather significant result when compared to the mildly negative skewness that most equity indices have.[11] Next, note the difference in the risk of the $L$ = 2 portfolio vs. the portfolios with $L$ = 5 or more pairs: as expected, a larger $L$ leads to a smaller standard deviation of the strategy but also to a smaller Sharpe ratio (for Panel B; in Panel A the Sharpe ratios are becoming larger with $L$ but the practicality of the event-day strategy is rather limited). The use of $L$ = 5 pairs appears to be giving the best overall performance throughout in Table 1; the annualized Sharpe ratio for the $L$ = 5 pairs portfolio for the one-day waiting period is about 1,86 (using 252 trading days per year).

The results of the table also reveal that the timing abilities of this strategy are rather good: the mean positive excess return of the strategy is always larger than the mean negative excess return of the strategy. This implies that the successful trades are on average larger (they are slightly over 50%) than the negative ones but, more importantly, they tend to be more accurate in their timing. This is important for making an investor using this strategy accept the inherent risks. Finally, it's also important to note that the strategy is almost unrelated to the returns of the S&P500 index (especially for $L$ = 2 or $L$ = 5); this reflects on either the international composition of our ETF group (which, nevertheless, includes the ETF for the S&P500) or on the timing ability of the strategy to correctly identify disequilibria in the price paths.

The evolution the strategy's wealth (cumulative return), corresponding to Panel B of Table 3, is given in Figure 2. There we plot the pairs trading performance, the S&P500 and also the long and the short components of the strategy, all for $L$ = 2, 5, 10 and 20 pairs. There are some interesting features in the plots: first, the strategy's performance during the boom years before 2000 is below that of S&P500 but it sharply picks up and outperforms the S&P500 after we go into the bear market; second, the strategy's performance increases almost monotonically for all pairs except for $L$ = 2, when we can see a large drawdown period after 2002; third, the apparent success of the strategy's timing ability shows through the domination of the short component – this makes sense since the strategy's performance starts going over the S&P500 when the bear market started; finally, this figure leaves open the question as to whether the strategy would

[11] Goetzmann et al (2002) argued that evaluation results based on the Sharpe ratio can be misleading if the strategy's return distribution exhibits negative skewness but this problem disappears when we observe positive skewness.

perform equally well if it was implemented from a different starting point. We return to this question later in our discussion.

Before continuing we give a very brief comparison of performance of pairs trading between this paper and GGR (2006). For the top $L$ = 5 eligible our asset selection and implementation gave an average monthly excess of 1.49% versus a 0.78% for GGR; for $L$ = 20 the numbers are much more similar, being 0.93% and 0.81% respectively.

The relative comparison between short 20days and long strategy 60days is given in Table 4. 20days outperforms the 60days trading in means of mean return, while both the risk profile and the risk-return profile is improving as we let the trade open beyond 20days.

Figure 4, illustrates the empirical distribution of the mean 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).

### 5.6. Results based on market capitalization

Are the results we have seen so far affected by market size? After all our grouping is one that includes data on ETFs from different markets. We repeat our analysis by splitting the ETFs into "small" and "large" capitalization groups and examining the new results. In the context of their analysis, GGR (2006) argued that an examination of different levels of capitalization provides a robustness check against short-selling – and we have seen that the short component was pretty strong in driving the previous results. In the context of pairs trading and contrarian strategies, Avramov et al (2006) claim that large mean reversals are positively linked to illiquid stocks and higher turnover. Put differently, a 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.[12]

[12] In the context of more "traditional" approaches that rely on market capitalization there is some evidence that across countries small capitalization might outperform large capitalization; see De Bondt et al (1989), Conrad et al (1989), Rouwenhorst (1998), Zarowin (1990), Richards (1997), Chan (1988) and Knez et al (1996).

For the size split we consider "large" capitalization to correspond to ETFs with market cap between 384 millions to 65 billion while "small" capitalization to correspond to ETFs with market cap from 330 million down to 59 millions. Accordingly, we have in the "large" cap category the ETFs for: Australia, Brazil Canada, EMU, Hong Kong, Japan, Singapore and South Korea, Taiwan, UK, S&P500; and on the "small" cap category the ETFs from Austria, Belgium, France, Germany, Italy, Malaysia, Mexico, the Netherlands, Spain, Sweden and Switzerland Table 5 has the related results.

The most striking result from this split is that performance of the trading strategy is greatly reduced for both groups, in terms of terminal wealth, mean return and Sharpe ratio – although the strategy's performance remains unrelated to the S&P500. However, we can also see that there are differences between the "large" and "small" ETFs. First, the performance appears to be slightly better for the "small" cap group in terms of terminal wealth and Sharpe ratio – now for $L = 5$ the annualized Sharpe ratio for the "small" cap group is 1.03 and for the "large" cap group is 0.87. Due to the diminished size of the universe of ETFs in each group we also see that better performance is for $L = 2$ rather than $L = 5$ but with a lower Sharpe ratio. Second, the performance of the "small" cap group might be driven by the timing ability of the strategy in the smaller markets since we can see that the percentage of observations with positive returns is larger for this group than for the "large" cap group. Overall, the results here indicate that a blend large and small ETFs is better than either group alone – the strategy needs a larger, more diverse universe to be able to provide market timing results.

EGJ (2008) split their sample into two portfolios based on average market capitalization and level of liquidity, however they do not find anything conclusive in terms of the interaction of market capitalization and profitability for their data. This suggests that the type of exposure (domestic vs. international) may also be a significant factor behind pairs trading performance.

### 5.7. Results based on type of market (developed vs. emerging)

Splitting the ETFs into "small" and "large" cap groups is useful but it mixes markets that are mature with markets that are still developing. Since emerging markets are always seen as potential opportunities it is of interest to separately analyze the performance of the strategy in developed and emerging markets. Bekaert et al. (2000) claim that to treat emerging markets as identical to developed markets could lead to wrong conclusions.

Due to the pronounced heterogeneity of this new split we have to make some changes in the way we run our backtesting. First, due to differences in inception dates the backtesting starts on June of 2000. Second, there are only five ETFs classified as "emerging" markets:[13] Brazil, Malaysia, Mexico, Taiwan and South Korea; this limits the number of pairs to be considered to a max of $L = 10$.

Our results from this split are given in Table 6. Emerging markets as expected outperform developed markets in means of mean return. However, the risk of trading in emerging markets is higher than these of developed markets. In means of Sharpe ratio developed markets achieved better. However, the crucial fact is the evidence of mean reversion in emerging markets.

