

Pairs Trading on International ETFs

Panagiotis Schizas* Dimitrios D. Thomakos* TaoWang*

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 relatively successful trading strategy, allowing for multiple implementations of the same 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.

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

*Corresponding author. Department of Economics, University of Peloponnese, 22 100, Greece. Email: pschizas@uop.gr, panagiotis.schizas@gmail.com.

•Corresponding author. Department of Economics, University of Peloponnese, 22 100, Greece. Email: thomakos@uop.gr, thomakos@gmail.com. Tel.: +30-2710-230128, Fax: +30-2710-230139.

•Corresponding author. The Graduate Centre, Department of Economics, City University of New York, 22 100, New York, US.

Introduction

Investors and finance professionals are always on the lookout for successful trading strategies that account 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 is 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. The pairs trading strategy exploits this 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 distinguishes their works from ours where we concentrate on international ETFs.

There is a limited number of, neutral and non-neutral, strategies that use pairs and distances for formulating combinations of long/short positions. Jurek et al (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 know 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. Leaving aside 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 trading. The significant difference in this exercise, compared to previous studies, is that we use a family of international assets and that there may be some factors that do not fall within the “traditional” set of variables that are usually used in assessing the causes of strategy profitability.

Arbitrage, transaction costs, 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 et al (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 (1994). 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 (2000) 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 declines 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 et al (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.

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 and the majority of the ETFs are provided by Barclays Global Investors - (Ishares). The list of our series includes the following countries accompanied by their ticker: MSCI Australia (EWA), MSCI Belgium (EWK), MSCI Austria (EWO), MSCI Canada (EWC), MSCI France (EWQ), MSCI Germany (EWG), MSCI Hong-Kong (EWH), MSCI Italy (EWI), MSCI Japan (EWJ), MSCI Malaysia (EWM), MSCI Mexico (EWW), MSCI Netherlands (EWN), MSCI Singapore (EWS), MSCI Spain (EWP), MSCI Sweden (EWD), MSCI Switzerland (EWL), MSCI Japan (EWJ), MSCI S. Korea (EWY), MSCI EMU¹ (EZU), MSCI UK(EWU), MSCI BRAZIL (EWZ), MSCI TAIWAN (EWT) and S&P500 (SPY), the biggest ETF worldwide.

The majority of the ETF records starts on April, 01 1996. 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. Our analysis is based on daily observations including open, high, low and closing (dividend adjusted) prices for each ETF series. All of the

¹ EMU corresponds to the performance of publicly traded securities in the European Monetary Union markets.

ETFs we use have futures contracts and some of them also have options². 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 market capitalisation. This split allows to examine 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

² 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.

implicitly are aggregate major indices of the stock exchanges with no survivor bias as we refer extensively on the previous paragraph.

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:

$$P_t^a = \prod_{j=i+1}^{t+i} (1 + r_j^a), \text{ for } t = 1, 2, \dots, 120 \quad (1)$$

where $r_t^a = (P_t/P_{t-1}) - 1$ is the simple return of the a th ETF and the index i runs as a sequence of the form $i = \{0, 20, 40, \dots\}$ 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:

$$\Delta_{ab} = \frac{1}{120} \sum_{t=i+1}^{120+i} |P_t^a - P_t^b|, \text{ for all pairs } a, b \quad (2)$$

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 a bit 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. Suppose now that we consider the top L pairs, i.e. the pairs that have the L largest Δ_{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 Δ_{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:

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

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 $P_{t+s}^a > P_{t+s}^b$ then we go long on P_{t+s}^b and short on P_{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:

$$\begin{aligned} &\text{if } T_{t+s}^{ab} = 1 \wedge \text{sgn}(P_{t+s+1}^a - P_{t+s+1}^b) = \text{sgn}(P_{t+s}^a - P_{t+s}^b) \text{ then } T_{t+s+1}^{ab} = 1, \\ &\text{else } T_{t+s+1}^{ab} = -1 \end{aligned} \quad (4)$$

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:

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

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

$$R_{t+s}^P = \sum_{a,b} W_{t+s}^{ab} R_{t+s}^{ab} \quad (6)$$

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

$$W_{t+s}^{ab} = \frac{\omega_{t+s}^{ab}}{\sum_{a,b} \omega_{t+s}^{ab}} \text{ and } \omega_{t+s}^{ab} = (1 + R_{t-1+s}^{ab}) \times \dots \times (1 + R_{t-20+s}^{ab})$$

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.

Empirical results

Choice of trading horizon

The pairs trading methodology relies on certain user-defined conditions, such as the choice of ϵ 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 ϵ and a sequence of trading horizons $k=1, 2, 3, 4, 5, 10, 20, \dots, 120$ 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 ϵ . 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.

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.

Profitability of pairs trading: baseline results

Pairs trading is a profitable strategy. 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 backtesting 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.³ 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

³ 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.

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.⁴

For the size split we consider “large” capitalization to correspond to ETFs with market cap between 384 millions to 65 billions while “small” capitalization to correspond to ETFs with market cap from 330 millions 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 4 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

⁴ 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 Bondt et al (1989), Conrad et al (1989), Rouwenhorst (1998), Zarowin (1990), Richards (1997), Chan (1988) and Ball et al (1989) and Knez et al (1996).

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.

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 (1998) claim that to treat emerging markets as identical to developed markets could lead to wrong assumptions and 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:⁵ Brazil, Malaysia, Mexico, Taiwan and South Korea; this limits the number of pairs to be considered to a max of $L = 10$.

Results based on long and short components separately

⁵ We followed the MCSI classification for this.

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.⁶ In Table 6 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, its 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 broadly in alignment with those in GGR (2006).

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 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 7. The performance details during the second sub-sample immediately stand out: performance is increasing

⁶ GGR (2006) argued about the necessity of examining separately these two components of the strategy.

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.

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.

