PAIRS TRADING STRATEGY AND IDIOSYNCRATIC RISK.

EVIDENCE IN SPAIN AND EUROPE.

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ABSTRACT (max 100 words)

Pairs trading strategy's return depends on the divergence/convergence movements of a selected pair of stocks' prices. However, if the stable long term relationship of the stocks changes, price will not converge and the trade opened after divergence will close with losses. We propose a new model that, including companies' fundamental variables that measure idiosyncratic factors, anticipates the changes in this relationship and rejects those trades triggered by a divergence produced by fundamental changes in one of the companies. The model is tested on European stocks and the results obtained outperform those of the base distance model.

Keywords: pairs trading, stocks, idiosyncratic risk, EPS, BVPS.

JEL classification: G170, G120, G140

1. Introduction

The purpose of this research it to propose a pairs trading model that increases return compared to the model of distance (Gatev et al., 2006). We will introduce some rules in the model, based on fundamental variables, so that persistent divergence in the relationship of the prices of the two selected stocks could be foreseen.

When we analyze the results of the distance method in previous works (Gatev et al, 2006; Do and Faff, 2010), we found that the number of trades with losses was high and the increase of such trades was one of the reasons of the decline of pairs trading strategy return (Do and Faff, 2010).

Depending on the reason why a divergence on a stock price pair leads to execute the trade, it will be more or less likely that the stock price pair will convergence again. Thus, if the stock price pair divergence is due to irrational investors that leads to liquidity tensions, later convergence is likely to happen. However, if the reason of such divergence is new information about the companies' fundamentals, divergence is likely to remain and there will be another equivalence relation between both stocks (Andrade et al., 2005). This is the starting point of this paper: beginning from the basic model of distance, we test which variables related to companies' performance could anticipated if divergence is temporal or permanent. So that, strategy's return outperforms.

First of all, in this paper we have tested the distance model (Gatev et al., 2006) to Ibex 35, as well as to two of the main European indexes (Euro Stoxx 50 and Stoxx Europe 50). The distance model has also been tested on restricted portfolios. These restricted portfolios arise from considering certain criteria, such as country, currency, industry size and supersector in the indexes described before. Afterwards, we have included variables that represent idiosyncratic firms' risk, in order to detect permanent divergences in relative prices of the considered stocks so that strategy return can increase. We have tested which one has a higher effect on strategy's return. The variables are (i) Earnings per Share in the next 12 months; (ii) Book Value per Share (iii) Target price; (iv) Recommendation; and (v) Knowledge of the firm, measured as the number of estimations of each stock. They will be further explained in section 3.3.

The paper is organized as follows. In section 2 there is a review of literature. In section 3 we explain the data used in the paper and the sources. In section 4 we explain how the two models (distance model and the proposed in this paper) are implemented. In section 5 we the model: first of all we test the distance model on the three indexes (Ibex 35, Euro Stoxx 50, Stoxx Europe 50); latter we test the model proposed on those indexes and compare results to the ones obtain with the distance model. Finally we show the main conclusions.

2. Review of Literature

Pairs trading strategy is a statistical arbitrage strategy that leads to excess returns that are non justified by traditional risk factors (Gatev et al, 2006; Bowen and Hutchinson, 2014). Therefore, it is considered a financial markets' anomaly (Jacobs, 2015).

The aim of this strategy is to find two stocks that have a parallel and long-term performance in order to benefit from convergence-divergence movements that occur via buying (or selling) the relatively undervalued (or overvalued) stock. You can obtain positive returns since the differential of prices returns to its mean in a long-term basis (Gatev et al., 2006).

The asset valuation model that lies under this strategy is the Arbitrage Pricing Theory (APT). APT theory states that financial assets, which share the same risk factors should be priced equally and that their idiosyncratic factor has a zero mean (Vidyamurthy, 2014). Therefore, divergence of the historic price relationship between two stocks is appealed to a deviation of their idiosyncratic factor from its equilibrium mean (zero).

Although in recent research, pairs trading has been considered as an anomaly initself (Jacobs, 2014; 2015), previous works have included it into the anomalies either on the violation of law of one price (Gatev et al., 2006) or into the group of contrary strategies reverse to the mean (Herlemont, 2004). The explanation of this anomaly depends whether authors support traditional finance or behavioral finance.

Traditional finance, based on the problem of the joint hypothesis (market efficiency – asset valuation model) states this unjustified return is due to the use of no proper asset valuation models. In fact, it is said that the models developed so far are not the definitive ones. Even though some models have used up to 50 variables, such models do not clear up the problem of valuation (Subrahmanyan, 2010). Gatev et al. (2006) consider unjustified return as what arbitragers get to restore the law of one price. Burton and Shah (2013) also state that the assets used to implement this strategy are not totally equal and are not fungible; this characteristics should be meet in order to admit the existence of such anomaly.

Behavioral finance uses the limits to arbitrage and investor’s psychology to explain this anomaly. Investor’s psychology makes to appear pricing errors and the limits to arbitrage avoid them to be corrected (Jacobs, 2015). Andrade et al. (2005) propose that it is the irrational investors’ behavior and liquidity tensions the reasons why this strategy is profitable. Jacobs and Weber (2015) argue that return is influenced by (a) the kind of information that leads to the divergence, (b) investors’ level of attention, and (c) limits to arbitrage.

3. Data

We use stocks selected from different stock European indexes in order to test the model: Ibex 35, EuroStoxx 50 and Stoxx Europe 50. Stocks have been split up regarding the following criteria (according to the one STOXX uses in its indexes): industry, supersector, size and investment style. Additionally, we have included two more criteria: country were the stock is traded and its traded coin.

Regarding IBEX 35, we have selected 105 companies whose stock have been traded any moment since 2002. We have analyzed a portfolio including all the stocks, as well as seven additional portfolios. In order to create these seven portfolios, we have used the criteria provided by ICB[1] (regarding industry and supersector). The maximum number of stocks in a portfolio is ten.

Euro Stoxx 50 index is formed by 50 companies from 12 Eurozone countries[2]. It represents circa 57% of market capitalization of those 12 countries. The distance method has been tested over the whole number of stocks, as well as over 13 portfolios which has a minimum of 10 stocks resulting of using the following criteria: (a) country, (b) industry, (c) supersector and (d) investment style.