### 5.8. Results based on long and short components separately

As we already discussed in the baseline results (see Figure 2), the short component in the pairs trading appear to be dominating the long component.[14] In Table 7 we present more detailed results that document that indeed this is the cases (here we are again using all ETFs as in the baseline results). The better performance of the short component is evident across all $L$ pairs but note that its effect diminishes as $L$ increases. While there is a differences in terminal wealth, mean return and Sharpe ratio, it's interesting to note that the differences in the standard deviations of the short and long components are rather small. Another interesting result in the table is that we can now see a pronounced, positive correlation of both the short and long component with the S&P500: this probably supports the timing ability of the strategy, since we require a positive correlation even when the S&P500 is falling so as to effect the short side of the trade. See that the correlation with the S&P500 is larger for the short component, thus supporting what we saw in Figure 2 (the strategy picking up in terms of performance when the S&P500 started falling in 2000). Our results are in contrary with those in GGR (2006). We should argue about that, probably has to do with the volatile environment during the crisis 2007-2009, or the narrow distance criterion.

### 5.9. Results based on sub-samples: sensitivity analysis

Does it matter when this (or any other trading strategy) starts? It should matter otherwise we would have a "universal" winner. To examine the sensitivity of our results so far we break the full sample into four sub-samples covering different periods of interest: first

[13] We followed the MCSI classification for this.

[14] GGR (2006) argued about the necessity of examining separately these two components of the strategy.

sub-sample goes from April 1, 1996 until the end of 1999; the second sub-sample goes from January, 1 2000 and ends on 2002; the third sub-sample starts in 2003 and ends in 2005 while the last sub-sample spans 2006 to March 2009. As we already noted in passing, the first period is one of a bull market, the second period has the bear market that followed, the third period can be thought of as the "recovery" period for global markets while the fourth and last period has a structural break in it (first going into a small uptrend and then getting into the subprime crisis and the ensued global financial turmoil).

If pairs trading is a "true" market-neutral strategy we would expect to maintain its profitability even in bear markets where a significant downturn is occurring. We can examine whether this is the case by looking at the results in Table 8. The performance details during the second sub-sample immediately stand out: performance is increasing with $L$ as does the positive correlation of the strategy with the S&P500. The annualized Sharpe ratio for L = 5 (for comparability with the baseline results) is now 2.06 (compared to 1.86 in the baseline case), a value that falls in the range of practitioners' interest. Then, note that the strategy's performance is (obviously) best during trending markets, i.e. in the first or the second subsample, irrespective of the trend direction. During the "recovery" period of the third sub-sample the performance is worse among all four sub-samples considered. During the second and third sub-samples there appears to be increased "risk aversion", and that a higher $L$ gives better performance. On the fourth sub-period that contains both a positive trend and a break components we can see that performance has the same characteristics as in the first sub-sample although all measures are now smaller in magnitude; note that here we have, as in the second sub-sample, increased correlation with the S&P500.

## 6. Pairs Trading Profitability and Economic Fundamentals

Our discussion so far shows that, in GGR (2006) and EWJ (2008), pairs trading is a viable and profitable trading strategy that exploits price divergence among co-moving assets. However, where does its profitability come from? This question has been addressed in these two studies but here we have a different family of assets that we are working with. We therefore have to use not just the literature standards, such as the Fama and French factors, but also other economic and market variables that are suitable to the international aspect of our dataset.

We cannot possibly review the literature that relates to factors here in any degree of detail. We briefly go over some references that are related to the work that we discuss in this section. We can split the work on factors on three major categories, according to the purpose that the asset pricing model has been constructed. We have:

(1) Firm–Level Characteristics (Idiosyncratic), as in Cavaglia, Brightman and Aked (2000), Carrieri, Errunza and Sarkissian (2005), Hou, Karolyi and Kho (2006) and EWJ (2008).

(2) Market level characteristics (local and global markets), as in Fama and French (FF) (1993, 1996, 1998), Rouwenhorst (1998) and Griffin (2002).

(3) Macro-economic or country characteristics, as in Chan, Chen and Hsieh (1985), Chan and Chen (1991), Cooper, Gulen and Vassalou (2001), Liew and Vasalou (2000), Vasalou (2003), Brennan, Wang and Xia (2004) and Petkova (2006).

Financial practitioners have also employed several risk models including explanatory factors, the most popular being (according to Hou et al., 2006) the 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).

### 6.1. Pairs trading against the FF-type factors

Table 9 has the results of a regression of compounded monthly returns from our backtesting on the three FF factors and a momentum factor.[15] For both the 20 and the 60-day trading horizon we can see that there are significant excess returns that cannot be explained by any factor except the HML one, which is based on book-to-market. The estimates are negative and significant for all choices of $L$ pairs. Our results reveal a different source of pairs trading profitability compared to GGR (2006) and EWJ (2008), which was expected due to the different composition of the universe of assets that we considered here.

Performing the same analysis but in sub-samples, and adding two more momentum indicators, we can see a variety of interesting results at Table 10. First, note that the

[15] The conversion to monthly returns was done for conformability with the earlier literature; results are available for a daily frequency as well. Moreover, all the estimations have been conducted with the long and short term reversal factor as they are presenting in Ken French site. However, their explanatory power was and we drop; results are available as well. We run the results using the rolling p-value in order to check; results are available on request.

significant excess returns now only appear in the first and second sub-sample of the bull/bear markets that goes until 2000 and 2002; this is in accordance of our earlier result that pairs trading appeared to worked strongly in trending markets. During these two sub-samples no factor appears to be statistically significant, except the short-term reversal indicator for the second sub-sample – which again validates the timing ability of the strategy. Second, for the third and fourth sub-samples it is difficult to discuss the explanatory ability of the factors since the excess returns are statistically zero. The significant coefficients appeared scattered with no discernible pattern.

In Tables 11 and 12 we present results similar to Table 9 but using the ETF splits to emerging vs. developed markets and "small" vs. "large" capitalization – as we have done for the presentation of baseline results in Tables 5 and 6. For the split based on market development, in Table 11, we can see that excess returns are significant in both types of markets but profitability is explained by different factors. In the case of emerging markets the market and momentum factors loads negatively and significantly while in the case of developed markets the book-to-market factor leads negatively and significantly. These results are intuitive since the emerging markets could not possibly be explained by structural factors like book-to-market but rather by the leading U.S. market and the underlying momentum. Note that the $R^2$ values from the emerging markets regressions are the highest so far, up to 17% for the top $L$ = 5, 10 pairs. Turning next to the split based on capitalization, in Table 12, we can see that for the "large" cap portfolio we have significance excess returns and negative and significant the size factor – that was to be expected. For the "small" capitalization portfolio the excess returns are significant but not as significant as in the "large" cap case; no factor appears to be overall significant

Finally, in Tables 13 and 14 we present results from a regression based on FF-type international factors, constructed from international indices that were weighted based on the MCSI EAFE index. The results of the full sample in Table 13[16] show that we have excess returns that are significant and cannot be explained by any of these factors, maybe except the book-to-market factor for $L = 2$ – but then again this choice of $L$ was not the most successful one in backtesting. On the other hand in Table 14, where we have the sub-samples that were discussed before, we can see some more interesting results. For the first sub-period the excess returns remain significant while there is some (limited) explanatory power to the earnings to price variable; for the second sub-period (the bear

[16] We conduct the estimations with the earnings-to-price variable and dividend yield as they appear in Ken French website; Results are available on request.

market after 2000) no factor has any explanatory value – this is important as the strategy has a very good performance even during downturns and it's interesting to know that this performance is unrelated to these international factors. However, the most interesting of all results in Table 14 are those for the last period, which is after 2006. Note here the magnitude of the $R^2$ values, which ranges from 37% to 59% indicating that these international factors can explain a large percentage of variation for pairs trading during this period that includes the onset of the financial crisis. Two variables account for this percentage of explanatory power, earnings-to-price and dividend yield, especially the last one.