- (1) Firm-Level Characteristics (Idiosyncratic), as in Cavaglia, Brightman and Aked (2000), Carrieri, Errunza and Sarkissian (2005), Hou, Karolyi and Kho (2006) and Engelberg (2008).
- (2) Market level characteristics (local and global markets), as in Fama and French (FF) (1992, 1996, 1998), Rouwenhorst (1998) and Griffin (2002).
- (3) Macro-economic or country characteristics, as in Chan, Chen and Hsieh (1985), 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).

Pairs trading against the FF-type factors

Table 8 has the results of a regression of compounded monthly returns from our backtesting on the three FF factors and a momentum factor.⁷ 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. WHAT IS THE EXPLANATION OF THIS? 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. BUT I NEED MORE 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 9. First, note that the 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 10 and 11 we present results similar to Table 8 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 10, we can see that excess returns are significant in both types of

⁷ The conversion to monthly returns was done for conformability with the earlier literature; results are available for a daily frequency as well.

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 11, 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 12 and 13 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 12 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 13, 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 market after 2000) no factor has any explanatory value – this is important for the strategy has a very good performance even during downturns and its interesting to know that this performance is unrelated to these international factors. However, the most interesting of all results in Table 13 are those for the last period, that 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.

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. 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 while GGR (2006) have not considered it. Concentrating on the $L = 5$ top pairs portfolio and looking at the 20-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 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).

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

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

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

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

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

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

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

Money Market Rates: outline interbank rates of each country.

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

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

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

International Portfolio Flows: The difference between portfolio inflows and outflows of each country. Brennan and Cao 1997, Froot, O'Connell and Seasholes (2001), stated about the importance of international portfolio flows in the equity returns and loaded in their estimations. Taylor and 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.

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

References

- Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31-56.
- Amihud, Y., Mendelson, H., 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, pp223-249.
- Avramov, D., Chordia T., Goyal, A., 2006, "The impact of Trades On Daily Volatility", *Review of Financial Studies*, 19, pp1241-2394.
- Bakshi, G., Chen, Z., 1997, "Stock Valuation in Dynamic Economies," working paper, Ohio State University.
- Balvers, R., Wu Y., Gilliland, E., 2000, "Mean Reversion across National Stock Markets and Parametric Contrarian Investment Strategies" *Journal of Finance* 2, pp745-772
- Ball, R., Kothari, S.P., 1989, "Nonstationary expected returns: Implications for market efficiency and serial correlations in returns," *Journal of Financial Economics* 25, 51-74.
- Bikker, J.,A., Spierdijk, L., Van der Sluis, P.,J., 2007, "Market impact costs of institutional equity trades", *Journal of International Money and Finance* 26, pp974-1000
- Bwardwaj, R,K., Brooks, L,D., 1992, "The January anomaly Effects of low share price, transaction costs, and bid-ask bias", *Journal of Finance* 47, pp553-574
- Brennan, M., J., Chordia, T., Subrahmanyam, A., 1998, "Alternative Factor Specifications, Security Characteristics, and the Cross-Section of Expected Stock Returns", *Journal of Financial Economics* 49, 345-373.
- Brennan, M.,J., Subrahmanyam, A., 1996, "Market microstructure and asset pricing: On the compensation for illiquidity in stock returns", *Journal of Financial Economics* Volume 41, pp 441-464
- Brennan, M., Ashley, J., Wang W., Xia, Y., 2004, "Estimation and Test of A Simple Model of Intertemporal Capital Asset Pricing," *Journal of Finance*, 59, pp1743-1776.
- Bock, M., Mestel, R., 2008, "A regime-switching relative value arbitrage rule" working paper, University of Graz
- Brock, W., Lakonishok, J., Lebaron, B., 1992, "Simple technical trading rules and the stochastic properties of stock returns," *Journal of Finance*, 5, pp 1731-1764.
- Brockwell, P., J., Davis, R., A., 1990, Time Series: Theory and Methods Springer Series, US
- Brown, D., Jennings, R., H., 1989, "On technical Analysis" *Review of Financial Studies* 2, 527-551
- Bushee, B., Raedy, J., S., 2005, "Factors Affecting the Implementability of Stock Market Trading Strategies", working paper

Carrieri, F., Vihang E., Sarkissian, S., 2005, "The Dynamics of Geographic Versus Sectoral Diversification: Is There a Link to the Real Economy?" McGill University working paper.

Cavaglia, S., Brightman, C., Aked, M., 2000. "The Increasing Importance Of Industry Factors," *Financial Analysts Journal*, 56, pp41-54.

Chan, L.,K.,C., 1988, "On the contrarian investment strategy," *Journal of Business* 61, pp147-163.

Chan, K.,C., Chen, N.,F., Hsieh, D., A., 1985. "An Exploratory Investigation of The Firm Size Effect", *Journal of Financial Economics*, 14, pp 451-471.

Chan, K.,C., Chen, N.F., 1991, "Structural and return characteristics of small and large firms", *The Journal of Finance* 46, pp1467-1484.

Chen, Z., Knez, P., 1995, "Measurement of Market Integration and Arbitrage," *Review of Financial Studies*, 8, pp287-325.

Chen, Z., Dong, M., 2001, "Stock Valuation and Investment Strategies," working paper Yale University

Chordia, T., Swaminathan, B., 2000, Trading Volume and Cross-Autocorrelations in Stock Returns, *The Journal of Finance* 55, pp913-935.

Conrad, J., Kaul, G. 1989, "Mean Reversion in Short-horizon Expected Returns," *The Review of Financial Studies*, 2, pp225-240.

Conrad, J., Kaul, G., 1998, "An anatomy of trading strategies" *The Review of Financial Studies* 11, p.p.489-519.

Cooper, M., Gulen, H., Vassalou M., 2001, "Investing in size and book-to-market portfolios using information about the macroeconomy: some new trading rules"

D'Avolio, G., 2002, "The market for borrowing stock", *Journal of Financial Economics*, 66, pp 271- 306.