Stoxx Europe 50 index includes the leading companies of European supersectors. It is formed by 50 companies that come from over 18 different European countries. Tests have been done over all the stocks, as well as 18 portfolios with a minimum of ten stocks

[1] ICB (Industry Classification Benchmark) is a company owned by FTSE Group. ICB splits 70,000 companies and over 75,000 stocks worldwide into four different sectorial levels (industry, supersector, sector and subsector). Thus, it allows to compare one with another. The ICB used in this paper is that of July, 13rd, 2015 (http://www.icbenchmar.com/).

[2] Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Holland, Portugal and Spain. (Data considered as that of July, 13rd, 2015, www.stoxx.com/index-details?symbol=sx5e).

each. Such porfolios have been constructed using the following criteria: country, investment style, currency, industry and supersector.

3.1. Prices

In order to test the models, we have used daily stock prices between January 1st 2002 and May 31st 2015. We have used adjusted prices by capital increases, splits and dividends following Gatev et al. (1999, 2006).

Stock prices are used on their legal currency in each market. When considering Eurozone countries, we have used euro in the whole stock price series. When there is no stock quotation for a certain day due to public holidays which are not the common to all of the considered markets, we have used the quotation of the previous day.

3.2. Variables

The return of pairs trading strategy has been analyzed considering a wide variety of events that take place both in the financial markets and in the company itself such as: (i) accounting events, e.g. announcement of quarterly results (Papadakis and Wysocki, 2008) (ii) different recommendations regarding the stocks of the traded pair (Yu, 2011); (iii) considering different market volatility (Huck, 2015); (iv) relationship between return of the strategy and systematic risk factors using Fama and French models of three and five factors, which leads to the conclusion that market, size, value, momentum and reversion factors do not explain returns of pairs trading strategy (Gatev et al., 2006; Bowen and Hutchinson, 2014).

In this paper, we propose a model that increase return thanks to reducing the number of trades which results in losses due to the lack of convergence of the differential of the selected pair of stocks. In this model we assume that the reason of this lack of convergence is that new company's information shows up.

Andrade, di Pietro and Seascholes (2005) states that the reason behind a long-time divergence, which results in a permanent change in the relative relation between two stocks, relies on an idiosyncratic factor. Therefore, if there are any changes in the idiosyncratic factor due to release of new specific information of a company, there will be a change in its future expectative. Thus, it leads to a sustainable change in their relative prices.

In the model we propose in the paper, we will test five variables as indicators of the future performance of the company's expectative. Therefore, a change in the relative relation of the variables of two companies lead to a change of relative perception of their expectative. This change can justify the long-time divergence or a new relative relation between the prices of both stocks.

The variables we use in the model are selected from analysts' consensus. The data is obtained from FactSet, a financial information provider. The reason to choose the values provided by analysts' consensus is that they consider the implicit information in analysts' recommendations that follow a certain stock (Barber et al., 2001).

The variables considered in the model are:

a) Earnings per Share in the next 12 months. (EPS).
b) Book Value per Share (BVPS).
c) Target Price (TP).
d) Recommendation.
e) Knowledge of the firm, measured as the number of estimations of each stock.

Earnings per Share and Book Value per Share are basic items when valuing shares. Chen and Zhang (2002) show that the influence of both, EPS and BVPS, in stock valuation depends on the return: the better the return, the more influence of EPS and the lesser influence of BVPS. There are some critics to considering analyst's consensus, because of their over or underreaction to new information (Easterwood and Nutt, 1999). However, Brown, Hagerman, Griffin and Zmijewski (1987) consider that analysts' recommendations about companies' profits outperform those obtained by quantitative models.

Target price has been recently introduced in analysts' reports. It shows analysts' opinion about the real value of a stock (Gleason et al., 2013).

Analysts' recommendations are very appreciated by investors because such recommendations help them to achieve high returns (Barber et al., 2001). Besides, it is very significant the change in consensus' recommendation (Jegadeesh et al., 2004).

Finally, the number of estimations (that is, how many analysts follow a certain company) has a positive relation with company's market value: the more the analysts follow a stock, the higher its market value (Chung and Jo, 1996).

In this paper we test which of the five variables added to the distance method proposed by Gatev et al. (1999, 2006), most increases pairs trading strategy's return because such variables capture changes in the idiosyncratic risk, therefore anticipating reversion or not to the mean.

In the following table it is shown the number of firms of each Index from which Factset provides information for each variable.

Table 1. Fundamental variables Factset Information and firms.

Fundamental Variables	Number of companies indexed with data available		
	Ibex 35	Euro Stoxx 50	Stoxx Europe 50
EPS	96	75	84
BVPS	95	75	84
Target price	83	75	84
Recommendation	84	75	84
Number of estimations	96	75	84

4. Implementing the model

In order to implement pairs trading strategy, we have to choose those pairs of stock that shows a minimum price difference. Such price difference is measured through different methods, such as distance of normalized prices (Gatev et al., 1999, 2006; Song and Zhang, 2013) or cointegration models (Burguess, 1999; Vidyamurthy 2004; Lin et al., 2006; Gianetti and Viale, 2011; Chun and Wong, 2015).

Return of this strategy depends upon the divergence and convergence movements between the chosen pair of stocks when this strategy is being executed. Properly implementation of this strategy requires to determine a limit to price differential. Such limit will point out when a stock is overvalued or undervalued in comparison with the other one (its pair), as well as when it reaches convergence again which indicates that relative value of the pair of stocks is accurate. It is interesting to highlight that the higher the limit is, the higher the potential return could be but the lesser number of trades will be undergone. Therefore, the total result of this strategy depends on (i) how many trades will take place; (ii) the return of each trade.

4.1. The Distance Model

In this section we will describe the distance model, starting from the formation period, then the trading period and how returns are computed.

4.1.1. Formation period.

The formation period lasts 12 months. A new formation period starts the first day of the next month to the one where the initial period started (Gatev et al., 2006). The period analyzed is January 1st 2002 up to May 31st 2015, that is 276 different formation periods. The first step is to normalize the stock price series. We have constructed an accumulated return index for each period, being 1 the value of the first day of each formation period. This methodology is used by Gatev et al. (2006) and is different to the one proposed by Perlin (2009) who normalizes the series via mean and variance.

We select all the stocks from which we have all the daily pices of the formation period, so that we avoid considering non liquidity stocks (Gatev et al., 2006). Regarding the Euro Stoxx 50 and Stoxx Europe 50, we have reconstructed the series in order to consider all the national days of each country. In those days we have considered the price of the previous day. Our intention was to avoid pushing out of stocks which absence of trading had nothing to do with their liquidity rather than the stock market calendar of its home country.