### 6.2. What drives signals in pairs trading? Opening and duration of positions

While it is clearly interesting to examine the potential factors that explain pairs trading profitability, it is also of interest to consider whether there are economic or financial variables that can explain the generation of signals in pairs trading. Is it then possible to identify if profitability can be linked to economic fundamentals, the emphasis now being that we are using international ETFs for the trades. Such an exercise requires that we track all individual trading signals and then associate them with, appropriately time-aligned, variables. EWJ (2008) have done a similar exercise for their universe of U.S. stocks only in terms of idiosyncratic risk, while GGR (2006) have not considered it. Concentrating on the $L = 5$ top pairs portfolio and looking at the 20-day and 60-day trading horizon, we next discuss our approach and results for explaining signal generation. Note that we pool all signals from the top 5 pairs and form a "cross-sectional" regression (in the sense that the time ordering of the signals is not used) where the explanatory variables are properly aligned with the time of the signals.

To begin with, we have to define the variables that we will be using to explain signal generation and a method for model reduction. The variables that we use are both economic and financial and are listed and are detailed in the appendix. As for model reduction we follow the simplest possible approach that maintains a solid statistical foundation: all variables are entered in at the initial estimation stages and they are removed (one-at-a-time) based on their *p*-value; estimates with the largest *p*-value go off first. This approach maintains the appropriate level of significance at all times and we have found it to be robust against other variable selection methods, such as stepwise regression. This model reduction approach is used both on all set of explanatory variables and also on various sub-groups (macroeconomic, market, fundamentals).

Furthermore, it is important to note that we (a) use the long and short component of the strategy separately, in addition to using the full strategy results alone and (b) we pairwise align the explanatory variables in all regressions so that they correspond to each member of the pair: each time that a new pair is initiated for trading the explanatory variables change accordingly to the members of the pair.

We thus estimate five (5) groups of regressions as follows:

- The first group includes all variables.
- The second group includes only the macroeconomic variables.
- The third group includes the market variables.
- The fourth group includes fundamental variables.
- Finally, the fifth group contains the variables that survived model reduction from the above four groups.

In Tables 15 and 16 we present results on the explanatory power of variables for the opening of a pair and for the duration that a trade stays open.[17] For breity we discuss below the results from the first group.

The short position is more volatile and risky than the long position and it is well known that the hedge funds suffer more to bear short positions in an uptrend market. As anticipated, the longer trading horizon can be explained with more factors that the 20days trading. Regarding the significant factors we find that investors pay attention on the dividend yield, probably investors during the last ten years were driven by value equities instead of growth. The EPS forward factor is also significant and this result is of interest since it would imply that investors are taking under consideration (again, as anticipated) the forward looking outlook of the markets. Moreover, portfolio inflows also are found to have explanatory power to the divergence of the underlying assets. Turning next to the macroeconomics factors, unemployment is found to have more explanatory power instead of GDP – this accords well with recent market moves where unemployment is gauged as a more important indicator that can lead to substantially volatile movements in equity markets. Furthermore, turnover and volatility are also significant factors for the presented strategy as they contain momentum information for the capital flows and investors pay attention to them. Aggressive positions can be disclosed by these flows (heavy trading). It is well established that volatility creates

[17] The results on Table 15 are from a standard binary data regression (logistic) on the event of a trade being opened for any of the top 5 pairs. The results on Table 16 are from a negative binomial regression on the duration of days that a trade stays opened.

divergence and consequently increases the opportunities for trading and arbitrage opportunities.

Finally, in Table 17, we present results on the explanatory power of variables for the pairs returns of a pair. Regarding the 20-days trading, the factor EPS and dividend yield appeared to be significant while in 60-days trading, divergence is explained only with the short side of the components. Money market rates and country credit rating is also found to have explanatory power on the return of the pairs. As anticipated, the money market rates exhibits a positive effect, while the country credit rating exhibits a negative link with the pairs returns.

## 7. Concluding remarks

We examine in detail the performance of a popular and successful trading strategy, pairs trading, using international ETFs. Our study supports the existing literature on the profitability of this strategy and also brings forth some new insights, now in the context of the popular investment vehicle that are ETFs. Our results show that there is an asymmetric response between the long and the short component of the strategy which enhances overall profitability. We find that the strategy dominates the profitability of the S&P500 benchmark in a variety of parameter combinations and also that it has very small correlation with this benchmark. This profitability survives over different market periods and over different sub-samples on the composition of our ETF universe, such as based on market capitalization and market development. We then examine the sources of profitability of the strategy using the standard Fama-French factors and a variety of other variables. This analysis confirms the presence of excess returns, although the explanatory power of these variables is limited. Finally, we discuss the underlying drivers for initiating a trade and for the duration of the relevant position, both of which directly affect overall profitability. The combined results from this exercise suggest that the most important factors boil down to be earnings per share, dividend yields and the unemployment rate. All in all our analysis strongly supports the merits of pairs trading as an economically meaningful and practical investment approach.

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# Tables and Figures

## Table 1

### Summary of Trading Statistics

The table represents the trading statistics of the excess return portfolios. Due to different inception dates of dataset, I 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. On Panel A, 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 takes place the next business day of the 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 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

## 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 tests. Stochastic dominance test examines the order of dominance between two assets according to their distribution. The test refers to the null hypothesis that pair profitability is stochastically dominated 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 3

## Summary Statistics of Daily Estimations of Baseline results

The table represents the summary statistics in percentages 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 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 Wealth | 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 Wealth | 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 4

## 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* | | | | *60 days* | | | |
|---|---|---|---|---|---|---|---|---|
| ***Pairs Portfolio*** | *Top 2* | *Top 5* | *Top10* | *Top20* | *Top 2* | *Top 5* | *Top10* | *Top20* |
| Terminal Wealth | 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 5