De Bondt Werner F.,M., Thaler H.,R., 1989, "Anomalies: A mean Reverting Walk Down Wall Street" *The Journal Of Economic Perspectives*, 3 pp 189-202

Do, B., Faff, B.,R., Hamza, K., 1996, A New Approach to Modelling and Estimation for Pairs Trading In Proceedings of 2006 Financial Management Association European Conference, Stockholm

Eleswarapu V., R., 1997, "Cost of Transacting and Expected Returns in the Nasdaq Market", *The Journal of Finance*, 52, pp. 2113-2127

Elliott, R., J., John Van Der Hoek, Malcolm, W., P., 2005, "Pairs Trading," *Quantitative Finance* 5, pp 271-276.

Engelberg, J., Gao P., Jagannathan R., 2008, "An Anatomy of Pairs Trading: the role of idiosyncratic news, common information and liquidity," working paper

Engle, R., and C. Granger, 1987, "Co-integration and Error Correction: Representation, Estimation and Testing," *Econometrica*, 55, pp251–276.

Fama, Eugene F., Kenneth R. French, 1993, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics* 33, pp3-56.

Fama, Eugene F., Kenneth R. French, 1996, "Multifactor explanations of asset pricing anomalies," *Journal of Finance* 51, pp55-84.

Fama, Eugene, Kenneth French, 1997, "Industry costs of equity," *Journal of Financial Economics* 43, pp153-193.

Fama, Eugene F., Kenneth R. French, 1998. "Value Versus Growth: The International Evidence," *Journal of Finance*, 53, pp1975-1999.

Fama, Eugene F., and James D. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *The Journal of Political Economy* 81, pp607-636.

Fama, E., and K. French, 1996, "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance*, 51, 131–155.

Fama, E., and Blume, M., 1966, "Filter Rules and Stock market Trading," *Journal of Business* 39, pp 226-241

Ferson, W., E., Campbell, R., H., 1993, "The Risk And Predictability Of International Equity Returns," *Review of Financial Studies*, 6, pp 527-566.

Fong, W., M., Wongb, W., K., Leanb, H., H., 2005, "International momentum strategies: a stochastic dominance approach" *Journal of Financial Markets* 8 ,1 , 89-109

Fong, W., M., Wong, W., K., Lean, H., H., 2005, International momentum strategies: a stochastic dominance approach, *Journal of Financial Markets* 8, pp 89-109

French, K., R., Poterba J., M., 1991, "Investor Diversification and International Equity Markets" *The American Economic Review*, Vol. 81, pp. 222-226

Froot, K., Dabora, E., 1999, "How are Stock Prices Affected by the Location of Trade?," *Journal of Financial Economics*, 53, pp189–216.

Fung, W., Hsieh, D., A., 1997, "Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds", *The Review of Financial Studies* 10, pp. 275–302

Gastineau, G., L., 2002 *The Exchange Traded Funds Manual*, The Frank J. Fabozzi Series US.

Gatev, E., W., Goetzmann, N., Rouwenhorst, K., G., 2006, "Pairs Trading: Performance of a Relative-Value Arbitrage," *Review of Financial Studies* 19, pp 797 - 827.

Griffin J., M., 2002, "Are the Fama and French Factors Global or Country Specific?" *Review of Financial Studies* 5, pp 783-803

Goetzmann W., Ingersoll, J., Spiegel, M., Welch, I., 2002, "Sharpening Sharpe Ratios," working paper, Yale School of Management.

Goh, J., C., Ederington L., H., 1993, "Is a Bond Rating Downgrade Bad News, Good News, or No News for Stockholders?", *Journal of Finance* 48, pp. 2001-2008.

Holthausen, R., W., Leftwich, R., W., 1986, "The Effect of Bond Rating Changes on Common Stock Prices" *Journal of Financial Economics* 17, pp. 57-89.

Hou. K., Karolyi, G., A., Kho, B., C., 2006, What Factors Drive Global Stock Returns? Working paper

Jacobs, B. Levy, K. (1993) "Long/Short Equity Investing", *Journal of Portfolio Management*, 20, pp.52-64

Jagannathan, R., Viswanathan, S., 1988, "Linear Factor Pricing, Term Structure of Interest Rates and the Small Firm Anomaly," Working Paper 57, Northwestern University.

Jang, B.,G., Koo, H.,K., Liu, H., Loewenstein, M., 2007, 'Liquidity Premia and Transaction Costs', *Journal of Finance*, 62, pp 2329–2366.

Jarrow, R., 1986, "The Relationship between Arbitrage and First Order Stochastic Dominance" *The Journal of Finance*, Vol. 41, pp. 915-921

Jegadeesh, N., 1990, "Evidence of Predictable Behaviour of Security Returns," *Journal of Finance*, 45, pp 881–898.

Jegadeesh, N., Titman, S. 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", *The Journal of Finance*, 48, pp65–91.

Jegadeesh, N., Titman, S. 1995, "Overreaction, Delayed Reaction, and Contrarian Profits," *Review of Financial Studies*, 8, pp973–993.

Jegadeesh, N., Titman, S., 2001, "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations", *The Journal of Finance* 56, pp699-720.

Jones, C. M. 2001, A Century of Stock Market Liquidity and Trading Costs, Graduate School of Business, Columbia University

Jones, C., Lamont, O., 2002, "Short-Sale Constraints and Stock Returns," *Journal of Financial Economics*, 66, pp207–239.