Table 2. Number of stocks

	Ibex 35	EuroStoxx 50	Stoxx 50
Overlapped periodss			
Number of periods	276	276	276
Maximum number of stocks	63	71	82
Miminum number of stocks	40	24	39
Average number of stocks	55	61	75

In a second step, we form all the possible stock pairs from the previously selected stocks. For each pair, we compute: (a) the average distance of the formation period; (b) the standard deviation of the distance during the formation period; (c) the sum of the square distances of the formation period. The distance is defined as the difference between the normalized stock prices at a certain moment[3].

When implementing the model we have computed 1.703.246 pairs[4] (24.52% belongs to Ibex 35, 30.25% belongs to Euro Stoxx 50 and 45.24%% to Stoxx Europe 50).

The criterion to select the chosen pairs is the lowest of the sum of the square of the normalized distance prices. For each portfolio in section 4.3. we will choose the 5, 10, 20, 50, 100 and 150 pairs with the lowest square distance, except for those portfolios whose number of stocks does not allow to get such number of pairs.

Table 3. Number of selected stock pairs

Per period	Ibex 35	EuroStoxx 50	Stoxx 50	Total
Maximun	364	878	1,136	2,378
Minimum	220	247	484	951
Mean	302	727	996	2,025
Total	886	1,852	2,616	5,354

4.1.2. Trading period

Trading period lasts six months starting the day after the formation period ends (Gatev et al. 2006).

The prices series continues the return index that started the first day of the formation period (Karvinen, 2012) in contrast to Gatev et al. (2006) who restart the accumulated

[3] Papadakis and Wysocki (2008) propose to rank the pairs selected according to their six and twelve months return and organize them into quintiles in order to optimize selection.

[4] For further information about these pairs, email the corresponding author.

return series the first trading day. The methodology used in this paper allows to trade from the first trading day.

We compute the difference between the daily normalized pairs for each pair. It will be compared to the upper and lower divergence limit. Thus, it will show over or under relative valuation of the stocks of the pair. The entrance criteria will be defined from the upper and lower limit. These limits are calculated as the mean of the distance of the formation period plus/minus a certain number of standard deviations. Gatev et al. (2006) consider two standard deviations. In this paper we have done a sensitivity analysis using 17 different standard deviations[5] (that is, from 1.0 up to 5.0 computed by intervals of 0.25). The consequences of using one or another number of standard deviations is quite obvious: the lower the number of standard deviations is considered, the higher the number of time when an entrance signal will take place; however, the potential return of the trade will be lower. Lucey and Walshe (2013) also undergo a sensitivity test.

Given two stocks, A and B, when the normalized price distance of A minus B is higher than the upper limit, it is considered that stock B is relatively undervalued compared to A. Therefore, stock B will be purchased and A will be sold. This strategy is self-financed, thus we invest the same amount of money on B than what we get from selling A and vice versa.

Once the entrance signal has been activated, it remains until exit signal is appears or until the end of the period. Gatev et al. (2006) only establish one exit criteria to get profits: reversion to the mean. Prices convergence is related to the property of reversion to the mean (De Bondt and Thaler, 1985, 1987; Jegadeesh and Titman, 1993). If the reversion to the mean does not take place, we will held the position until last day of the

[5] See table 16.

implementation period. That last day, all the open positions will be executed and we could get whether profits or losses regardless stock pairs strategy.

When the difference of the normalized prices of two stocks is equal or lesser (if the upper limit has been activated) to the mean distance between the normalized price stocks during the formation period (that is, a reversion to the mean) the exit signal is activated. Once it is activated, the opposite trades to the ones undertaken when the entrance signal was activated will take place.

The outcome of all the trades undertaken for the pair of stocks A and B will be positive and equal to the difference of the prices of B minus the difference of prices of A, regardless transaction costs. This difference is always positive because the only way so that the differential between both stocks has been reduced is that stock B performance has outperformed that of stock A. Therefore, the relative undervaluation of B compared to A has disappeared.

It should be noticed that the relative under or overvaluation between two stocks is corrected without considering if the stocks are accurately priced in absolute terms. This is one of the main targets of pairs trading strategy: to avoid the problem of stock valuation in absolute terms and propose a solution to the problem of relative valuation between two stocks, because it is a simpler problem to solve (Vidyamurthy, 2004).

4.1.3. Returns calculation

Pairs trading strategy has outcomes when pairs convergence during the trading period, that is, when exit criteria with profits is activated. At the end of each period all pairs that have not previously converged are closed. Therefore, we meet positive and negative cash flows, depending if the closing has led to profits or losses.

The first point to do is to measure the gross exposure considering that it is a self-financed stratregy. Gatev et al. (2006) consider that the net cash flow obtained in each entrance plus exit trade can be considered an excess of return since its profits and losses are computed over short and long positions of a monetary unit. Such computation means that one monetary unit is the gross exposure. Rad et al. (2016) also consider one monetary unit as the total value of long and short positions. However, Karvinen (2012) and Augustine (2014) argue that the gross exposition should only consider both long and short exposures with one monetary unit each, which amounts for a total of two monetary units. In this paper we will consider gross exposure to be one monetary unit since it is widely accepted among researchers.

Another question that arises is how to compute total return of the strategy: considering invested capital of compromised capital. Employed capital considers that investment is equivalent to the gross exposure of the pairs that have actually been traded. Meanwhile, compromised capital includes all the pairs of the period, whether they have been traded or activated (Gatev et al., 2006). Return over employed capital in a month is computed as the sum of the returns of the pairs that have been executed during that month, using stock market prices and divided by the number of pairs executed along that month. Return over compromised capital is computed using the same numerator but is divided by the number of pairs that could have been executed. The second one, compromised capital, shows more conservative results and takes into account the cost of opportunity of the capital that has been compromised (Rad et al., 2015). In this paper we will use compromised capital.

When implementing this strategy we face three types of transaction costs: (a) direct trading costs; (b) implicit costs that arise from the impact in the market and the differential between the bid and ask price; and (c) the cost of stock borrowing and the difficulties to get it. Perlin (2007, 2009) considers a transaction cost of 10 b.p., then a total of 40 b.p. for completely trading the pair; however this costs are considered in the Brasilian market. Bolgün et al., (2010) computes 21 b.p. per trade, 5% of the short position as the cost of stock borrowing and 110% of the value of the short position as guarantee of the loan. Caldeira and Moura (2013) considers a cost of 25 b.p. per trade, which is equivalent to 100 b.p. per each pair completely traded. Do and Faff (2012) do a deep study of the costs of implanting pairs trading strategy. They conclude that average transaction cost per trade for institutional investors in US between 1963 and 2009 was 34 b.p.; exactly between 1991 and 2009 the average dropped down to 11 b.p. In their research they compute the cost of stock borrowing to be 1% annual for each pair.