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

The table represents the summary statistics in percentage basis of the excess return distribution including the segmentation of the data set into two portfolios according to their capitalization: The first portfolio includes the first 50% of the sample with the larger capitalization and the supplementary 50% included in the second portfolio. 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. The implementation of the strategy occurs the next business day after the event of divergence occurs

| | Large Capitalization Portfolio | | | | Small Capitalization Portfolio | | | |
|---|---|---|---|---|---|---|---|---|
| ***Pairs Portfolio*** | *Top 2* | *Top 5* | *Top10* | *Top 20* | *Top 2* | *Top 5* | *Top10* | *Top 20* |
| Terminal Wealth | 4,352 | 3,511 | 2,301 | 2,000 | 4,766 | 3,197 | 2,038 | 1,873 |
| Mean | 0,052 | 0,043 | 0,029 | 0,024 | 0,053 | 0,039 | 0,024 | 0,021 |
| Standard Deviation | 1,010 | 0,785 | 0,667 | 0,647 | 0,829 | 0,595 | 0,517 | 0,447 |
| Sharpe Ratio | 0,051 | 0,055 | 0,043 | 0,037 | 0,064 | 0,065 | 0,046 | 0,047 |
| Maximum | 8,300 | 7,940 | 6,260 | 4,790 | 4,400 | 2,940 | 3,340 | 2,620 |
| Minimum | -5,810 | -5,050 | -4,740 | -4,190 | -7,200 | -2,660 | -2,320 | -1,980 |
| Skewness | 0,385 | 0,934 | 0,679 | 0,525 | 0,009 | 0,020 | 0,133 | 0,183 |
| Kurtosis | 7,260 | 12,100 | 11,000 | 8,700 | 7,180 | 4,690 | 5,280 | 5,340 |
| Correlation with S&P500 | -0,022 | 0,037 | 0,066 | 0,112 | 0,094 | 0,110 | 0,135 | 0,178 |
| Observations with Excess return>0 | 50,32% | 50,32% | 50,96% | 51,27% | 50,96% | 53,18% | 51,59% | 51,91% |
| Mean of Excess Return >0 | 0,767 | 0,579 | 0,485 | 0,466 | 0,628 | 0,448 | 0,393 | 0,338 |
| Mean of Excess Return <0 | -0,693 | -0,504 | -0,444 | -0,440 | -0,565 | -0,427 | -0,369 | -0,320 |
| Mean of top ten excess return | 5,004 | 5,078 | 3,966 | 3,690 | 3,590 | 2,327 | 2,307 | 2,061 |
| Mean of bottom ten excess return | -4,222 | -3,128 | -2,943 | -2,698 | -3,614 | -2,225 | -1,944 | -1,698 |

# Table 6

## 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 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 7

## 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 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 8

### 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 9

## Profitability of Pair Trading Strategies

The 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 French. 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 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 year long losers (MOMENTUM). The corresponding p-values are reported for each separate variables and statistics are corrected for autocorrelation and heteroscedasticity using the Newey-West estimator with 4 lags. The sample period is from 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 | 0,016 | 0,012 | 0,009 | 0,012 | 0,009 | 0,007 | 0,006 |
| | 0,000 | 0,000 | 0,000 | 0,000 | 0,004 | 0,001 | 0,000 | 0,000 |
| Market | -0,049 | 0,004 | -0,014 | -0,019 | -0,068 | -0,005 | -0,012 | 0,010 |
| | 0,454 | 0,949 | 0,763 | 0,660 | 0,540 | 0,941 | 0,727 | 0,805 |
| HML | -0,206 | -0,183 | -0,188 | -0,107 | -0,248 | -0,108 | -0,097 | -0,091 |
| | 0,005 | 0,008 | 0,001 | 0,047 | 0,023 | 0,103 | 0,041 | 0,035 |
| SMB | -0,031 | -0,031 | 0,048 | 0,038 | -0,031 | 0,054 | 0,021 | -0,013 |
| | 0,817 | 0,708 | 0,429 | 0,500 | 0,778 | 0,335 | 0,568 | 0,724 |
| Momentum | 0,076 | 0,074 | 0,025 | 0,059 | 0,042 | 0,012 | -0,001 | -0,006 |
| | 0,211 | 0,157 | 0,527 | 0,130 | 0,410 | 0,739 | 0,950 | 0,821 |
| *Observations* | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 |
| $R^2$ | 0,039 | 0,062 | 0,115 | 0,086 | 0,049 | 0,046 | 0,050 | 0,047 |

# Table 10

## 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 11

## 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). 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* |
| Intercept | 0,012 | 0,010 | 0,005 | 0,014 | 0,013 | 0,010 |
| | 0,037 | 0,025 | 0,146 | 0,000 | 0,000 | 0,000 |
| Market | -0,345 | -0,494 | -0,419 | -0,025 | -0,015 | -0,022 |
| | 0,155 | 0,027 | 0,014 | 0,709 | 0,808 | 0,602 |
| HML | -0,099 | -0,184 | 0,006 | -0,173 | -0,250 | -0,075 |
| | 0,727 | 0,502 | 0,976 | 0,020 | 0,002 | 0,253 |
| SMB | -0,011 | 0,024 | 0,028 | -0,191 | -0,096 | -0,031 |
| | 0,953 | 0,911 | 0,877 | 0,088 | 0,136 | 0,546 |
| Momentum | -0,214 | -0,242 | -0,276 | 0,063 | -0,010 | 0,042 |
| | 0,118 | 0,002 | 0,002 | 0,269 | 0,784 | 0,175 |
| *Observations* | 98 | 98 | 98 | 150 | 150 | 150 |
| $R^2$ | 0,060 | 0,166 | 0,170 | 0,046 | 0,088 | 0,037 |

## Table 12

## 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). The corresponding p-values are reported for each separate variable, and statistics 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.

| | Large Capitalization Portfolio | | | | Small Capitalization Portfolio | | | |
|---|---|---|---|---|---|---|---|---|
| Monthly Pairs Portfolio | *Top 2* | *Top 5* | *Top 10* | *Top 20* | *Top 2* | *Top 5* | *Top 10* | *Top 20* |
| Intercept | 0,013 | 0,009 | 0,005 | 0,005 | 0,010 | 0,008 | 0,005 | 0,005 |
| | 0,000 | 0,000 | 0,001 | 0,001 | 0,018 | 0,016 | 0,033 | 0,055 |
| Market | -0,005 | 0,043 | 0,081 | 0,021 | 0,000 | -0,133 | -0,061 | -0,030 |
| | 0,943 | 0,405 | 0,044 | 0,527 | 0,999 | 0,175 | 0,265 | 0,584 |
| HML | -0,276 | -0,072 | 0,051 | 0,015 | -0,068 | -0,071 | -0,011 | -0,059 |
| | 0,000 | 0,250 | 0,237 | 0,711 | 0,490 | 0,559 | 0,897 | 0,526 |
| SMB | -0,193 | -0,175 | -0,085 | -0,066 | 0,250 | 0,027 | 0,032 | 0,036 |
| | 0,027 | 0,006 | 0,069 | 0,122 | 0,037 | 0,791 | 0,712 | 0,659 |
| Momentum | -0,060 | -0,014 | -0,018 | -0,055 | 0,027 | 0,065 | 0,072 | -0,003 |
| | 0,096 | 0,775 | 0,571 | 0,063 | 0,789 | 0,323 | 0,196 | 0,952 |
| *Observations* | 150 | 150 | 150 | 150 | 150 | 150 | 150 | 150 |
| $R^2$ | 0,074 | 0,070 | 0,070 | 0,059 | 0,056 | 0,049 | 0,037 | 0,012 |