Jurek, J.,W., Yang, H., 2006 Profiting from Mean-Reversion: Optimal Strategies in the Presence of Horizon and Divergence Risk, Working Paper, Harvard Business School

- Jurek, J.W., Yang, H., 2007, Dynamic Portfolio Selection in Arbitrage, working Paper, Harvard University.
- Kandel, S., Stambaugh, R.F., 1996, "On the Predictability of Stock Returns: An Asset-Allocation Perspective", *The Journal of Finance*, Vol. 51, pp. 385-424
- Keim, D., Madhavan, A., 1997, "Transactions Costs and Investment Style: An Inter-exchange Analysis of Institutional Equity Trades," *Journal of Financial Economics*, 46, 265–292.
- Kestner Lars 2003, Quantitative Trading Strategies Mc Graw Hill Companies, US
- Knez, P.J., Ready, M., J., 1996, Estimating the Profits from Trading Strategies, *The Review of Financial Studies*, Vol. 9, No. 4, pp. 1121-1163
- Knez, P.J., Ready, M., J., 1997, On the Robustness of Size and Book-to-Market in Cross-Sectional Regressions, *The Journal of Finance*, Vol. 52, No. 4 pp. 1355-1382
- Kondor, Peter, 2008, Risk in Dynamic Arbitrage: The Price Effects of Convergence, *Journal of Finance*, Forthcoming
- Lehmann, B., 1990, "Fads, Martingales and market efficiency," *Quarterly Journal of Economics* 105, 1-28
- Lesmond, D.A., Ogden, J.P., Trzcinka, C.A., 1999, "A new estimate of transaction costs", *Review of Financial Studies*, 12 pp1113-1141
- Levy, H., 2006, Stochastic Dominance: Investment Decision Making under Uncertainty 2006 Springer Series, US
- Liew, J., Vassalou, M., 2000. "Can Book-To-Market, Size And Momentum Be Risk Factors That Predict Economic Growth?," *Journal of Financial Economics*, 57, pp 221-245.
- Liu, J., Longstaff, F., A., 2004, "Losing money on arbitrage: optimal dynamic portfolio choice in markets with arbitrage opportunities" *Review of Financial Studies*, 17, pp 611-641
- Llorente, G., Michael, R., Saar, G., Wang J., 2002, "Dynamic models of limit-order executions", *Journal of Financial Studies* 3, pp175-205.
- Lo, A.W., MacKinlay, A.C., 1990, "When are Contrarian Profits due to Stock Market Overreaction?" *Review of Financial Studies* 3, pp175-205.
- Lo, A.W., Mamaysky, H., Wang, J., 2000, "Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation" *The Journal of Finance*, 4 pp1705-1765.
- Loewenstein, M., 2000, "On optimal portfolio trading strategies for an investor facing transactions costs in a continuous trading market", *Journal of Mathematical Economics* 33 pp 209–228

Lucke, B., 2003, "Are Technical Trading Rules Profitable? Evidence for Head-and-Shoulder Rules" *Applied Economics*, 35, pp. 33-40

Lynch, A., Balduzzi, W., P., 2000, "Predictability and Transaction Costs: The Impact on Rebalancing Rules and Behaviour", *The Journal of Finance*, 55, pp. 2285-2309

Matolcsy, Z., P., Lianto, T., 1995, "The Incremental Information Content of Bond Rating Revisions: The Australian Evidence", *Journal of Banking and Finance* 19, pp. 891-902.

Mitchell, M., Pulvino, T., 2001, "Characteristics of Risk and Return in Risk Arbitrage" *The Journal of Finance*, 56, pp. 2135-2175.

Mech, T., 1993, "Portfolio Return Autocorrelation" *Journal of Financial Economics*, 34, 307-344

Nath, P., 2003, "High Frequency Pairs Trading with U.S. Treasury Securities: Risks and Rewards for Hedge Funds" working paper, London Business School.

Peterson, M., and D. Fialkowski, 1994, "Posted versus Effective Spreads: Good Prices or Bad Quotes?," *Journal of Financial Economics*, 35, pp269–292.

Petkova, R., 2006. "Do the Fama-French Factors Proxy for Innovations in Predictive Variables?" *Journal of Finance*, 61, pp582-613.

Ready, M., 2002, "Profits from Technical trading rules" *Financial Management*, Vol. 31, pp. 43-61.

Post, T., 2003, "Empirical Tests for Stochastic Dominance Efficiency", *The Journal of Finance*, Vol. 58, pp. 1905-1931

Poterba, J., Summers, L., 1988, "Mean reversion in stock returns: Evidence and implications" *Journal of Financial Economics* 22, p.p. 27-60

Richards A., J., 1997, "Winner-Loser Reversals in National Stock Market Indices: Can They be Explained?" *The Journal of Finance*, Vol. 52, pp. 2129-2144.

Rouwenhorst, K.,G., 1998, "International Momentum Strategies" *Journal of Finance*, 53 pp 267-284.

Shapiro, S.,S., Wilk, M.,B., Chen, H., J., 1968, "A Comparative Study of Various Tests for Normality" *Journal of the American Statistical Association*, Vol. 63, pp. 1343-1372

Shleifer, A., Vishny, R.,W., 1997, "The limits of arbitrage", *Journal of Finance* 52, pp35-55.

Stambaugh, R.,F., 1999 "Predictive regressions", *Journal of Financial Economics* 54 pp375-421.

Stoll, H.,R., Whaley R.,E., 1983, "Transaction costs and the small firm effect", *Journal of Financial Economics*, 12, pp 57-79

Sullivan, R., Timmermann A., White H., 1999, "Data-Snooping, Technical Trading Performance, and the Bootstrap" *The Journal of Finance* 54, pp 1647-1691

Tsay, R., S., 2005, Analysis of Financial Time Series, John Wiley & Sons, Canada

Vassalou, M., 2003. "New Related To Future GDP Growth As A Risk Factor In Equity Returns", *Journal of Financial Economics*, 68, pp47-73.

Vayanos, D., 1998, "Transaction costs and asset prices: a dynamic equilibrium model" *Review of Financial Studies*, 11, pp1-58

Vidyamurthy, G. 2004, Pairs Trading, Quantitative Methods and Analysis, John Wiley & Sons, Canada.