In this paper we will consider a transaction cost of 10 b.p. per execution and 20 b.p. for its impact on the market; that is, 120 b.p. per every completed traded pair. These transaction costs are higher to those that institutional investors are facing in European markets nowadays. For example, in Spain for trades over €100,000, transaction costs are[6] 5 b.p. if you trade via Bankinter, 6 b.p. via Ahorro.com or 8 b.p. via Activo Trade, for instance.

Finally, regarding computation of pairs trading return we will use the methodology proposed by Perlin (2009) and Caldeira and Moura (2013), among other researchers.

4.2. The Model Proposed

The aim of the model proposed in this paper is to increase returns due to the reduction of trades with losses. The model is primarily based on the existence of some variables

[6] Transactions costs based on data from Rankia.com at October 14th, 2015.

that define the stocks co-movement. The correlation of the variation among the variables of two stocks affects the correlation between those stocks' returns, thus, it affects their co-movement (Chen, et al., 2012). It can be inferred that if fundamentals variables show an opposite behavior during a certain period of time, correlation among them will decrease as well as the correlation between stocks' returns. Therefore, the chance for a reversion to the mean of the average of the differential of normalized stock prices will be lower.

In order to include this idea in the model proposed, we will add a variable of control during the execution period. This variable will be equal to the relation between every fundamental variable of the stocks that form the pair, so that if the relationship is above the variable of control during the forming period plus/minus a certain number of standard deviations, even though the criteria of entrance according to the distance method will be activated, the trade would not be executed.

It is supposed that the change in value of the variable of control is due to an opposite performance of the fundamental variables of the two stocks, therefore, the divergence in prices is based on a change of the relative idiosyncratic risk. That is:

Variable of control Y_1: $Y_1 = \frac{EPS_A}{EPS_B}$

Average of Y_1 in the formation period : $\bar{Y}_1 = \frac{1}{n}\sum_{i=1}^{n} Y_{1,i}$

Standard deviation Y_1 in the formation period:

$$s_{Y_1} = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}\left(Y_{1,i} - \bar{Y}_1\right)^2}$$

Criteria of control:

$$Limits = \overline{Y_1} \pm \#\, times * s_{Y_1}$$

When the value of Y1 exceeds the limits, the trade will not be executed.

4.2.1. Formation Period

We will redesign the samples considering the available data regarding the five fundamental variables. The model will be run from January 1st 2002, which is the first day we have data of target prices.

The formation period will last 12 months, the same as in the base model. The number of periods will be 144 in the case of overlapped portfolios, and 24 for non-overlapped ones. We will include an average of 50 stocks per period in Ibex 35, 65 stocks in Euro Stoxx 50 and 79 stocks in Stoxx Europe 50.

Table 4. Number of stocks with available data for each period

Year	Ibex 35	Euro Stoxx 50	Stoxx 50
2002	48	71	81
2003	49	69	80
2004	50	68	80
2005	53	67	79
2006	49	67	80
2007	51	66	80
2008	53	65	78
2009	52	63	77
2010	50	63	77
2011	50	64	76
2012	52	64	77
2013	48	64	77

Table 5. Number of analyzed stocks

	Ibex 35	Euro Stoxx 50	Stoxx 50
Overlapped periods			
Number of periods	144	144	144
Maximum number of stocks	55	71	81
Minimun number of stocks	46	63	76
Average number of stocks	50	66	79

Afterwards, we will follow the same steps explained in section 4.1.1: price normalization, pairs composition, computation of the mean distance of the normalized prices of each pair, standard deviation of the mean distance and the sum of the square mean distances. Then, we compute the mean and standard deviation of the five variables of control (Y_1, Y_2, Y_3, Y_4 and Y_5):

$$Y_1 = \frac{EPS_A}{EPS_B}$$

$$Y_2 = \frac{BVPS_A}{BVPSA_B}$$

$$Y_3 = \frac{TP_A}{TP_B}$$

$$Y_4 = \frac{Recommendation_A}{Recommendation_B}$$

$$Y_5 = \frac{Number\ of\ estimations_A}{Number\ of\ estimations}$$

Finally, we will choose among the pairs following the criterion of the least square sum of the distances. In this paper we will analyze portfolios with 5, 10, 20 and 50 pairs[7]

[7] You are welcome to ask for the selected pairs of each index and the selected portfolios to the corresponding author.

4.2.2. Trading Period.

The trading period will last the same as the trading period in the model base, six months. First of all, for each pair we will compute: (a) the distance between the normalized price of stocks A and B; (b) the value of the five variables of control.

These figures will be compared to two criteria: (a) the distance to the criteria defined in the base model; (b) every variable of control with the criterion of its mean plus/minus a certain number of standard deviations. So that a trade will be undertaken if the following two conditions are met: (a) entrance criteria are activated; (b) the variables of control do not exceeds their limits. Regarding entrance criteria, we will test the model with 9 different standard deviations (from 1 to 5, in steps of 0.5); regarding variable of control, we will test the model for five standard deviations (1, 1.25, 1.5, 1.75 and 2).

Upper limit entrance criterion:

$$Distance_{A,B,i} > \mu_{Distance,T} + x\ times * \sigma_{Distance,T}$$

$$Y_{1,i} < \overline{Y_1} + x\ times * s_{Y_1}$$

The trade will be executed when the distance between the normalized prices of stocks A and B exceeds the mean plus x times the standard deviation of the distance only if the relationship between EPS of both stocks do not exceed the mean of the relationship of the formation period plus x times its standard deviation. If such limit is not overpassed, it means there has not been new specific information that affects any of the two firms that is appears in the variable of control, so that the relationship between the two stock prices will not persistently change. It means that the differential will converge to the mean, so the trade will be executed: buying stock B and selling stock A.

If on the other hand, the limit would be surpassed, the variable would reflect a relative increase of EPS of stock A in comparison to stock B that could justify a wider price differential in favor of stock A. That divergence could be explained in terms of a change of expectations of any of both stocks. Thus, the trade would not take place since there is a risk of maintaining the divergence leading to loses if trade.

Lower limit entrance criterion:

$$Distance_{A,B,i} < \mu_{Distance,T} - x\ times * \sigma_{Distance,T}$$

$$Y_{1,i} > \overline{Y_1} - x\ times * s_{Y_1}$$

In this case is the other stock which is relatively over or undervalued: stock A should be bought and stock B should be sold.