# Table 13

## 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). 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 | 0,018 | 0,016 | 0,012 | 0,010 | 0,013 | 0,007 | 0,006 | 0,006 |
| | 0,000 | 0,000 | 0,000 | 0,000 | 0,009 | 0,010 | 0,001 | 0,000 |
| Market | 0,011 | 0,052 | 0,023 | -0,011 | 0,102 | 0,117 | 0,036 | 0,041 |
| | 0,869 | 0,294 | 0,618 | 0,842 | 0,354 | 0,119 | 0,328 | 0,384 |
| B/M | 0,068 | 0,174 | 0,142 | 0,081 | 0,034 | -0,131 | -0,101 | -0,122 |
| | 0,825 | 0,403 | 0,314 | 0,476 | 0,868 | 0,300 | 0,234 | 0,075 |
| CE/P | -0,200 | -0,184 | -0,199 | -0,124 | -0,362 | 0,030 | -0,016 | 0,014 |
| | 0,406 | 0,233 | 0,109 | 0,237 | 0,068 | 0,816 | 0,843 | 0,858 |
| Observations | 136 | 136 | 136 | 136 | 136 | 136 | 136 | 136 |
| $R^2$ | 0,009 | 0,015 | 0,021 | 0,010 | 0,068 | 0,048 | 0,041 | 0,047 |

# Table 14

## 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 3 factors market excess return (MKT), book-to-market (B/M), cash earnings to price (CE/P).

| Period: | *1996:09-1999:12* | | | | *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 | 0,026 | 0,018 | 0,016 | 0,008 | 0,034 | 0,033 | 0,024 | 0,022 | 0,010 | 0,010 | 0,008 | 0,008 | 0,008 | 0,006 | 0,006 | 0,004 |
| | 0,027 | 0,023 | 0,010 | 0,082 | 0,005 | 0,001 | 0,002 | 0,002 | 0,032 | 0,013 | 0,007 | 0,014 | 0,039 | 0,009 | 0,014 | 0,038 |
| Market | 0,114 | 0,125 | 0,046 | 0,115 | 0,135 | 0,230 | 0,152 | 0,048 | -0,311 | -0,112 | -0,167 | -0,174 | -0,010 | 0,109 | -0,016 | -0,077 |
| | 0,421 | 0,294 | 0,667 | 0,216 | 0,182 | 0,009 | 0,070 | 0,599 | 0,102 | 0,348 | 0,136 | 0,076 | 0,931 | 0,280 | 0,906 | 0,168 |
| B/M | 0,501 | 0,439 | 0,295 | 0,218 | 0,274 | 0,515 | 0,407 | 0,135 | -0,448 | -0,159 | -0,040 | 0,049 | 0,214 | -0,122 | -0,024 | 0,113 |
| | 0,348 | 0,054 | 0,094 | 0,057 | 0,696 | 0,416 | 0,405 | 0,728 | 0,211 | 0,384 | 0,750 | 0,697 | 0,486 | 0,571 | 0,912 | 0,136 |
| CE/P | -0,610 | -0,580 | -0,333 | -0,345 | -0,468 | -0,451 | -0,485 | -0,212 | 0,473 | 0,001 | 0,147 | 0,078 | -0,088 | -0,108 | -0,159 | -0,088 |
| | 0,300 | 0,053 | 0,092 | 0,025 | 0,278 | 0,298 | 0,210 | 0,544 | 0,249 | 0,995 | 0,281 | 0,522 | 0,669 | 0,531 | 0,400 | 0,381 |
| *Observations* | 40 | 40 | 40 | 40 | 36 | 36 | 36 | 36 | 36 | 36 | 36 | 36 | 24 | 24 | 24 | 24 |
| $R^2$ | 0,037 | 0,103 | 0,064 | 0,141 | 0,067 | 0,100 | 0,111 | 0,030 | 0,119 | 0,064 | 0,100 | 0,158 | 0,027 | 0,100 | 0,046 | 0,082 |

# Table 15

## Analysis of Opening Probability of the pairs

The table represents a cross-sectional logistic regression of pairs opening probability from pair trading portfolios where the independent variables are the days that every pair is opening and takes the value of one. In panel A and panel B, the profits are computed from a strategy of 20days and 60days respectively. We run 4 different regressions. Regression 1 includes all the variables, regression 2 only the macro variables, regression 3 the market variables, regression 4 the fundamental variables and regression 5 only the variables that survived from the previous 4 regressions. 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.

**Panel A: 20 Days**

| | **All Variables (1)** | | **Macro (2)** | | **Market (3)** | | **Fundamentals (4)** | | **Optimized (5)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 5 pairs Portfolio | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value |
| Intercept | -1,579 | 0,000 | -1,852 | 0,000 | | | -1,447 | 0,000 | -1,482 | 0,000 |
| Inflation Long | | | | | | | | | 10,760 | 0,063 |
| Inflation Short | 10,585 | 0,063 | | | | | | | | |
| Default Premium Long | | | | | | | 0,104 | 0,002 | 0,104 | 0,002 |
| Dividend Yield Long | -5,571 | 0,064 | | | | | -8,728 | 0,002 | -7,803 | 0,008 |
| EPS forward Long | 0,000 | 0,036 | | | | | 0,000 | 0,014 | 0,000 | 0,012 |
| Eps Forward Short | -0,001 | 0,000 | | | | | -0,001 | 0,002 | -0,001 | 0,002 |
| FX Long | | | | | | | -0,723 | 0,001 | -0,607 | 0,005 |
| Market Volatility Long | -0,151 | 0,037 | | | | | | | -0,168 | 0,054 |
| Unemployment Rate Short | | | 0,022 | 0,090 | | | | | | |
| McFadden R-squared | 0,003 | | 0,000 | | | | 0,003 | | 0,004 | |
| Obs with Dep=0 | 11.360 | | 12.754 | | | | 11.488 | | 11.288 | |
| Obs with Dep=1 | 1.719 | | 1.999 | | | | 1.738 | | 1.713 | |

**Panel B: 60 Days**

| | **All Variables (1)** | | **Macro (2)** | | **Market (3)** | | **Fundamentals (4)** | | **Optimized (5)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 5 pairs Portfolio | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value |
| Intercept | -1,907 | 0,000 | -2,265 | 0,000 | -1,332 | 0,000 | -2,223 | 0,000 | -1,712 | 0,000 |
| Inflation Long | | | 11,014 | 0,096 | | | | | | |
| Default Premium Short | 0,129 | 0,002 | | | | | 0,066 | 0,050 | 0,128 | 0,003 |
| Dividend Yield Short | -9,843 | 0,020 | | | | | | | -12,010 | 0,006 |
| EPS forward Long | -0,001 | 0,003 | | | | | -0,001 | 0,001 | -0,001 | 0,000 |
| GDP Short | | | -0,037 | 0,052 | | | | | 0,053 | 0,040 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Market Cap Short | | | | | | | 0,000 | 0,076 | 0,000 | 0,034 |
| Market Volatility Short | 0,354 | 0.0421 | | | | | | | 0,421 | 0,011 |
| Unemployment Rate Short | -0,039 | 0.0575 | -0,034 | 0,074 | | | | | -0,050 | 0,029 |
| Turnover Long | 0,000 | 0.0444 | | | 0,000 | 0,000 | | | | |
| McFadden R-squared | 0,004 | | 0,001 | | 0,088 | | 0,002 | | 0,006 | |
| Obs with Dep=0 | 11140 | | 13082 | | 14107 | | 12127 | | 10598 | |
| Obs with Dep=1 | 1076 | | 1268 | | 1363 | | 1154 | | 1007 | |

# Table 16

## Survivor Analysis of Time to Convergence

The table represents a negative binomial regression of the days to convergence of each separate pair, where the independent variables are the days of each individual pair. In panel A and panel B, the profits are computed from a strategy of 20days and 60days respectively. We run 4 different regressions. Regression 1 includes all the variables, regression 2 only the macro variables, regression 3 the market variables, regression 4 the fundamental variables and regression 5 only the variables that survived from the previous 4 regressions. 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. Standard errors have been corrected with Huber-White.