Xia, Y., 2001, "Learning about Predictability: The Effects of Parameter Uncertainty on Dynamic Asset Allocation," *The Journal of Finance* 56, pp205-246

Zarowin, P., 1990, "Size, Seasonality, and Stock Market Overreaction" *The Journal of Financial and Quantitative Analysis*, Vol. 25, pp. 113-125

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	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top 20</i>
Average Number of Trading Days per pair	19,115	19,070	19,056	18,951
Standard Deviation Average Number of Trading days	1,416	1,506	1,645	1,813
Average Number of Round-Trips per pair	0,952	0,920	0,857	0,805
Standard Deviation of Average Number of Round-Trips	1,064	1,042	1,021	0,997
Average Number Pairs Open in 20days	1,913	4,772	9,537	18,969
Standard Deviation of Average Number Pairs Open	0,099	0,161	0,281	0,472
Panel B: Pairs that Convergence within N trading days				
Trading Horizon	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top 20</i>
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 test. 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 stochastically dominates S&P500 profitability

<i>Panel A: Event Day</i>				
Pairs Portfolio	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top 20</i>
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
<i>Panel B: One Day Waiting</i>				
Pairs Portfolio	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top 20</i>
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 percentage basis of the excess return portfolios. 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.

<i>Panel A: Event day</i>				
<i>Pairs Portfolio</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top20</i>
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

<i>Panel B: One day waiting</i>				
<i>Pairs Portfolio</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top20</i>
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				60days			
Pairs Portfolio	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top20</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top20</i>
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

<i>Pairs Portfolio</i>	Large Capitalization Portfolio				Small Capitalization Portfolio			
	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top 20</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top10</i>	<i>Top 20</i>
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

<i>Pairs Portfolio</i>	<i>Emerging Countries</i>			<i>Developed Countries</i>			
	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 10 ETFs and we add each separate ETF by its own inception date. The sample period is from April, 01 1996 to March, 31 2009 (3.140 observations). The "top n" represents the "n" best eligible ranked pairs according to the historic 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 estimation represents the implementation of the strategy the next business day

<i>Pairs Portfolio</i>	<i>Top 2</i>		<i>Top 5</i>		<i>Top10</i>		<i>Top20</i>	
	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	-0,286
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:	<i>1996:04-1999:12</i>				<i>2000:01-2002:12</i>				<i>2003:01-2005:12</i>				<i>2006:01-2009:03</i>			
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 variable 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		<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 20</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 20</i>
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
<i>Observations</i>		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 11

Regression of Monthly Returns of the Subsamples Estimations

The table represents the results of monthly excess return from pair trading portfolios segment by regions of emerging and developed markets where the independent variables are 6 risk factors as represented by Fama and French. The implementation of the strategy occurs the next business day of the divergence and the trading horizon is constant 20days. Daily returns are compounded to calculate monthly returns. The independent variables are: the value weighted market excess return (V_{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 R² 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 are estimated for a rolling window of and R^2 from each time-series regression are reported in nominal form.

Monthly Pairs Portfolio	Emerging markets			Developed markets			
	<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 20</i>
Intercept	0,012	0,010	0,005	0,014	0,013	0,010	0,010
	0,037	0,025	0,146	0,000	0,000	0,000	0,000
Market	-0,345	-0,494	-0,419	-0,025	-0,015	-0,017	-0,022
	0,155	0,027	0,014	0,709	0,808	0,721	0,602
HML	-0,099	-0,184	0,006	-0,173	-0,250	-0,130	-0,075
	0,727	0,502	0,976	0,020	0,002	0,026	0,253
SMB	-0,011	0,024	0,028	-0,191	-0,096	0,045	-0,031
	0,953	0,911	0,877	0,088	0,136	0,424	0,546
Momentum	-0,214	-0,242	-0,276	0,063	-0,010	0,005	0,042
	0,118	0,002	0,002	0,269	0,784	0,824	0,175
<i>Observations</i>	98	98	98	150	150	150	150
R^2	0,060	0,166	0,170	0,046	0,088	0,075	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 c 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), book-to-market portfolio of high minus low stocks (HML), a portfolio of year long winners minus a year long loser (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.

Monthly Pairs Portfolio	Large Capitalization Portfolio				Small Capitalization Portfolio			
	<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 20</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 20</i>
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
<i>Observations</i>	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 weights are according to the weights of MSCI EAFE. The implementation of the strategy occurs the next business day after 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		<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 20</i>	<i>Top 2</i>	<i>Top 5</i>	<i>Top 10</i>	<i>Top 20</i>
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 15

Regression of monthly returns of the subsamples International evidence

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

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

Analysis of Opening Probability of the pairs

Panel A: 20 Days

	All Variables		Macro		Market		Fundamentals		Optimized	
Top 5 pairs Portfolio	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Val
Intercept	-1,579	0,000	-1,852	0,000	-1,288	0,000	-1,447	0,000	-1,458	0,0
Inflation Long									10,223	0,0
Inflation Short	10,585	0,063								
Default Premium Long							0,104	0,002	0,117	0,0
Dividend Yield Long	-5,571	0,064					-8,728	0,002	-8,255	0,0
EPS forward Long	0,000	0,036					0,000	0,014	0,000	0,0
Eps Forward Short	-0,001	0,000					-0,001	0,002	-0,001	0,0
FX Long							-0,723	0,001	-0,726	0,0
Market Volatility Long	-0,151	0,037							-0,149	0,0
Turnover Long					0,000	0,035				
Turnover Short					0,000	0,000				
Unemployment Rate Short			0,022	0,090					0,024	0,0

Panel B: 60 Days

	All Variables		Macro		Market		Fundamentals		Optimized	
Top 5 pairs Portfolio	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Val
Intercept	-1,797	0,000	-2,265	0,000			-1,969	0,000	-1,819	0,0
Inflation Long			11,014	0,096						
Default Premium Short	0,153	0,000					0,070	0,094	0,117	0,0
Dividend Yield Short	-12,470	0,005					-8,353	0,034	-9,923	0,0
EPS forward Long	-0,001	0,001					0,000	0,084	-0,001	0,0
Eps Forward Short							0,000	0,027		
GDP Short			-0,037	0,052					-0,044	0,0
Market Cap Long							0,000	0,052	0,000	0,0
Credit Rating	-0,196	0,084								
Market Volatility Short	0,430	0,009							0,342	0,0
Unemployment Rate Short	-0,041	0,055	-0,034	0,074					-0,043	0,0

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.