The other variables of control, Y_2, Y_3 e Y_5, will be introduced in the same way as explained with Y_1. We draw attention to variable $Y_{4,,}$ since the sign (plus or minus) will be the opposite because low figures show a better recommendation, so that a lowering of the figure means a better stock performance.

All of the other processes of the trading period will be the same as the ones explained in the base model.

4.2.3. Returns calculation.

Computation of the results of the proposed model will be the same as the one of the base model.

5. RESULTS

5.1. IBEX 35.

We test the distance model on Ibex 35 index for non-restricted portfolios and restricted ones. Afterwards, we add, one by one, the fundamental variables and check which variable, if included in the distance model, leads to higher returns.

Regarding the distance model, the return of non-restricted portfolios has been negative when considering five and ten pairs in each portfolio (results are not statically significant).

Table 6. Ibex 35. Distance Model outcomes for non-restricted portfolio.

	Period 2003-2015			
	5 pairs	**10 pairs**	**20 pairs**	**50 pairs**
Montly return (capital employed)				
Average	-0,19%	-0,05%	0,05%	0,12%
Long position	0,43%	0,45%	0,50%	0,57%
Short position	-0,51%	-0,48%	-0,47%	-0,51%
Median	-0,25%	-0,12%	0,06%	-0,13%
Standard Deviation	3,35%	3,00%	2,40%	2,22%
Minimun	-7,88%	-6,80%	-6,17%	-5,78%
maximum	9,32%	10,88%	10,72%	13,97%
t - Student	-0,48	-0,01	0,40	0,79
Trades	1.025	2.018	3.855	9.056
Average return per trade	-0,40%	-0,11%	0,13%	0,26%
Average return per trade with positive returns	8,31%	8,80%	9,42%	10,36%
Average return per trade with losses	-11,53%	-12,08%	-12,10%	-12,72%
Average maturity (number of trading days)	61	61	63	64
Trades with return<0	43,9%	42,7%	43,1%	43,7%
Annualized monthly return	-2,2%	-0,6%	0,6%	1,5%
Sharpe ratio	-0,06	-0,02	0,02	0,05

Among all the restricted portfolios, we study in depth the Financial Services one since it shows positive returns in all the simulations and results are statically significant.

Table 7. Results of Financial Services portfolio

# of pairs in Financial Services portfolio	Monthly return	Annual return	Average return per trade
5	0.52%	6.4%	2.21%
10	0.60%	7.4%	2.89%
20	0.57%	7.1%	3.39%

The average trade maturity is between 64 and 68 trading days. The long position provides 0.56% to the total average return, and the short position only provides 0.09%, considering the portfolio of five stocks. This composition of the strategy return differs from previous reported evidence (Gatev et al, 2006) where the short position accounted for a significant part of the total return.

Finally, we compute strategy return introducing, one by one, the five fundamental variables. The trades of the distance model strategy will be filtered to check that the day of entrance into the trade the limits of the relation among the different variables are not exceeded. If the fundamental variable of both firms shows a deviation above the average of the relation between the formation period and a certain number of standard deviations, the trade will not be executed.

The impact of implementing this strategy to a non-restricted portfolio of 20 pairs is positive for EPS, BVPS, TP and number of estimations variables and negative regarding recommendation one. Even though the results are non-statically significant, the number of trades with losses is reduced and the return of pairs trading strategy increases (table 8).

Table 8. Ibex 35. Non- restricted porfolio of 20 pairs (criterium: one standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.25%	0.17%	0.16%	-0.24%	0.07%
Trades	-37.8%	-32.3%	-39.1%	-27.9%	-24.9%
Trades with positive returns	-34.1%	-30.0%	-36.7%	-31.2%	-22.9%
Trades with losses	-42.7%	-35.3%	-42.3%	-23.5%	-27.5%
Average return per trade	0.88%	0.59%	0.57%	-0.73%	0.10%

Implementation of the proposed model in the Financial Services portfolio is positive and statically significant for the variables EPS, BVPS, TP and number of estimations. See table 9 for results.

Table 9. Ibex 35. Cartera restringida de 20 pares: impacto (criterio 1 desviación típica)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.18%	0.09%	0.16%	-0.07%	0.02%
Trades	-68.2%	-28.5%	-67.6%	-57.5%	-56.8%
Trades with positive returns	-65.1%	-29.1%	-65.2%	-58.0%	-55.0%
Trades with losses	-72.9%	-27.6%	-71.3%	-56.7%	-59.6%
Average return per trade	1.05%	0.26%	0.92%	-0.68%	0.22%

We highlight the percentage of trades with losses has slopped down. Such decrease is key to understand why returns are higher with these model.

EPS variable is the variable that best determines fundamental risk according to results achieved. Using the criteria of non-executing the trades when EPS deviation of the two stocks is above the average plus one standard deviation, the number of executed trades drops down a 68.2% (until 924) and the number of trades with losses is reduced to 33%. Considering returns, average trade return increases by 105 b.p., and monthly return up to 18 b.p.

We have done the following sensitivity analysis: (i) considering the number of standard deviations used in the entrance criterion of the basic model; (ii) number of standard deviations considered in the EPS fundamental variable. Results are shown on table 10.

All of the results are statically significant with a confidence level of 95%. In all cases, considering EPS variable in the proposed model outperforms returns of the distance model.

Table 10. Ibex 35. Montly return of portfolio "4": sensitivity analyis EPS vs Standard Deviation Entrance Criterion