**Panel A: 20days**

| | All Variables (1) | | Macro (2) | | Market (3) | | Fundamentals (4) | | Optimized (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 5 pairs Portfolio | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value |
| Intercept | 1,455 | 0,000 | 2,009 | 0,000 | | | 1,532 | 0,000 | 2,253 | 0,000 |
| GDP Short | | | -0,028 | 0,070 | | | | | | |
| Default Premium Long | | | | | | | -0,071 | 0,013 | | |
| Dividend Yield Short | 10,990 | 0,001 | | | | | 8,657 | 0,002 | | |
| EPS forward Long | 0,001 | 0,003 | | | | | | | 0,001 | 0,019 |
| Eps Forward Short | 0,001 | 0,001 | | | | | 0,001 | 0,000 | | |
| FX Long | | | | | | | 0,406 | 0,017 | | |
| Portfolio Inflows Short | 0,000 | 0,053 | | | | | 0,000 | 0,014 | | |
| Unemployment Rate Long | -0,109 | 0,039 | -0,079 | 0,077 | | | | | | |
| Unemployment Rate Short | | | -0,026 | 0,021 | | | | | | |
| Turnover Short | 0,000 | 0,038 | | | | | | | 0,000 | 0,077 |
| R-squared | 0,020 | | 0,003 | | | | 0,018 | | 0,005 | |
| Observations included | 1.216 | | 1.510 | | | | 1.756 | | 1.246 | |

**Panel B: 60days**

| | All Variables (1) | | Macro (2) | | Market (3) | | Fundamentals (4) | | Optimized (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 5 pairs Portfolio | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value |
| Intercept | 1,883 | 0,000 | | | | | 1,880 | 0,000 | 1,880 | 0,000 |
| Default Premium Short | -0,143 | 0,002 | | | | | -0,143 | 0,002 | -0,143 | 0,002 |
| Dividend Yield Short | 13,797 | 0,004 | | | | | 13,797 | 0,004 | 13,797 | 0,004 |
| R-squared | 0,007 | | | | | | 0,007 | | 0,007 | |
| Observations included | 1.254 | | | | | | 1.254 | | 1.254 | |

# Table 17

## Times-Series Cross Sectional Regressions of Pairs Returns

The table represents a times series cross-sectional regression of excess returns from pair trading portfolios where the independent variables are the pairs returns of each individual pairs profit. In panel A and panel B, the profits are computed from a strategy of 20days and 60days respectively. We run 4 different regressions. Regression 1 includes all the variables, regression 2 only the macro variables, regression 3 the market variables, regression 4 the fundamental variables and regression 5 only the variables that survived from the previous 4 regressions. 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.

**Panel A: 20Days**

| | **All Variables (1)** | | **Macro (2)** | | **Market (3)** | | **Fundamentals (4)** | | **Optimized (5)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 5 pairs Portfolio | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value |
| Intercept | -1.168 | 0,08 | -3,43 | 0,00 | | | -1,34 | 0,03 | -2,47 | 0,00 |
| Default Premium Long | | | | | | | 0,46 | 0,01 | 0,56 | 0,00 |
| Dividend Yield Short | -46,68 | 0,02 | | | | | -50,98 | 0,01 | -31,35 | 0,04 |
| EPS forward Short | 0,00 | 0,05 | | | | | 0,00 | 0,06 | | |
| FX Long | | | | | | | -2,12 | 0,05 | -2,53 | 0,02 |
| Money Market Rates Short | | | | | | | | | | |
| Portfolio Inflows Short | 0,00 | 0,00 | | | | | 0,00 | 0,00 | | |
| Inflation Long | | | -55,15 | 0,06 | | | | | -64,14 | 0,04 |
| R-square | 0,02 | | 0,00 | | | | 0,02 | | 0,01 | |
| Observations | 1.641 | | 2.096 | | | | 1.756 | | 1.856 | |

**Panel B: 60Days**

| | **All Variables (1)** | | **Macro (2)** | | **Market (3)** | | **Fundamentals (5)** | | **Optimized (6)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Top 5 pairs Portfolio | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value | Coefficient | p-Value |
| Intercept | -0,002 | 0,003 | -0,001 | 0,472 | -0,003 | 0,000 | -0,004 | 0,000 | -0,004 | 0,000 |
| Inflation Short | | | -0,202 | 0,035 | | | | | | |
| Default Premium Short | 0,001 | 0,021 | | | | | 0,001 | 0,035 | 0,002 | 0,008 |
| EPS Forward Short | 0,000 | 0,067 | | | | | 0,000 | 0,021 | 0,000 | 0,004 |
| GDP Short | | | -0,001 | 0,018 | | | | | | |
| Market Cap Short | 0,000 | 0,011 | | | | | | | 0,000 | 0,008 |
| Money Market Rates Short | 0,008 | 0,077 | 0,010 | 0,047 | | | | | 0,011 | 0,038 |
| Portfolio Inflows Short | | | | | | | 0,000 | 0,015 | 0,000 | 0,089 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Credit Rating Short | -0,003 | 0,062 | | | | | | | | |
| Market Volatility Short | | | | | 0,005 | 0,007 | | | 0,005 | 0,004 |
| Turnover Short | 0,000 | 0,040 | | | | | | | 0,000 | 0,016 |
| R-square | 0,020 | | 0,011 | | 0,052 | | 0,009 | | 0,032 | |
| Observations | 986 | | 1.116 | | 1.388 | | 1.230 | | 937 | |