Panel A: 20Days										
Maximum Trading Horizon	All Variables		Macro		Market		Fundamentals		Optimized	
Top 5 pairs Portfolio	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
Intercept	-2,61	0,00	1,92	0,00			1,66	0,00	-2,61	0,00
Default Premium Long	0,44	0,03					-0,10	0,00	0,44	0,00
Dividend Yield Long							8,58	0,00		
EPS forward Long	0,00	0,02							0,00	0,00
FX Long	-2,22	0,06					0,56	0,00	-2,22	0,00
Money Market Rates Short	1,89	0,09							1,89	0,00
Portfolio Inflows Short	0,00	0,00							0,00	0,00
Unemployment Rate Short			-0,02	0,04						
Panel B: 60Days										
Maximum Trading Horizon	All Variables		Macro		Market		Fundamentals		Optimized	
Top 5 pairs Portfolio	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
Intercept	0,00	0,00	0,00	0,47	0,00	0,00	-0,01	0,00	0,00	0,00
Inflation Long										
Inflation Short			-0,20	0,04						
Default Premium Long										
Default Premium Short	0,00	0,02								
Dividend Yield Short							0,12	0,04		
EPS forward Long										
Eps Forward Short	0,00	0,04					0,00	0,03		
GDP Short			0,00	0,02					0,00	0,00
Market Cap Long										
Market Cap Short	0,00	0,01							0,00	0,00
Money Market Rates Long										
Money Market Rates Short	0,01	0,07	0,01	0,05					0,01	0,00
Portfolio Inflows Short							0,00	0,02		
Credit Rating Short	0,00	0,05								
Market Volatility Short	0,01	0,01			0,01	0,01			0,00	0,00
Turnover Short	0,00	0,04							0,00	0,00

Survivor Analysis of Time to Convergence

The table represents the survival analysis of pairs time to convergence. The survival analysis applies a negative binomial model, where the dependent variable represents the number of trading days of each trading pair.

Panel B: 20days										
Top 5 pairs Portfolio	All Variables		Macro		Market		Fundamentals		Optimized	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Intercept	1,425	0,000	1,915	0,000			1,485	0,000	1,425	0,000
Default Premium Long							-0,090	0,004		
Dividend Yield Long							8,739	0,004		
Dividend Yield Short	12,002	0,001							12,002	0,001
EPS forward Long	0,001	0,010					0,000	0,035	0,001	0,010
Eps Forward Short	0,001	0,001					0,001	0,001	0,001	0,001
FX Long							0,618	0,002		
Market Cap Long									0,000	0,000
Market Cap Short	0,000	0,037								
Portfolio Inflows Short	0,000	0,044					0,000	0,053	0,000	0,044
Market Volatility Long	0,173	0,038							0,173	0,038
Unemployment Rate Long	-0,102	0,067							-0,102	0,067
Unemployment Rate Short			-0,024	0,041						

Panel B: 60days										
Top 5 pairs Portfolio	All Variables		Macro		Market		Fundamentals		Optimized	
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Intercept	1,883	0,000	2,366	0,000			2,110	0,000	1,883	0,000
Default Premium Short	-0,143	0,001							-0,143	0,001
Dividend Yield Short	13,797	0,001					7,642	0,041	13,797	0,001
Eps Forward Short							0,000	0,071		
Market Cap Long							0,000	0,002		
Market Volatility Long			-0,142	0,082						

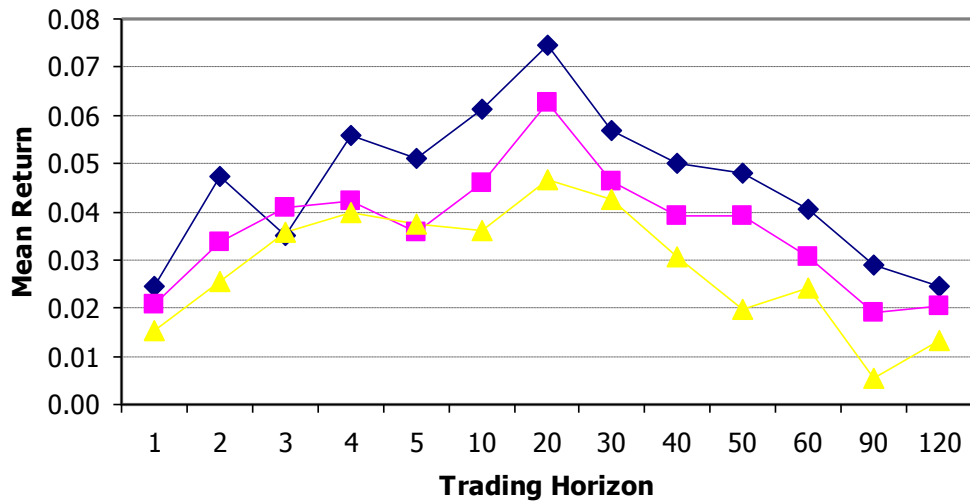


Figure 1: The lines plot the distribution of mean returns of the best 5 eligible pairs according to different measures of standard deviations on the identification of the opportunities. During the formation period (120 days), the strategy is evaluating two price absolute differences according to three different scales of distance. For different k trading horizons, where $k=1, \dots, 120$, 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