Pairss	Entrance Criterion	EPS Standard Deviation 1.00	1.25	1.50	1.75	2.00	Distance Model	Difference vs. max.
5								
	1.00	0.60%	0.56%	0.52%	0.46%	0.41%	0.37%	0.24%
	1.50	0.72%	0.63%	0.60%	0.55%	0.52%	0.46%	0.26%
	2.00	0.76%	0.72%	0.66%	0.61%	0.59%	0.52%	0.24%
	2.50	0.77%	0.78%	0.74%	0.75%	0.74%	0.52%	0.26%
	3.00	0.77%	0.78%	0.68%	0.72%	0.76%	0.58%	0.20%
	3.50	0.76%	0.75%	0.63%	0.60%	0.62%	0.57%	0.19%
	4.00	0.71%	0.71%	0.70%	0.76%	0.76%	0.49%	0.27%
	4.50	0.79%	0.79%	0.77%	0.79%	0.80%	0.45%	0.35%
	5.00	0.75%	0.77%	0.78%	0.79%	0.81%	0.58%	0.23%
10								
	1.00	0.66%	0.61%	0.58%	0.53%	0.48%	0.46%	0.19%
	1.50	0.74%	0.68%	0.64%	0.62%	0.59%	0.56%	0.19%
	2.00	0.82%	0.77%	0.75%	0.73%	0.70%	0.60%	0.22%
	2.50	0.81%	0.81%	0.78%	0.80%	0.75%	0.61%	0.20%
	3.00	0.87%	0.91%	0.83%	0.84%	0.83%	0.64%	0.27%
	3.50	0.78%	0.84%	0.73%	0.70%	0.67%	0.64%	0.20%
	4.00	0.92%	0.91%	0.91%	0.92%	0.93%	0.61%	0.32%
	4.50	0.95%	0.93%	0.91%	0.90%	0.91%	0.70%	0.25%
	5.00	0.86%	0.88%	0.88%	0.89%	0.88%	0.57%	0.33%
20								
	1.00	0.62%	0.58%	0.56%	0.52%	0.48%	0.43%	0.19%
	1.50	0.69%	0.65%	0.61%	0.59%	0.57%	0.51%	0.18%
	2.00	0.76%	0.73%	0.71%	0.69%	0.66%	0.57%	0.18%
	2.50	0.71%	0.72%	0.71%	0.74%	0.70%	0.61%	0.13%
	3.00	0.84%	0.86%	0.81%	0.83%	0.80%	0.63%	0.23%
	3.50	0.74%	0.82%	0.73%	0.71%	0.67%	0.62%	0.20%
	4.00	0.82%	0.82%	0.83%	0.86%	0.87%	0.63%	0.23%
	4.50	0.82%	0.80%	0.79%	0.78%	0.80%	0.67%	0.15%
	5.00	0.76%	0.77%	0.77%	0.77%	0.77%	0.76%	0.01%

The variable Target Price is the second one that makes a positive impact on pairs trading strategy. The number of executed trades was reduced by 67.8% (down to 941), and the trades with loss drops down to 35%. Return per trade increases by 91 b.p.. Another sensitivity analysis have been done (table 11), according to the previous one. All the results are statically significant with a confidence level of 95%. Results are similar to those achieved with EPS, that is, in all cases return achieved considering EPS variable is higher to that of the distance model. However, there is an exception: when considering a 1.50 TP deviation ratio for the 20 pairs portfolio, the distance model outperforms the proposed model, and the model with TP (0.76% monthly return vs 0.72%).

Table 11. Ibex 35. Montly return of Financial Services portfolio: sensitivity analyis TP vs Standard Deviation Entrance Criterion

Pairs	Entrance Criterion	1.00	1.25	TP Standard Deviation 1.50	1.75	2.00	Distance Model	Difference vs. max.
5								
	1.00	0.60%	0.62%	0.66%	0.65%	0.65%	0.37%	0.30%
	1.50	0.54%	0.56%	0.60%	0.58%	0.52%	0.46%	0.14%
	2.00	0.60%	0.62%	0.65%	0.63%	0.61%	0.52%	0.13%
	2.50	0.65%	0.67%	0.69%	0.68%	0.66%	0.52%	0.16%
	3.00	0.47%	0.53%	0.68%	0.65%	0.67%	0.58%	0.10%
	3.50	0.62%	0.64%	0.65%	0.63%	0.64%	0.57%	0.08%
	4.00	0.41%	0.45%	0.56%	0.58%	0.60%	0.49%	0.11%
	4.50	0.67%	0.53%	0.57%	0.54%	0.60%	0.45%	0.22%
	5.00	0.75%	0.79%	0.78%	0.75%	0.69%	0.58%	0.20%
10								
	1.00	0.74%	0.76%	0.77%	0.76%	0.74%	0.46%	0.31%
	1.50	0.63%	0.63%	0.62%	0.60%	0.55%	0.56%	0.08%
	2.00	0.66%	0.67%	0.67%	0.64%	0.62%	0.60%	0.07%
	2.50	0.75%	0.75%	0.75%	0.74%	0.70%	0.61%	0.14%
	3.00	0.69%	0.71%	0.74%	0.71%	0.69%	0.64%	0.10%
	3.50	0.73%	0.75%	0.75%	0.76%	0.73%	0.64%	0.12%
	4.00	0.74%	0.80%	0.85%	0.78%	0.77%	0.61%	0.24%
	4.50	0.85%	0.77%	0.78%	0.81%	0.82%	0.70%	0.15%
	5.00	0.81%	0.89%	0.91%	0.93%	0.90%	0.57%	0.37%
20								
	1.00	0.71%	0.71%	0.71%	0.70%	0.68%	0.43%	0.28%
	1.50	0.62%	0.62%	0.61%	0.59%	0.55%	0.51%	0.11%
	2.00	0.66%	0.66%	0.65%	0.63%	0.61%	0.57%	0.08%
	2.50	0.74%	0.74%	0.73%	0.72%	0.68%	0.61%	0.13%
	3.00	0.68%	0.70%	0.71%	0.68%	0.67%	0.63%	0.09%
	3.50	0.68%	0.70%	0.71%	0.73%	0.71%	0.62%	0.11%
	4.00	0.72%	0.77%	0.79%	0.73%	0.73%	0.63%	0.15%
	4.50	0.82%	0.73%	0.71%	0.74%	0.75%	0.67%	0.15%
	5.00	0.67%	0.71%	0.72%	0.72%	0.69%	0.76%	-0.04%

5.2. EURO STOXX 50

We have used a sample of 75 stocks (see table 12) that belong, or have belonged to, Euro Stoxx 50 index.

The distance model of a non-restricted portfolio shows positive and statically significant results. After considering transaction costs, return is positive for all the portfolios considered except for the one with 5 pairs, that achieves 1.06% return per trade.

Table 12. Euro Stoxx 50. Distance Model outcomes for non-restricted portfolio

	Period 2003-2015			
	5 pairs	**10 pairs**	**20 pairs**	**50 pairs**
Montly return (capital employed)				
Average	0.31%	0.35%	0.37%	0.36%
Long position	0.44%	0.52%	0.55%	0.56%
Short position	-0.19%	-0.26%	-0.29%	-0.31%
Median	0.34%	0.33%	0.27%	0.18%
Standard Deviation	2.02%	1.66%	1.56%	1.46%
Minimun	-6.08%	-4.08%	-3.24%	-2.63%
maximum	9.00%	7.06%	8.46%	9.97%
t - Student	1.98	2.61	2.90	3.08
Trades	1.074	2.101	4.021	9.518
Average return per trade	1.06%	1.26%	1.28%	1.30%
Average return per trade with positive returns	6.64%	7.30%	7.68%	8.36%
Average return per trade with losses	-8.97%	-8.87%	-9.01%	-9.46%
Average maturity (number of trading days)	58	59	60	62
Trades with return<0	35.9%	37.5%	38.5%	39.8%
Annualized monthly return	3.8%	4.3%	4.5%	4.5%
Sharpe ratio	0.15	0.21	0.23	0.25

As done in section 5.1., we analyze the impact of the basic model on 13 restricted portfolios. If we rank the 13 restricted portfolios and the non-restricted one from high return down to low return, the non-restricted portfolio is ranked on the 13rd place. The portfolios with the higher returns are: industrial products (# 4), financial services (# 6) and financial services-value style (# 7) (see table 13).