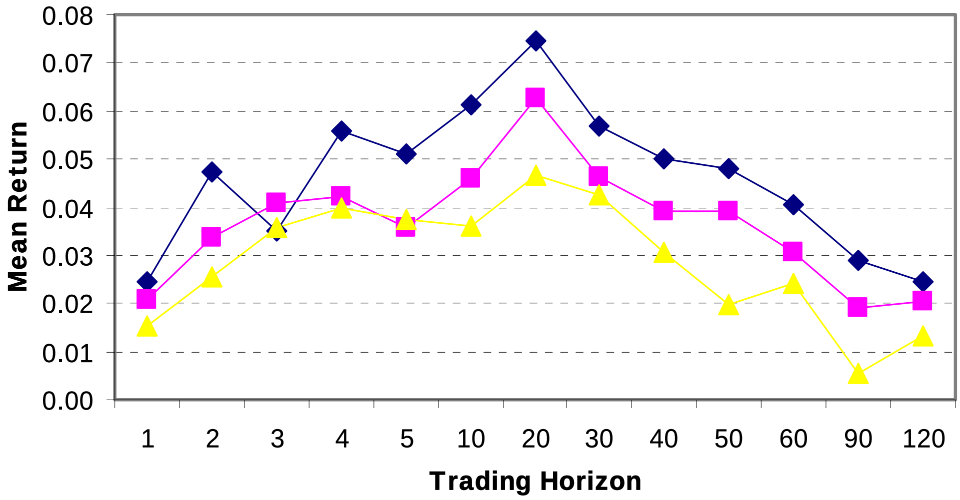



**Figure 1:** The lines plot the distribution of mean returns of the best 5 eligible pairs according to different measures of standard deviations on the identification of the opportunities. During the formation period (120 days), the strategy is evaluating two price absolute differences according to 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

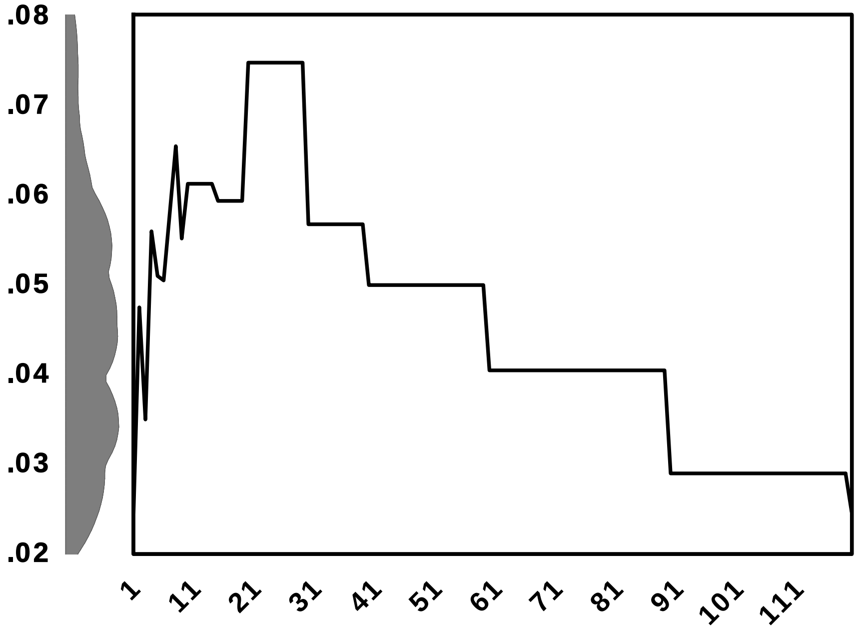



**Figure 2:** Distribution of Mean Returns according to different Time Exit Strategies. The testing period is between 1day and 120days. The mean returns are represented also from Kernel density on the left. The execution of the strategy occurs the next business after the divergence and the evidence have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

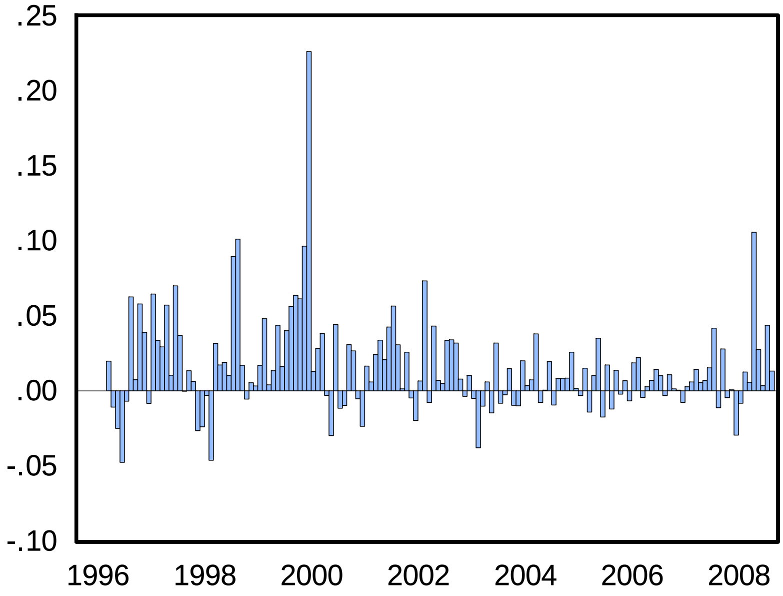
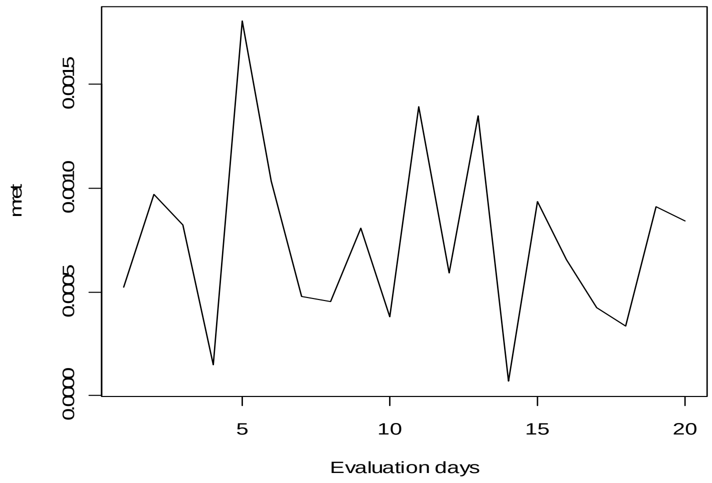



**Figure 3:** The line plots the distribution of the monthly Excess Return of Pair Trading Strategy for the top 5 eligible pairs. The trading period is extended from September 1996 to March 2009. The execution horizon is 20days. The strategy is implemented the next business day of the divergence day.

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




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

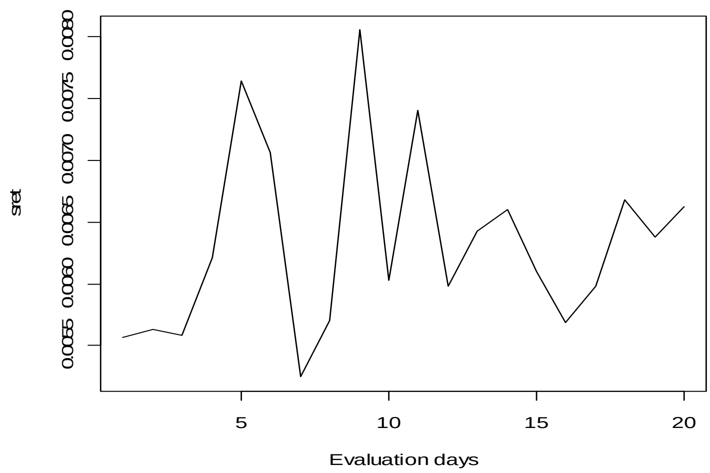



**Figure 4:** Panel A and Panel B plots the distribution of mean returns and standard deviation of top 5 eligible pairs of pairs trading strategy. The execution horizon is 20 days. The implementation of the strategy occurs one day after the divergence.