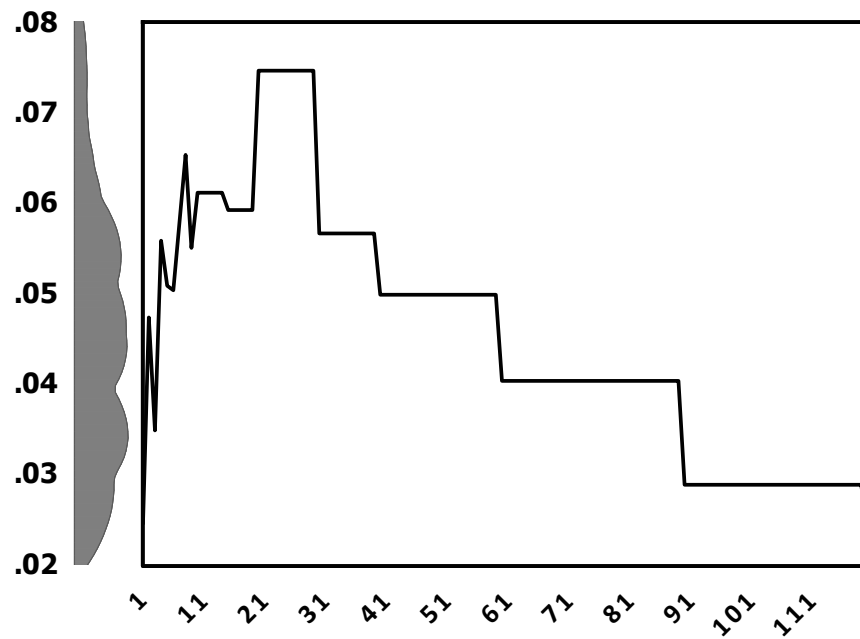


Figure 2: Distribution of Mean Returns according to different Time Exit Strategies. The testing period is between 1day and 120days. The mean returns are represented also from Kernel density on the left. The execution of the strategy occurs the next business after the divergence and the evidence have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

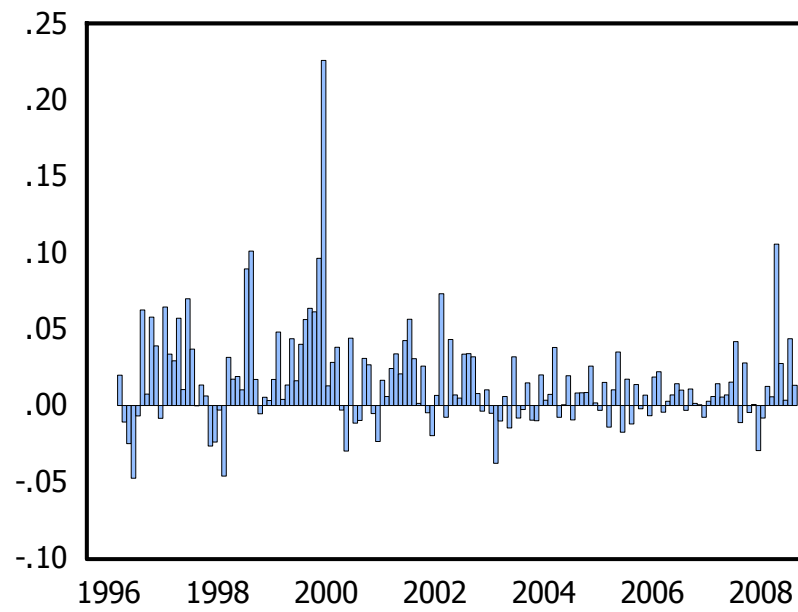
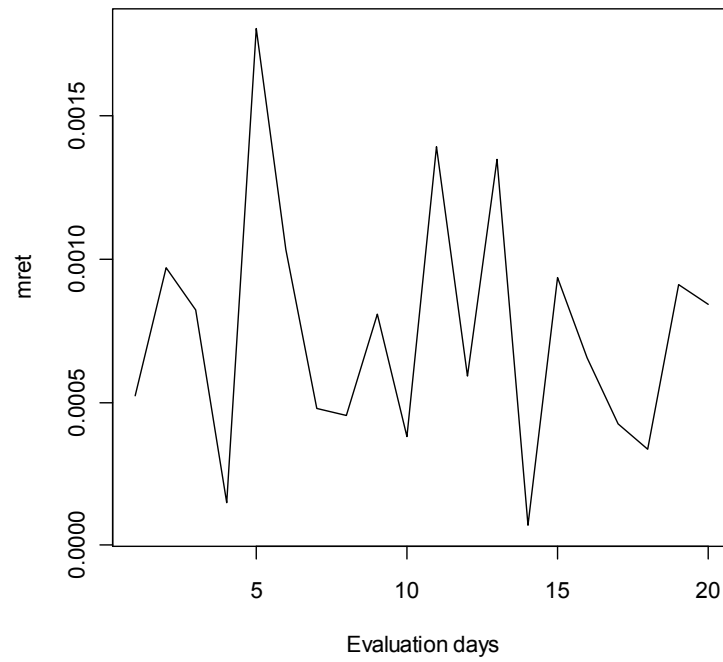


Figure 3: The line plots the distribution of the monthly Excess Return of Pair Trading Strategy for the top 5 eligible pairs. The trading period is extended from September 1996 to March 2009. The execution horizon is 20days. The strategy is implemented the next business day of the divergence day.