Table 13. Euro Stoxx 50. Distance model outcomes for non-restricted porffolo and restricted portfolios with higher return (20 pairs and 2 standard deviations)

	Period 2003-2015			
# portfolio	Non-restricted	4	6	7
Montly return (capital employed)				
Average	0.37%	0.45%	0.60%	0.65%
Long position	0.55%	0.70%	0.58%	0.62%
Short position	-0.29%	-0.42%	0.04%	0.06%
Median	0.27%	0.20%	0.40%	0.43%
Standard Deviation	1.56%	2.39%	2.18%	2.23%
Minimun	-3.24%	-3.95%	-8.64%	-6.56%
maximum	8.46%	10.24%	12.42%	13.95%
t - Student	2.90	2.39	3.42	3.61
Trades	4.021	2.789	3.250	2.887
Average return per trade	1.28%	1.76%	2.51%	2.84%
Average return per trade with positive returns	7.68%	11.04%	9.33%	9.84%
Average return per trade with losses	-9.01%	-10.71%	-8.79%	-9.22%
Average maturity (number of trading days)	60	75	65	68
Trades with return<0	38.5%	42.7%	37.7%	36.9%
Annualized monthly return	4.5%	5.5%	7.4%	8.0%
Sharpe ratio	0.23	0.19	0.27	0.29

Fuente: elaboración propia.

The proposed model increases return in the non-restricted portfolio using the following variables: EPS, BVPS, TP and recommendation. The number of estimations does not lead to an increase on return. Among the previous four variables, the one which shows a bigger impact on return is Target Price (TP): average return increases by 12 p.b. and average return per trade by 55 p.b.

Table 14. Euro Stoxx 50. Non-restricted 20 pairs portfolio (criterion 1 standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0,07%	0,05%	0,12%	0,02%	-0,03%
Trades	-39,8%	-34,9%	-41,2%	-30,0%	-22,4%
Trades with positive returns	-38,3%	-34,9%	-38,2%	-28,0%	-21,7%
Trades with losses	-42,2%	-34,9%	-45,9%	-33,1%	-23,5%
Average return per trade	0,38%	0,15%	0,55%	0,17%	-0,11%

The proposed model increases Industrial Products portfolio return using the following three variables: EPS, TP and recommendation. Target Price variable is the one that leads to a higher return, 27 b.p.. The use of EPS variable increases strategy return by 18 b.p. In both cases it is due to the reduction of the number of trades with losses (table 15).

Table 15. Euro Stoxx 50. Restricted 20 pairs portfolio #4 (1 standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.18%	-0.10%	0.27%	0.02%	-0.05%
Trades	-52.2%	-39.8%	-58.8%	-31.1%	-21.3%
Trades with positive returns	-49.3%	-42.8%	-56.5%	-30.4%	-21.6%
Trades with losses	-56.0%	-35.7%	-61.8%	-32.1%	-21.0%
Average return per trade	0.58%	-1.13%	0.74%	0.19%	-0.09%

If we analyze the effect of these variables on Financial Services portfolio 6, Target Price is the one with a higher impact on return (10 b.p.) and 45 b.p. on return per trade. Trades with profits get 9.25% return, while trades with losses get -8.66% return. Again, it is remarkable the decrease of the number of trades with losses (table 16).

Table 16. Euro Stoxx 50. Restricted 20 pairs portfolio #6 (1 standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.01%	0.07%	0.10%	-0.01%	-0.02%
Trades	-43.4%	-36.4%	-45.4%	-30.2%	-24.7%
Trades with positive returns	-42.4%	-34.6%	-43.2%	-30.0%	-23.9%
Trades with losses	-45.0%	-39.5%	-49.1%	-30.4%	-26.1%
Average return per trade	0.12%	0.25%	0.45%	-0.27%	0.07%

Finally, we analyze the impact of the variables on Financial Services – Value Style portfolio performance. Target Price variable increases monthly return by 18 b.p. The average return per trade goes up to 3.07% from 2.84% of the base model. The number of trades with losses diminishes, as well as in the other portfolios. Book value per share variable also leads to an increase of this strategy return of 9 b.p, along with EPS which increases return by 6 b.p. (all results are statically significant). See table 17.

Table 17. Euro Stoxx 50. Restricted 20 pairs portfolio #7 (1 standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.06%	0.10%	0.18%	-0.01%	-0.08%
Trades	-50.2%	-39.2%	-49.5%	-30.2%	-23.9%
Trades with positive returns	-48.5%	-38.0%	-47.7%	-30.6%	-23.9%
Trades with losses	-53.0%	-41.4%	-52.5%	-29.6%	-24.0%
Average return per trade	0.15%	0.15%	0.24%	-0.30%	-0.42%

5.3. STOXX EUROPE 50

Return of the basic model over the non-restricted portfolio of Stoxx Europe 50 stocks shows positive outcomes for 2003-2015. However, returns are low. If we consider transaction costs, it would lead to losses. One of the reasons may be the high level of trades with losses, which is above 50% (see table 18).

Table 18. Stoxx Europe 50. Distance Model outcomes for non-restricted portfolio

	Periodo 2003-2015			
	5 pares	10 pares	20 pares	50 pares
Montly return (capital employed)				
Average	0,29%	0,35%	0,37%	0,38%
Long position	0,45%	0,48%	0,51%	0,53%
Short position	-0,23%	-0,21%	-0,23%	-0,23%
Median	0,12%	0,07%	0,11%	0,32%
Standard Deviation	2,99%	2,36%	1,86%	1,58%
Minimun	-7,76%	-4,13%	-3,49%	-2,88%
maximum	29,42%	23,12%	15,93%	12,68%
t - Student	1,32	1,90	2,47	3,00
Trades	1.063	2.119	4.206	9.989
Average return per trade	0,31%	0,64%	1,00%	1,17%
Average return per trade with positive returns	4,17%	5,68%	6,59%	7,51%
Average return per trade with losses	-8,68%	-8,68%	-8,82%	-9,24%
Average maturity (number of trading days)	46	52	55	59
Trades with return<0	30,3%	35,4%	36,5%	38,0%
Annualized monthly return	3,5%	4,3%	4,5%	4,7%
Sharpe ratio	0,10	0,15	0,20	0,24

All the restricted portfolios achieve higher monthly return than non-restricted one in all the simulations done. The portfolios that we analyze deeply are number 6 (financial services – value style), 8 (financial services – bank – value style) and 9 (financial services – assurance) which are the ones with a better performance. See table 19.

Table 19. Stoxx Europe 50. Distance model outcomes for non-restricted porffolo and restricted portfolios with higher return (20 pairs and 2 standard deviations)

	Period 2003-2015			
# portfolio	**Non-restricted**	**6**	**8**	**9**
Montly return (capital employed)				
Average	0,37%	0,64%	0,68%	0,65%
Long position	0,51%	0,63%	0,57%	0,73%
Short position	-0,23%	0,02%	0,34%	-0,18%
Median	0,11%	0,45%	0,46%	0,38%
Standard Deviation	1,86%	2,07%	2,41%	2,59%
Minimun	-3,49%	-7,09%	-7,49%	-6,07%
maximum	15,93%	10,62%	9,14%	16,12%
t - Student	2,47	3,84	3,52	3,16
Trades	4.206	3.192	2.736	2.874
Average return per trade	1,00%	3,12%	2,79%	3,11%
Average return per trade with positive returns	6,59%	10,45%	12,01%	9,93%
Average return per trade with losses	-8,82%	-9,76%	-10,75%	-8,17%
Average maturity (number of trading days)	55	66	71	67
Trades with return<0	36,5%	36,5%	40,8%	37,9%
Annualized monthly return	4,5%	8,0%	8,5%	8,1%
Sharpe ratio	0,20	0,31	0,28	0,25

The proposed model gets higher returns than that of the distance model for a non-restricted portfolio when we use EPS, BVPS and TP variables. The increase of return is low, though. The variable that influences more on return is BVPS: 4 b.p. The number of trades with losses is reduced, as well as stated in previous analysis. TP variable just increases return by 2 b.p. It is remarkable that these returns do not take into account transaction costs. If taken into consideration, return of non-restricted portfolio would be negative. See table 20.

Table 20. Euro Stoxx 50. Non-restricted 20 pairs portfolio (1 standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.00%	0.05%	0.02%	0.00%	-0.06%
Trades	-37.2%	-29.5%	-34.8%	-25.9%	-23.2%
Trades with positive returns	-35.8%	-27.7%	-32.0%	-23.8%	-23.7%
Trades with losses	-39.5%	-32.5%	-39.8%	-29.5%	-22.5%
Average return per trade	0.17%	0.15%	0.15%	0.07%	-0.26%

Regarding the restricted Financial Services portfolio, all the variables have a positive impact on return. Among them, TP variable is the variable with a higher impact on return: monthly return increases by 21 b.p. and average return per trade goes up to 3.76% from 3.12%. The number of trades with losses drops down, too, up to 55.5%. The second variable with a high impact on return is BVPS: return increases by 10 b.p.

Table 21. Stoxx Europe 50. Restricted 20 pairs portfolio #6 (1 standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.01%	0.10%	0.21%	0.04%	0.00%
Trades	-44.9%	-37.8%	-49.1%	-30.1%	-23.7%
Trades with positive returns	-44.5%	-35.1%	-45.4%	-30.6%	-22.6%
Trades with losses	-45.5%	-42.7%	-55.5%	-29.3%	-25.4%
Average return per trade	-0.22%	0.47%	0.64%	-0.19%	0.12%

About restricted portfolio number 8, including EPS, BVPS and TP variables in the model, makes return of pairs strategy outperform. Along with the reported results on Financial Services portfolio, TP is the variable with a higher impact on return: 20 b.p. increase. Average return of executed trades goes up to 3.87% from 2.79%. There is a decrease of trades with losses of 33.5%. Besides, average maturity of the trades drops to 61 days from 71 days. Both decreases, on trades with losses and average maturity, make increase the return on capital employed. The impact of BVPS is 13 b.p. and BVPS is just 12 b.p.

Table 22. Stoxx Europe 50. Restricted 20 pairs portfolio #8 (1 standard deviation)

	BPA	VCPA	PO	Rec.	Est.
Difference with distance model					
Average of monthly return	0.13%	0.12%	0.20%	0.00%	-0.08%
Trades	-49.6%	-40.6%	-57.7%	-31.7%	-21.0%
Trades with positive returns	-46.4%	-35.7%	-52.5%	-31.6%	-22.6%
Trades with losses	-54.3%	-47.9%	-65.2%	-31.9%	-18.6%
Average return per trade	0.23%	1.08%	1.08%	-0.20%	-0.26%

6. CONCLUSIONS

Restricted portfolios show higher returns that non restricted portfolios. It is justified because they have more risk factors in common. We have to highlight the performance of portfolios with financial services stocks, which are the most profitable ones in all the indexes analyzed. Finally, we have tested a sensitivity analysis of results compared to different standard deviations (1, 1.25, 1.5, 1.75 and 2) regarding entrance criteria. Our better results are achieved when considering 3.5 standard deviations, which differs from previous works.

The main aim of this paper is to design a pairs trading model that outperforms returns' achieved by the traditional method of distance. The way to reach to this target was by (i) reducing the number of trades with losses via anticipating persistence divergences on stock prices, (ii) adding variables that represents firms' idiosyncratic risk.

Empirical analysis of the proposed model confirms the hypothesis of the paper: including in the model variables that represent idiosyncratic risk of a firm outperforms basic pairs trading strategy (distance model). In fact, adding ES, BVPS and TP variables leads to better returns in the analyzed portfolios of IBEX 35 index, Euro Stoxx 50 index and Stoxx Europe 50 Index.

The variable which has a more important impact on increasing return is Target Price. This variable has recently appear in analysts' reports. The variable with the second higher impact on return is EPS. Recommendation and number of estimations variables do not always lead to positive results.

The impact on the indexes analyzed is significant. For instance, considering EPS and TP on the 104 portfolios of Stoxx Europe 50 Index, average return's strategy has increased by circa 35%, which leads to an increase of 90 b.p. in monthly basis, that is 11% annually.

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