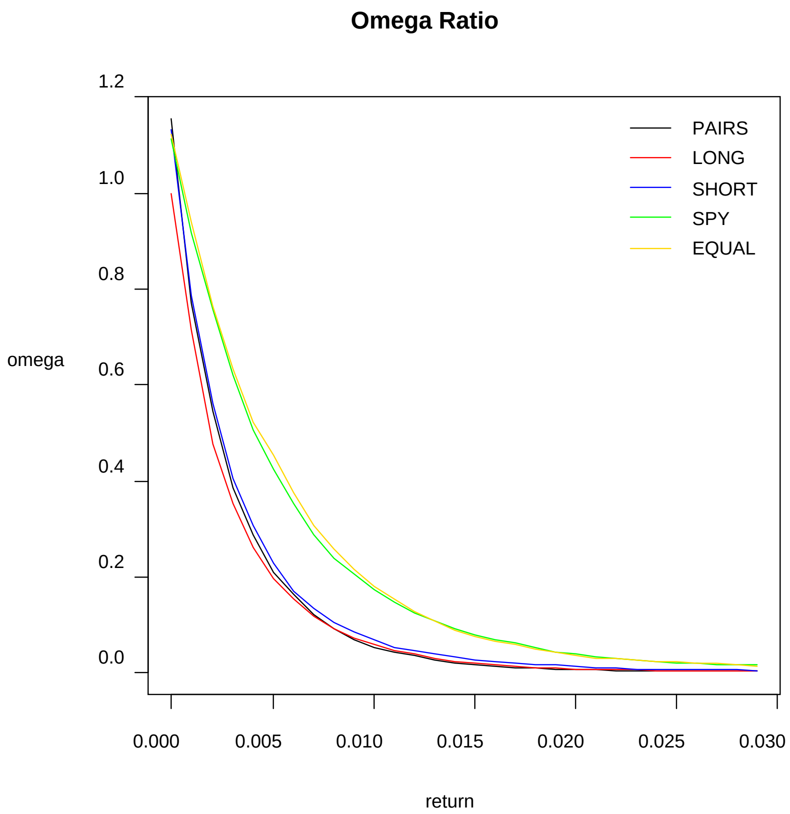
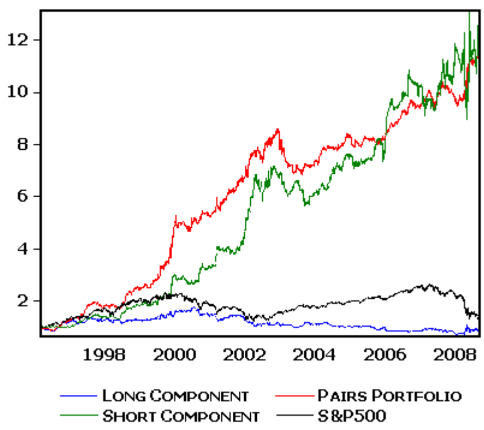
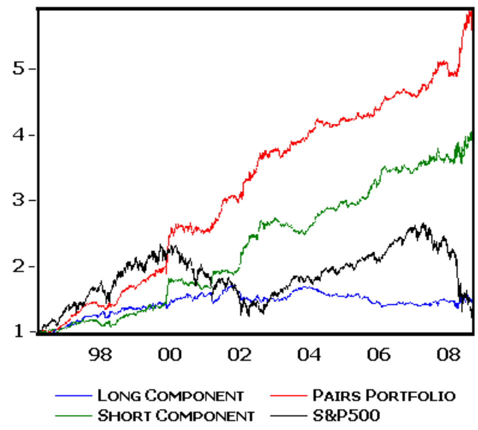



**Figure 5:** The plot exhibits the daily Omega Ratio using the best 5 eligible pairs. The threshold is set to zero and we are considering positive returns.

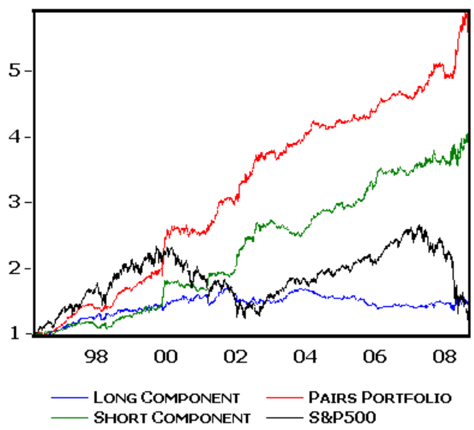
**Panel A:** Top2 Pairs Portfolio




**Panel B:** Top5 Pairs Portfolio




**Panel C:** Top10 Pairs Portfolio




**Panel D:** Top20 Pairs Portfolio

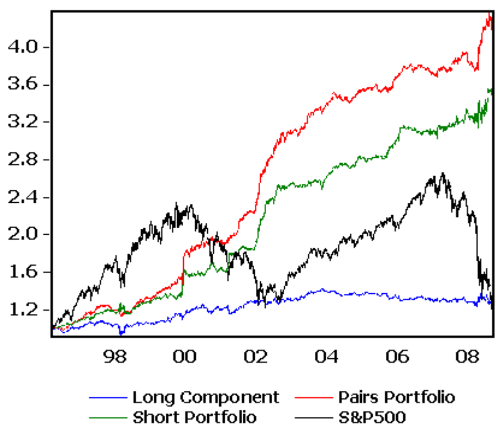



**Figure 6:** Presents daily terminal wealth of baseline results for different number of eligible pairs in the respective panels (A:2pairs, B:5pairs, C:10pairs, D:20pairs). In the figures, we represent in align with the terminal wealth, long and short component and S&P500 for the relative comparison.

## Appendix

### Variable Definitions

**Macroeconomic Variables:** In macros, we include a set of 4 variables, GDP, Inflation and Unemployment Rate and are represented as growth rates. Chen, Roll and Ross (1986), Ferson and Harvey (1993) Chan, 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.

**Money Market Rates:** outline interbank rates of each country and we transformed to daily rates.

**Market Variables:**

**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.

**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.

**Fundamental factors**

**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]).

**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.

**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 Sarno (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.

**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.

**Credit Rating:** credit rating is the a dummy variable that takes the value of one if there is an upgrade of the long term credit rating of each country, takes the value of zero if there is a unchanged evaluation and takes the value of minus one if there is a downgrade. Goh and Ederington (1993) argued about the importance of credit rating. The data download from the three biggest credit rating agencies, Moody's, S&P and Fitch.