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



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

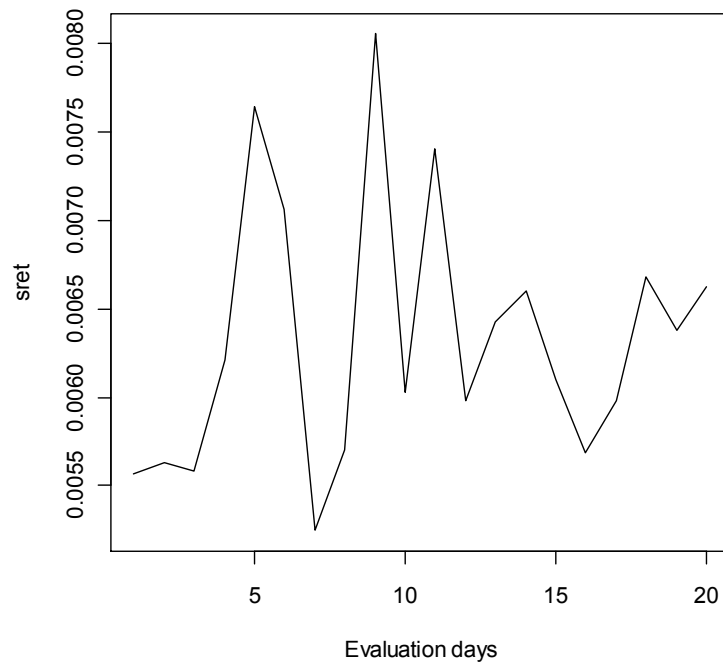


Figure 4: Panel A and Panel B plots the distribution of mean returns and standard deviation of top 5 eligible pairs of pairs trading strategy. The execution horizon is 20 days. The implementation of the strategy occurs one day after the divergence.

Omega Ratio

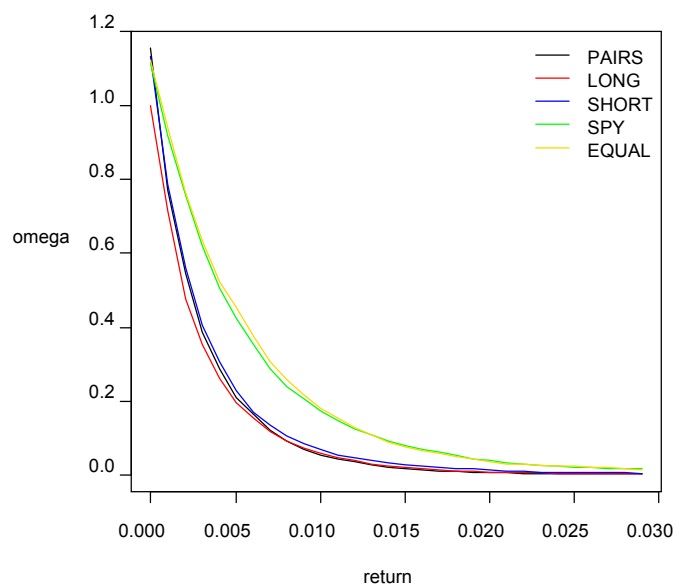
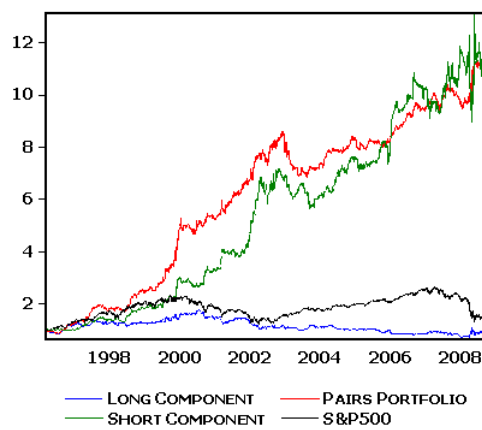
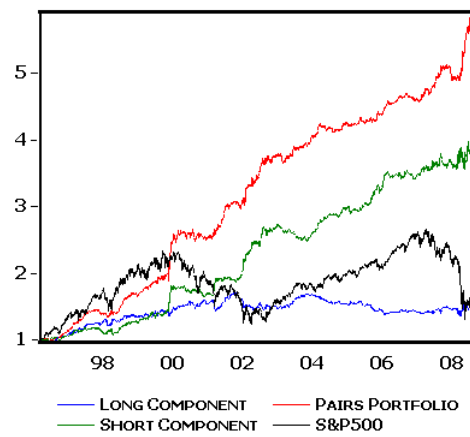


Figure 5: The plot exhibits the daily Omega Ratio produce with the best 2 eligible pairs. We set as r threshold 0 and we are considering the positive returns. In the plot, we are representing pairs trading strategy, and long and short component separately. For the relative comparison, we represent S&P500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

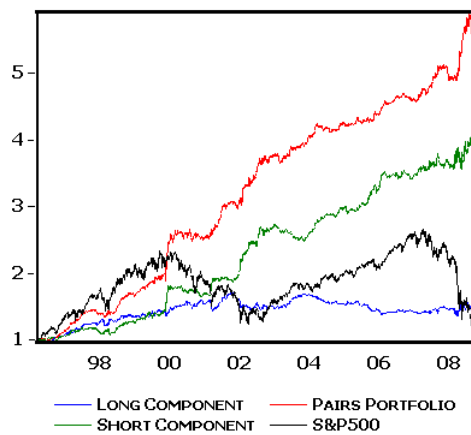
Panel A: Top2 Pairs Portfolio



Panel B: Top5 Pairs Portfolio



Panel C: Top10 Pairs Portfolio



Panel D: Top20 Pairs Portfolio

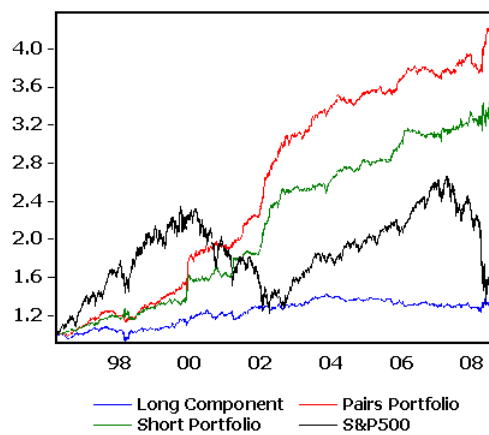


Figure 6: Presents daily terminal wealth of baseline results for different number of eligible pairs in the respective panels (A:2pairs, B:5pairs, C:10pairs, D:20pairs). In the figures, we represent in align with the terminal wealth, long and short component and S&P500 for the relative comparison.

Appendix: