Pairs trading in the index options market*

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This version: November 22

Abstract

We test the Index options market efficiency by means of a statistical arbitrage strategy, i.e. pairs trading. Using data on five Index Option Market of the Euro Area, we first identify any potential option mispricing based on deviations from the long-run relationship linking their implied volatilities. Then, we evaluate the profitability of a simple pair trading strategy on the mispriced options. Despite the signals of potential mispricing are frequent, the statistical arbitrage does not produce significant profits, thus providing evidence in support of Index Option market efficiency. The results, which remain unchanged in a variety of robustness checks, also prove that the observed profits are strongly associated to the moneyness of the options traded while they do not correlate to options' maturity or to financial market turbulence.

Keywords: pairs trading, option market efficiency

JEL Codes: G10, G12, C44, C55

* This paper was drafted when Roberta De Luca was PhD Candidate in Economics and Finance at the University of Rome Tor Vergata. The authors would like to thank Gianluca Cubadda, Tommaso Proietti, Philip Rosenthal and the participants to the European Financial Management Association 2021 annual conference and to Tor Vergata PhD Seminars for helpful comments and suggestions. Marianna Brunetti kindly acknowledges financial support from the University of Rome Tor Vergata, Grant "Beyond Borders" (NR: E84I20000900005). The views expressed herein are those of the authors and do not involve the responsibility of the Bank of Italy.

1. Introduction

This paper investigates the index option market efficiency through pairs trading, a specific kind of statistical arbitrage strategy usually applied to the stock market. This strategy requires the identification of pairs of assets whose prices co-move and the setting of a trading rule to profit from any price divergence.

Our work represents one among the few attempts in this direction, as the only study we are aware of performing a similar analysis is Ammann and Herriger (2002). We implement a variation with respect to their methodology, consisting in estimating the mean-reverting relationship aimed at identifying potential options' mispricing directly on the options' implied volatilities, rather than indirectly deriving it from the one estimated on underlying index returns. Then, whenever significant deviations from this mean-reverting relationship between implied volatilities (interpreted as signals of one option being not "correctly" priced with respect to the other) are observed, a simple pair trading strategy is triggered, buying the relatively underpriced option and contextually selling the relatively overpriced option. The positions are then unwounded as soon as the mispricing signal re-enters within the significance boundaries. According to the Efficient Market Hypothesis, as postulated by Fama (1970), in efficient markets no abnormal return can be obtained if the information is fully disclosed.[2] That is, arbitrage opportunities are short lived since mispricing are immediately identified and exploited. Therefore, significant profits generated by this trading strategy would be interpreted as disproving the index option market efficiency.

In our application, we use at-the-money one-month maturity index options traded on the European market. This choice comes with several advantages. First, since the underlying is a synthetic representation of a stock portfolio, the final payoff is cash-settled rather than paid by an exchange of goods. Hence, cashing-in the payoff does not incur additional transaction costs to those related strictly to the trade. Second, at-the-money options are the most informative in terms of volatility, as most of their value is driven by this component. This is crucial for our application since the long-run equilibrium relationship between pairs of options is established through their (implied) volatilities. Last, short-term-maturity options are among the most liquid in the market, thus guaranteeing sufficient and reliable data for the empirical application.

[2] The literature differentiates among levels of market efficiency, based on the definition of available information (Fama, 1991). In its weak form, the information is limited to historical prices; in its semi-strong form, it includes all publicly available information; in its strong form it considers all existing information, both public and private (Jensen, 1978). See López-Martín et al. (2021) for test of cryptocurrency market efficiency.

Being among the few applying pairs trading to test index options market efficiency, this paper represents a novel contribution to both the strands of literature dealing with option market efficiency, on the one hand, and with statistical arbitrage, and in particular pairs trading, on the other. Section 2 briefly reviews these two branches of literature. Section 3 outlines the methodology and the arbitrage strategy employed to test market efficiency, while Section 4 describes the dataset used and presents the results. Finally, Section 5 discusses the robustness of the results and last Section concludes.

2. Literature review

This work lies at the intersection between two distinct literature streams: the one testing for index option market efficiency and the one implementing statistical arbitrage strategies, such as pairs trading, which so far has been generally applied to stocks and few other kinds of assets, but not options.

Index options market efficiency can be tested by means of either model-based or model-free methodologies. The former approach involves the so called “joint hypothesis problem”, pointed out by Fama (1998). Indeed, model-based methodologies market efficiency and the appropriateness of the pricing model are jointly tested, so that evidence against efficiency may indeed be due to the (wrong) pricing model being used rather than disproof of the EMH. As a result, most of the previous contributions on index options market efficiency employ a model-free approach, which amount to simply test the absence of arbitrage opportunities.[3] Following the seminal paper by Stoll (1969), many contributions have tested the no-arbitrage relationships on the option market, with special focus on the US. For instance, Evnine and Rudd (1985) observed significant violations of the put-call parity and of the boundary conditions for the S&P100 option market, thus advocating market inefficiency. Several years later and working with S&P500 index options, Ackert and Tian (2001) reach the opposite conclusion. Tests on European markets, such as Capelle-Blancard and Chaudhury (2001) on the French index (CAC40) option market, Mittnik and Rieken (2000) on the German index (DAX) option market, and Cavallo and Mammola (2000) and Brunetti and Torricelli (2005) on Italian index (Mib30) option market, highlight the pivotal role of market frictions. Violations are frequent,

[3] The literature differentiates between cross-markets efficiency, which is based on tests of the joint efficiency of the options and the underlying markets (e.g., by verifying the put-call parity and the lower-boundary conditions), and internal option market efficiency, which aims to assess the existence of arbitrage opportunities in the same option market (by verifying, e.g., box and butterfly spreads).

but disappear almost completely once transaction costs are taken into account, thus eventually providing evidence in support of index option market efficiency.

As Bondarenko (2003) points out, however, two different types of arbitrage opportunities are identified in the literature: a '*Pure Arbitrage Opportunity*, that is a zero-cost trading strategy that offers the possibility of a gain with no possibility of a loss', and a '*Statistical Arbitrage Opportunity*, that is a zero-cost trading strategy for which (i) the expected payoff is positive, and (ii) the conditional expected payoff in each final state of the economy is non-negative'. In both cases, the average payoff in each final state is non-negative so that the main difference between them is the possibility of negative payoffs, which are allowed in the statistical but not in the pure arbitrage opportunity. All the above-cited works on index option market efficiency test the absence of *pure* arbitrage opportunities. This study relies on statistical arbitrage instead.

As for statistical arbitrage, the most well-known application is certainly pairs trading, which identifies assets whose prices share a similar historical behavior and tries to exploit short-term deviations from this long-run equilibrium to make profits. Pairs trading has been implemented using a variety of approaches, which differ in the way pairs are selected and in how their relationship is modelled (Krauss, 2017). For instance, in distance approach assets are paired by minimizing the sum of squared deviations between normalized prices, while in cointegration approach pairs are identified based on cointegration tests. Regardless of the approach used, the literature on pairs trading is almost entirely applied to the stock market. Many works focus on the U.S., such as Gatev *et al*. (2006), Avellaneda and Lee (2010), Do and Faff (2010), Miao (2014), Jacobs and Weber (2015), Rad *et al*. (2016), but some further applications can be found to other stock markets, such as the European (Dunis & Lequeux, 2000), the Japanese (Huck, 2015), the Brazilian (Perlin, 2009; Caldeira & Moura, 2013), the Chinese (Li, Chui, & Li, 2014) and the Taiwanese (Andrade, Di Pietro, & Seasholes, 2005) ones.[4] Regardless of the investigated market and of the employed methodology, they all conclude that pairs trading on stocks is a profitable strategy, which is able to exploit short-run deviations between co-moving prices. Moreover, the empirical literature has produced evidence that supports the superiority of cointegration with respect to distance methodology (Huck & Afawubo, 2015; Rad, Low, &

[4] Examples of works applying PT to securities other than stocks include: Girma and Paulson (1999) and Cummins and Bucca (2012), who focus on the 'crack spread', that is the difference between petroleum and its refined products futures prices; Simon (1999) works on the 'crush spread', namely the difference between soybean and its manufactured goods futures prices; Emery and Liu (2002) use the 'spark spread', i.e. the difference between natural gas and electricity future prices.

Faff, 2016; Blázquez, De la Orden, & Román, 2018), which has become less profitable in recent years (Do & Faff, 2010).

To sum up, the efficiency of the index options market has been so far investigated by testing for the profitability of pure arbitrage strategies and on sample periods mostly between the 90s and the 00s, while statistical arbitrage and, pairs trading in particular, has been applied typically to the stock market.[5]

The only paper we are aware of that investigate the option market efficiency through statistical arbitrage is Ammann and Herriger (2002). The authors use a Relative Implied Volatility arbitrage strategy, applied to options on S&P 500, S&P 100 and NASDQ indexes, in the period 1995 to 2000, to test the possibility of positive profits from relative mispricing of options. In their contribution, the authors estimate a stationary and mean-reverting relationship between underlying indexes returns, which is then used to derive a valid mean-reverting relationship for the options' implied volatilities. This long-run relationship is finally exploited to identify potential mispricing of options. Consistent with most of the literature on the index option market, they find evidence to support market efficiency since, although violations of the statistical arbitrage strategy are frequent, only few survive after accounting for transaction costs and bid-ask spread.

This paper contributes to the still unpopulated literature testing the efficiency of the index options market based on statistical arbitrage. In doing so, we differ from Ammann and Herriger (2002) in two main directions. First, the mean-reverting relationship is estimated directly on the implied volatilities, rather than indirectly derived from the one estimated on the underlying indexes returns. Second, their analysis is referred to the US market and relies on few pairs of options only, while our study evaluates the index option market efficiency of five European markets (Germany, France, Italy, UK and EU as a whole).

3. Methodology

We use statistical arbitrage, and in particular pairs trading, to test the index options market efficiency. Among the different approaches proposed in the pair trading literature, we will rely on the so called cointegration approach, given its proved superiority in term of profitability (Huck & Afawubo, 2015; Rad, Low, & Faff, 2016; Blázquez, De la Orden, & Román, 2018).

[5] See Hogan *et al*. (2004) and Krauss (2017) for a review of, respectively, statistical arbitrage applications and pairs trading strategies.

According to this approach (Vidyamurthy, 2004), the pairs of assets sharing a long-term equilibrium relationship are pinpointed based on cointegration tests. Then, a simple trading strategy is implemented anytime deviations from such equilibrium are observed. Pairs trading however is typically applied to stocks, so the procedure needs to be adapted to options, which are assets remarkably different (both financially and statistically) from stocks. To start with, applying cointegration to index options rather than to stocks poses a major challenge since, by their own nature, options have a finite life. This implies that we may not have enough data to train the classical cointegration approach, as in most applications the formation period employed to test for cointegration lasts one year.

To overcome this issue, Ammann & Herriger (2002) rely on the returns of the options underlying indexes. Specifically, using the pre-selected pairs of indexes that have highly correlated daily returns, they first check the stationarity of the returns and then estimate the long-run relationship linking the indexes returns. Next, based on linearity, they use the obtained estimates to derive the corresponding long-run relationship that should hold between the historical volatilities of the paired options, and assume that it also holds between the respective implied volatilities. The idea is that, if the quotations of the underlying indexes are highly correlated, and the market is efficient in pricing similar risks, the implied volatilities of the options on those indexes should also be related. Then, if violations of the equilibrium-relationship between volatilities are observed systematically and allow significant profits, market efficiency is disproved. Our methodology differs from Ammann & Herriger (2002) since it identifies the potential mispricing based on the long-run relationship estimated directly between the implied volatilities of the options, rather than estimating the relation between the returns from the underlying indexes, and then applying it to the volatilities. In doing so, we avoid the joint assumption that the long-run relationship linking the indexes returns is inherited by the historical volatilities and that the one that links the indexes option historical and implied volatilities is the same.

The proposed methodology is structured as follows:

1. Check for stationarity: using data over the full sample, run ADF tests to check for stationarity of the options' implied volatilities (IV);
2. Using 1-year observations, which serve as estimation period, regress the IV_Y on the IV_X, for all options written on the pairs of indexes (Y, X), so as to obtain the estimates required to derive the *Spread*;

3. Moving to the following 6-month observations, which serve as trading period, compute the *Spread*, implement a simple trading strategy whenever a misprice is suspected, i.e. when the *Spread* significantly diverges from its zero mean, and evaluate the profitability of this trading strategy;
4. Steps 2 to 3 are repeated shifting the sample one month ahead at each repetition, so as to evaluate the results independently of the starting point and to update the information set as time passes. Notice that this produces, for each month in the sample (except the first and last 5), 6 overlapping trading periods.

The profitability of the trading strategy is evaluated by looking at the total number of trades, as well as the average number of days a position is kept open and the average profits across the 6 different overlapping trading periods. Absence of significant profits, tested by means of the Newey-West statistics (Newey & West, 1987), is then interpreted as evidence in support of option market efficiency.

The next subsections describe steps 2 and 3 of the above procedure in more detail.

3.1 Estimation period

Using 1-year data, we estimate the following OLS regression:

$$IV_{t,Y} = \beta_0 + \beta_1 IV_{t,X} + \varepsilon_t \tag{1}$$

where:

- $IV_{t,Y}$ is the implied volatility of the option written on Index Y observed at day t
- $IV_{t,X}$ is the implied volatility of the option written on Index X observed at day t
- ε_t is the error term at time t
- β_0 is the intercept, that in this case simply acts as a scale parameter
- β_1 is the slope, measuring the linear relationship between the two implied volatilities

The estimation is performed for all possible pairs of indexes (Y, X).

Notice that using IV, which are typically stationary time series, allows a correct measurement of their association via OLS regression, as opposed to what happens when this approach is applied to stock prices, which typically are $I(1)$ time series.

3.2 Trading period

Each estimation period is followed by a six-months trading period, in which a simple trading strategy is implemented any time one of the options has an observed implied volatility that deviates sufficiently from the predicted value based on the estimates of model (1). When this divergence is detected, the agent sells the relatively overpriced option and buys the relatively underpriced, so as to close the position whenever the two volatilities align again. If this strategy is able to generate significant profits, the market efficiency in pricing relative risks is actually disproved.

In order to provide a definition of 'sufficient deviation', we rely on the estimates of β_0 and β_1 obtained in the estimation period and compute the *Spread*[6] as:

$$Spread_t = IV_{t,Y} - \hat{\beta}_0 - \hat{\beta}_1 IV_{t,X} \tag{2}$$

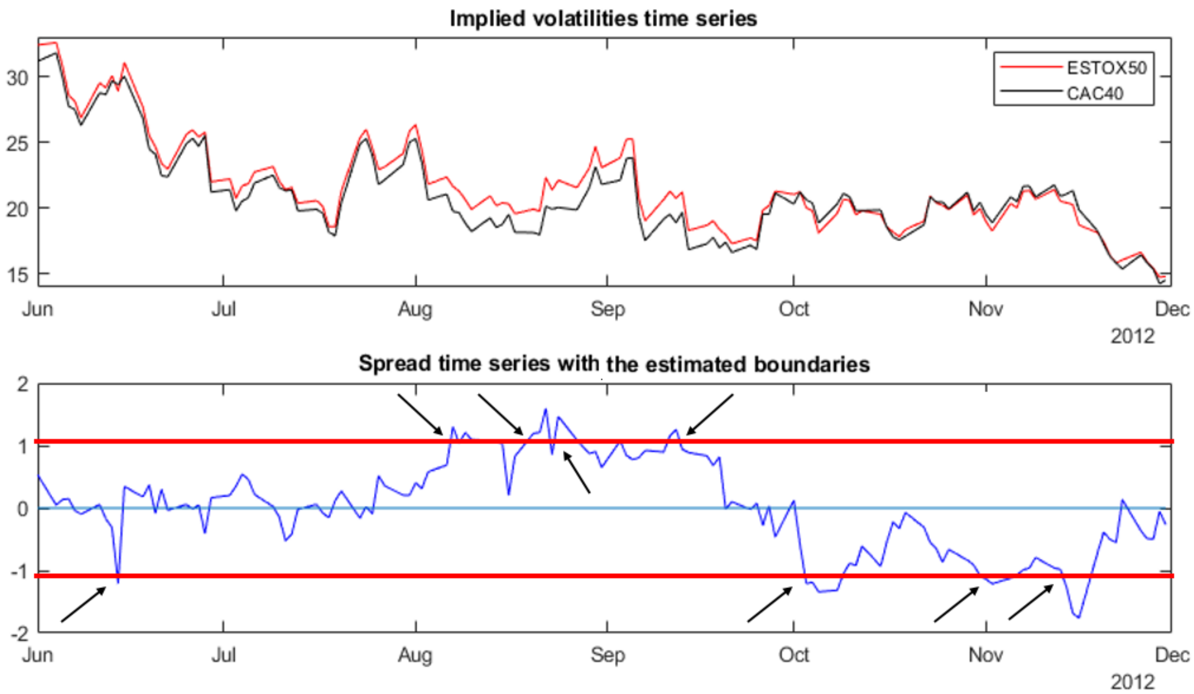
The Spread thus represents the out-of-sample residuals of model (1). Under stationarity of both the variables involved in the simple linear regression model, in-sample residuals are also a stationary process, mean-reverting towards 0. We take advantage of this characteristic out-of-sample and detect a 'significant' deviation of the $Spread_t$, from its long-run value of 0, any time the following condition is violated:

$$2\hat{\sigma} \geq Spread_t \geq -2\hat{\sigma} \tag{3}$$

where $\hat{\sigma}$ is the standard deviation of the residuals obtained in regression (1). All departures of the *Spread* form these boundaries is interpreted as a misalignment of the options implied volatilities from their relationship as estimated in model (1), and signals a potentially profitable mispricing, which leads the agent to trigger a trade. As an example, the top panel of Figure 1 reports the time-series of the Implied Volatilities of one-month maturity ATM call options written on CAC40 and ESTOX50 indexes, which clearly share the same pattern. The *Spread* between these implied volatilities, along with its $\pm 2\hat{\sigma}$ boundaries, are plotted in the bottom panel: the trading is triggered every time the *Spread* exists the boundaries, as pointed by the arrows.

[6] This definition, including the estimated intercept, follows the one proposed by Vidyamurthy (2004).

Figure 1 - Example of implied volatilities and Spread time series



Notes: The top panel reports the time-series of the Implied Volatilities of one-month maturity ATM call options written on CAC40 (black line) and ESTOX50 (red line) Indexes, between 1st July and 31st December 2012. The bottom panel reports the estimated *Spread* between these two implied volatilities (in blue) and $\pm 2\hat{\sigma}$ boundaries (in red). The black arrows indicate when the trading is triggered.

Consistently with the practice established in the pair-trading literature, we set a 'self-financing' strategy, in which the quantities traded in the two assets are such that no initial capital investment is required.

More specifically, if $Spread_t > 2\hat{\sigma}$, the option written on index Y is suspected to be overpriced with respect to the option written on index X. Therefore, we sell one unit of the option written on index Y and buy the amount of the option written on X affordable from the proceeds of the sale. Both positions are then unwounded when the *Spread* reverts to within the estimated boundaries. Alternatively, all the open positions are forcibly closed when the end of the trading period is reached or when the options get to maturity.[7]

Conversely, if $Spread_t < -2\hat{\sigma}$, the option written on Y is suspected to be underpriced with respect to the option written on X, and the trading scheme is reversed. The self-financing strategy requires to sell one unit of the option written on X and to buy an amount of the option Y using the proceeds from the sale. As above, all the positions are closed when the *Spread*

[7] To reduce the sensitivity of our results to the natural decline in the options prices as they approach expiration, all positions are actually closed two trading days before maturity.

reverts to within the estimated boundaries, or when the maturity of the option and/or the end of the trading period is reached.

Each transaction final payoff is computed once the initial trade is unwound. Notice that being the strategy self-financing, no initial investment in needed and the final payoff can be interpreted as a profit if positive and as a loss if negative.

4. Empirical application

In this section, we first present the dataset employed for the empirical application and then the results obtained in terms of profitability from the pairs trading strategy described above.

4.1 Data

The empirical application relies on daily data spanning the period 1st May 2007 to 31st December 2017, for a total of 2784 days, and referring to five Stock Indexes of the Euro Area, namely:

- CAC 40 (Cotation Assistée en Continu), quoted on the Paris Bourse;
- DAX 30 (Deutscher Aktienindex), quoted on the Frankfurt Stock Exchange;
- FTSE 100 (Financial Times Stock Exchange 100 index), quoted on the London Stock Exchange;
- FTSE MIB (Financial Times Stock Exchange Milano Indice di Borsa), quoted on the Milan Stock Exchange;
- ESTOX 50 (Euro STOXX 50): leading stock index for the Eurozone, covering 50 stocks from 11 Eurozone countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal and Spain).[8]

The advantage of focusing on options written on indexes is that, given that the underlying is a synthetic representation of the stock portfolio, the final payoff is cash-settled rather than paid by an exchange of goods. Hence, cashing-in the payoff does not incur additional transaction costs to those related strictly to the trade.

[8] The Estox 600 index, which also includes the companies listed within the FTSE 100 index, could not be used because the implied volatility is not available. We thus had to settle for Estox50 as index for the Eurozone.

For each Index, we use the following data, all retrieved from Thomson Reuters DataStream[9]:

- Stock Index Prices;
- Options Prices of all the Call options written on the index, along with their maturities and strike prices;[10]
- Implied Volatilities of the at-the-money 1-month maturity call options written on the indexes.

For each day and each underlying index in the sample, we first select the options with the shortest maturity, since they are among the most liquid in the market. In doing so, we exclude those with a residual life of less than 10 calendar days, with the aim of guaranteeing the possibility of trading on that option while reducing the chances of forced closure due to options expiration. This leaves us with options whose time-to-maturity ranges between 11 and 46 calendar days.

Among those options with the same (shortest) maturity, we select the at-the-money (ATM henceforth) call option. In other words, for each day in the sample, we select the option whose strike price is as close as possible to the value of the dividend-adjusted underlying index. If two options with the same maturity have the same absolute distance between the strike and the index price, we exclude the one with higher strike price, so as to maintain the more conservative one in terms of final payoff.[11] We focus on ATM options since most of their market value is determined by the volatility of the underlying asset, so that they are the most informative in this sense. This is very important in our application since the long-run equilibrium relationship between pairs of options is established directly through their (implied) volatilities.

We thus end up, for each day in our sample and for each of the underlying indexes considered, with one single ATM call option with maturity close to one month.[12]

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[9] Based on in-depth analysis of the data and with the support of the data provider, many recording errors were corrected directly on Thomson Reuters DataStream. Most were related to the same identification code being attributed to more than one series at different points in time.

[10] FTSE 100 call options prices are in pound sterling, all others are quoted in euros. The corresponding daily GB Sterling/Euro FX exchange rate is thus used to convert prices of options on FTSE 100 into euros. The identifying numbers of each series is 6239 for CAC 40, 12158 for DAX 30, 11939 for ESTOX 50, 9501 for FTSE 100 and 7303 for FTSE MIB. In DataStream missing values on option prices are replaced with the previous day observation.

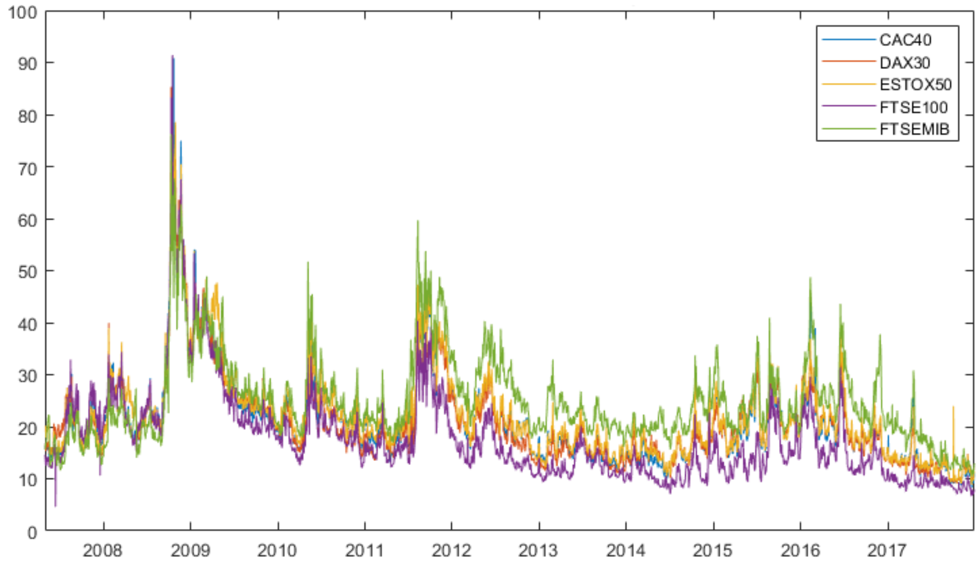
[11] In the selection process, we further exclude all call options with non-standard maturity, i.e. with a maturity settled in a different day from the third Friday of the month, as well as some calls presenting duplicated series, i.e. with the same strike price and maturity, which are suspected to be recording errors. For these reasons, we excluded one option on the CAC 40, one option on the ESTOX 50 and six options on the FTSE 100.

[12] Notice that the ATM call option selected in a certain day may have a different strike price from the ATM call option selected in another day. This means that the call selected for the day a trading is opened does not necessarily

4.2 Preliminary analyses

Figure 2 depicts the implied volatility time series of one-month maturity ATM options, written on the five Indexes. Two major shocks are distinctly common to all series, namely the outburst of the global Financial Crisis at the end of 2008 and the Sovereign Debt Crisis at the end of 2011, both having brought instability (i.e. higher volatility) to the European Financial Market. The series share a very similar pattern also outside these two extreme events, so the possibility of finding strong relationships between the IV of the five underlying indexes seems quite high.

Figure 2 – Implied Volatilies of the one-month ATM options, by underlying index.



Note: The figure reports the time series of the Implied Volatility of the at-the-money 1-month maturity call options written on the following stock market indexes: CAC40, DAX 30, FTSE 100, FTSE MIB, ESTOX 50, from 1st of May 2007 until the 31st of December 2017.

The similarity of the Implied Volatilities across the five underlying indexes is further confirmed by the degree of variability, which is very similar across the series (see panel A of Table 1) and the quite high level of correlation (panel B of Table 1), which on average never falls below 0.75.[13]

coincide with the one selected for the day the same trade is closed. Thus, in order compute the actual profits obtained trading an option, we need to have the prices of the traded option in both the day in which the trade is triggered and in the day in which the trade is closed. As consequence, we store, for each selected option, the entire time-series of the prices, ending up with 2784 (one for each day in our sample) option prices time-series for each underlying index.

[13] Notice however that while in classical pairs trading applications, the initial set of potential pairs is often artificially narrowed to highly correlated ones (for instance, Miao, 2014, and Ammann & Herriger, 2002, pre-select pairs of stocks with correlation greater than 0.90 and 0.95, respectively), in our application no pairs are excluded a-priori based on correlation. Besides, we further check for a potential variation of over time of pairwise correlations between implied volatiles and, despite a certain degree of time-variability, the values are overall pretty high all along the sample period. We are thus reassured that this is not an issue in the sample period considered.

Table 1 - Descriptive statistics, correlation and ADF test: one-month ATM options Implied Volatitlities, by underlying Index

	Panel A – Option Implied Volatilities				
	CAC 40	**DAX 30**	**ESTOX 50**	**FTSE 100**	**FTSE MIB**
Mean	21.59	21.14	22.23	17.75	24.98
St. Deviation	8.95	8.70	8.85	8.91	8.30
Min	8.34	9.05	8.84	4.62	10.36
Median	19.65	19.11	20.32	15.40	23.04
Max	90.74	89.41	78.49	91.41	76.24
	Panel B – Correlation across Option Implied Volatilities				
	CAC 40	**DAX 30**	**ESTOX 50**	**FTSE 100**	**FTSE MIB**
CAC 40	1	0.97	0.98	0.95	0.87
DAX 30		1	0.97	0.94	0.86
ESTOX 50			1	0.94	0.89
FTSE 100				1	0.75
FTSE MIB					1
	Panel C – ADF tests on Implied Volatilities				
	CAC 40	**DAX 30**	**ESTOX 50**	**FTSE 100**	**FTSE MIB**
ADF (drift)					
test statistics	-4.5478	-3.9562	-3.9516	-3.8173	-4.2839
pvalue	0.0010	0.0023	0.0023	0.0035	0.0010
ADF (trend and drift)					
test statistics	-5.2998	-4.5773	-4.6588	-4.9698	-4.5077
pvalue	0.0010	0.0013	0.0010	0.0010	0.0020

Notes: the table reports the main descriptive statistics for the Implied volatilities of one-month maturity ATM call options over the entire sample period (panel A), the Pearson Correlation Coefficient between the Implied Volatilities (panel B), and the t-statistics, and associated p-values, of the ADF test with drift only and with trend and drift run setting a maximum lag equal to 15, by underlying Index.

The Augmented Dickey-Fuller tests for stationarity are then run on the implied volatilities, setting a maximum lag length equal to 15 and with both drift-only and drift and trend specifications. In all cases, the null for the presence of a unit-root is rejected at the 95% confidence level. The IV are thus stationary time-series highly correlated across each other and apparently following a similar pattern over time, which we are going to exploit in the pair trading statistical arbitrage. If such trading strategy is able to produce significant profits, then EMH can be disproved.

4.3 Main Results

Table 2 reports the results of the self-financing trading strategy implemented over the trading period spanning from the 1st of May 2008 until the 31st of December 2017 (data from the 1st of May 2007 till 30th of April 2008 are used in the first estimation period).[14]

To begin with, the number of trades realized (column 7 of Table 2) is quite high, meaning that the spread kicked the estimated boundaries, thus signaling potential mispricing on the market, in several occasions during the sample period under analysis.[15] The vast majority of these trades (94%), which remains opened for 4 days on average, closes because the *Spread* reverts to within the boundaries; the remainder are forcibly closed either because the options expire (2%) or because the end of the trading period is reached (4%).

Despite the high number of suspected mispricing, the average profit eventually obtained are pretty low, on average around 8.95€, and not statistically significant, as shown in columns (1) and (2) of Table 2. By splitting the results based on the pairs of underlying indexes on which the options are written, we find that option pairs trading strategy is significantly profitable for 7 out of the possible 20 couples. For these pairs, the average profit ranges from 5.37€ for the couple ESTOX50-DAX30 to as much as 55.02€ for the FTSEMIB-DAX30. In other 8 cases, all but one of which include the FTSE100, it leads to statistically significant negative average profits, i.e. to losses, thus pointing towards the required exchange rate conversion in Euro as playing as an additional source of friction. In all other cases, the strategy does not provide significant profits.

[14] Summary statistics on the options participating to the trades are reported in Table 4.

[15] The total number of trades is cumulative across the six overlapping portfolios, so some trades might be double counted and the actual number of mispricing might be overestimated. Yet, even assuming that all trades are common across the six portfolios, the overall number of suspected mispricing would still be pretty high (equal to 10,605/6 = 1,768 trades). Considering that the trading days in our sample are 2,419 (2,784 - 365), this figure would suggest an average of more than 1 trade per day (2,419/1,768=1.37).

Table 2 – Results for the option pairs trading self-financing strategy, by pairs of underlying indexes.

	Average Profits (or losses)	NW stat	Closing			Average life	Total number of trades
			Boundary	Maturity	Trading period		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAC40-DAX30	4.48	1.37	0.90	0.05	0.05	5.86	433
CAC40-ESTOX50	-1.46***	-2.95	0.99	0.00	0.01	2.65	519
CAC40-FTSE100	-7.89***	-3.70	0.94	0.01	0.05	4.71	501
CAC40-FTSEMIB	28.02***	3.66	0.94	0.02	0.04	4.29	530
DAX30-CAC40	4.53*	1.66	0.90	0.05	0.05	6.02	416
DAX30-ESTOX50	1.90	1.25	0.94	0.03	0.03	4.59	458
DAX30-FTSE100	-5.85**	-2.16	0.95	0.02	0.03	4.54	611
DAX30-FTSEMIB	40.36***	3.38	0.92	0.03	0.04	5.18	527
ESTOX50-CAC40	0.02	0.04	0.99	0.00	0.01	2.65	547
ESTOX50-DAX30	5.37***	3.03	0.91	0.04	0.05	5.28	467
ESTOX50-FTSE100	-11.52***	-5.85	0.97	0.00	0.03	4.57	493
ESTOX50-FTSEMIB	28.20***	5.19	0.95	0.02	0.03	3.73	662
FTSE100-CAC40	-4.69**	-2.16	0.91	0.03	0.05	5.26	465
FTSE100-DAX30	-7.77***	-2.80	0.93	0.03	0.04	4.59	700
FTSE100-ESTOX50	-5.95***	-3.73	0.94	0.03	0.04	4.58	494
FTSE100-FTSEMIB	12.90	1.02	0.90	0.05	0.05	5.11	556
FTSEMIB-CAC40	17.12***	3.19	0.96	0.01	0.03	3.46	526
FTSEMIB-DAX30	55.02***	5.16	0.93	0.04	0.03	4.78	515
FTSEMIB-ESTOX50	21.98***	5.37	0.96	0.01	0.03	3.13	671
FTSEMIB-FTSE100	-3.62	-0.31	0.95	0.01	0.04	3.96	514
ACROSS ALL PAIRS	8.95	0.06	0.94	0.02	0.04	4.38	10,605

Notes: the table reports the results, overall and by pair of underlying indexes, of the self-financing pairs trading strategy implemented over the sample from May 2008 to December 2017, and refers to the trades triggered whenever the implied volatilities of the one-month maturity ATM call options deviate from the relationship in model (1), estimated based on the regression which uses the first between the indicated underlying Indexes as X and the second as Y, and closed when the Spread reverts to within the boundaries. Specifically, the table reports the average profits (if positive) or losses (if negative), whose statistical significance is tested based on the Newey-West heteroskedasticity and autocorrelation robust t-statistics (Newey & West, 1987). The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 3 to 5 report the shares of closed trades due to Spread reversion to within the boundaries, option expiration and reaching the end of the trading period, respectively. The last two columns report the average number of days the trades remained opened, and the total number of trades.

Overall, despite frequent signals of potential mispricing, the statistical arbitrage strategy does not produce statistically significant profits, thus providing evidence in support of the index option market efficiency. Notice that all the results presented so far are computed without considering transaction costs. Their inclusion would further reduce the profitability of the strategy, so our conclusion about index option market efficiency is reached under the most conservative condition.[16]

4.4 Profitability drivers

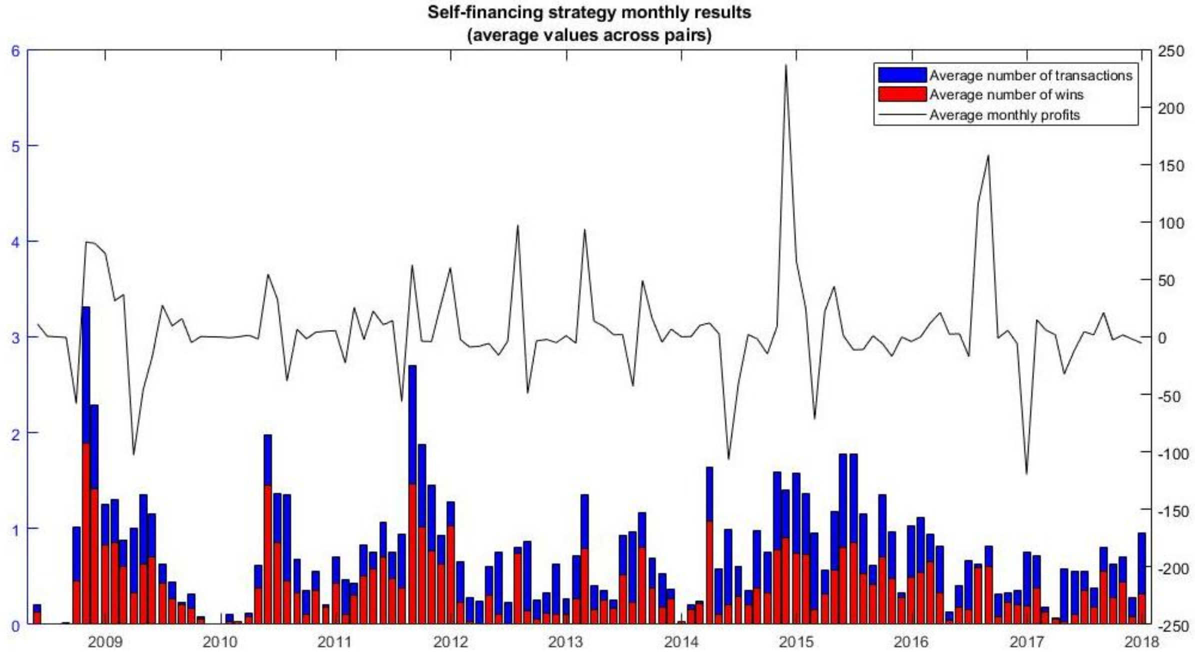
We are interested in spotting the potential drivers of the profitability of index option pairs trading, when this is found. To this end, we regress the observed per-transaction profits or losses on the characteristics of the options involved in the pair-trade and on the overall condition of the financial market at the moment the profit realizes, i.e. at the time the trade is closed.

First, we observe that the realized payoffs of the implemented index option pairs trading show a remarkable variability across time (see Figure 3).[17]

[16] We also investigate the results obtained using a pairs-trading "beta-arbitrage" strategy in which the traded quantities are determined by the estimated regression slope. Specifically, if $Spread_t > 2\hat{\sigma}$ we sell one unit of the option written on Y and buy a quantity of the option written on X equal to the amount bought in the self-financing strategy multiplied by $\hat{\beta}_1$. Instead, if $Spread_t < 2\hat{\sigma}$, one unit of the option on X is sold and the quantity bought of the option written on Y will be the same as the amount bought in the self-financing strategy divided by $\hat{\beta}_1$. Consistently with what reported for the self-financing strategy, the average profits obtained implementing the beta-arbitrage strategy are not statistically significant (results available upon request).

[17] The displayed results are obtained taking the average results, for each month of the trading period and then across the six overlapping trading periods, of all the trades occurred across all pairs.

Figure 3 – Trades, wins and average profits of the pair trading strategy, by month.



Number of trades, number of wins (trades with positive payoffs) and average profit of the pairs trading strategies implemented over the sample from May 2008 to December 2017.

We thus investigate whether the profitability significantly varies along with financial markets conditions and its periods of turbulence. To this end, we consider the conventional Fama-French 5 risk-factors (already employed in the pairs trading literature, e.g., by Gatev *et al*., 2006; Engelberg *et al*., 2009; and Clegg and Krauss, 2018), namely[18]:

(1) Market excess return (MKT): difference between the market and 30-day Treasury bill returns;

(2) Small-Minus-Big (SMB): difference between the average returns of the small and the big stock portfolios;

(3) High-Minus-Low (HML): difference between the average returns of the value and the growth stock portfolios;

(4) Robust-Minus-Weak (RMW): difference between the average returns of the robust and the weak operating profitability portfolios;

(5) Conservative-Minus-Aggressive (CMA): difference between the average returns of the conservative minus aggressive investment portfolios;

(6) Momentum factor (MOM): difference between last year winner and loser portfolios.

[18] The factors used refer to the European market. Data are available on the Kenneth R. French website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Moreover, we complete our model by adding a dummy indicating if the trade is closed during one of the following crisis: the Global Financial Crisis (according to Olbrys, 2021, dated from October 2007 to February 2009), the European debt crisis (dated from October 2009 until July 2012) and the Chinese stock market turbulence (from June 2015 to June 2016).

Turning to the characteristics of the options included in each trade, recall that the intrinsic value of an option is (and hence the observed market price should be) function of its moneyness and time to maturity, along with the volatility of the underlying, and the interest rate. Considering that the latter is unique across the market and that the underlying volatilities should be in fixed relations to each other, these variables would be time-varying only and not specific to each trade. Their effect would thus be perfectly absorbed by the other time-varying only factors capturing the overall financial market conditions already included into the model. We are thus left with moneyness and time to maturity only. Since in our exercise the paired options are forced to have the same maturity, our regressions will include one control capturing the time to maturity, i.e. the days left before expiration, and two controls for the moneyness of each of the two options traded, measured at the time the trade is closed.[19]

The value of the option increases with the time left to maturity, so the longer the maturity, the more (less) the chances of making a profit when a long (short) position is taken. Since our trades requires to buy and sell at the same time two options with the same time to maturity, we expect the two effects to offset, and hence an overall irrelevant effect for maturity.

As for moneyness, we rely on the strike-price ratio, (K/S), which in our sample ranges in the interval [0.804 - 1.363], and classify each traded option as follows:

$$\begin{cases} ITM & if \left(\frac{K}{S}\right) < 0.98 \\ OTM & if \left(\frac{K}{S}\right) > 1.02 \\ ATM & otherwise \end{cases} \tag{4}$$

where K is the option strike, S is the underlying index price (at the time the trade closes) and $OTM,\ ITM$, and ATM dummies denote the option being out-of-the-money, in-the-money or

[19] Notice that, even if the traded options are by construction both ATM when a position is opened, their moneyness might well have changed and be different for the two options at the time the position is closed (which is the moment the variables in the regression are measured at).

at-the-money, respectively.[20] Each trade involves two options, which can be in any of the three conditions of moneyness at closure, thus resulting in 9 possible combinations. In the regression we thus include 8 dummies capturing all the possible combinations for the long and short options being at-the-money, in-the-money, or out-of-the-money at the moment the trade is closed, having the combination of both options being ATM as reference category. Table 3 reports the distribution of the trades according to the moneyness of both options involved.

Table 3 – Self-financing strategy trades, by moneyness of the options involved

Long	**Short**		
	IN	**ATM**	**OUT**
IN	1,762	397	15
ATM	910	5,471	453
OUT	6	299	1,292

Notes: the table stratifies trades based on the moneyness of each call option forming the pair at the closure of the trade, depending on the long or short positions taken on it.

In our empirical application, we work with call options, whose intrinsic value increases the more the underlying price is higher than the strike price (i.e. the more strike-price ratio is lower than 1). This means that the lower is the strike-price ratio, the higher are the chances of making a profit when a long position is taken and, symmetrically, the higher the chances of a loss if the call is sold short. We thus expect the strategy payoff to be related positively with the bought option being ITM and the sold option being OTM. By the same token, we expect the opposite this relation to be negative when short options are ITM and long options are OTM.

Finally, in order to control for any potential time-variability in the relationship between the option implied volatilities (Londono, 2010), we also include the variance risk premiums (VRP) for both options involved in the trade. The VRP is the difference between the implied volatility (IV) and the realized volatility (RV). Hence, with reference to the long option, we use the following measure: $VRP_{it,long} = IV_{long,it} - RV_{long,it}$, where $IV_{long,it}$ is the Implied Volatility of the long option entering trade *i* observed on day *t*, and $RV_{long,it}$ is the standard deviation of the returns of the index underlying the same option observed in the 22 days following day *t*.

[20] Similarly, Gambarelli and Muzzioli (2019) or Elyasiani et al. (2021) classify options with the 0.97 and 1.03 thresholds. As a robustness check, we further tried classifications using as thresholds for ITM/OTM $\pm$ 0.01, 0.03, 0.04 and 0.05 and the results obtained (available upon request) remain qualitatively unchanged.

The VRP of the short option entering trade i closed on day t, denoted with $VRP_{it,short}$, is computed analogously.

Thus, the regression model is the following:

$$y_{it} = \beta_0 + \beta_1\tau_{it} + \beta_2 ITM_{it,short}ITM_{it,long} + \beta_3 ITM_{it,short}ATM_{it,long} + \beta_4 ITM_{it,short}OTM_{it,long} + \beta_5 OTM_{it,short}ITM_{it,long} + \beta_6 OTM_{it,short}ATM_{it,long} + \beta_7 OTM_{it,short}OTM_{it,long} + \beta_8 ATM_{it,short}ITM_{it,long} + \beta_9 ATM_{it,short}OTM_{it,long} + \beta_{10} VRP_{it,short} + \beta_{11} VRP_{it,long} + \beta_{12} MKT_t + \beta_{13} SMB_t + \beta_{14} HML_t + \beta_{15} RMW_t + \beta_{16} CMA_t + \beta_{17} MOM_t + \beta_{18} Crisis_t + \epsilon_{it} \quad (5)$$

where y_{it} is the strategy payoff realized on the trade i closing on day t, and τ_{it} is the time to maturity of the pair of traded options. The variables from $ITM_{it,short}ITM_{it,long}$ to $ATM_{it,short}OTM_{it,long}$ are dummies capturing the moneyness at day t of both the options involved in trade i. For instance, $ITM_{it,short}ITM_{it,long}$ takes value 1 if both options (long and short) involved in trade i are in-the-money on day t, i.e. at the time the trade is closed, and 0 otherwise. Analogously, $VRP_{it,short}$ and $VRP_{it,long}$ are the Variance Risk Premium observed at day t of both the options involved in trade i. Next, MKT_t, SMB_t, HML_t, RMW_t and CMA_t are the Fama and French 5 factors, while MOM_t is the momentum factor as measured on day t, at which the trade is closed. Finally, $Crisis_t$ takes value 1 if the day at which the trade is closed belongs to one of the periods of financial market turbulence indicated above, and 0 otherwise. Since both risk-factors and the $Crisis$ dummy only vary with time, the estimation is carried out clustering the standard errors by date.

Summary statistics of the price, time to maturity and moneyness of the options included in the trades, are reported in Table 4.

Table 4 – Descriptive statitics of the options at opening and closing of the trades, by underlying.

			Mean	Std. Dev.	Min	Max	Median	p25	p75
At trade opening	Price	CAC40	127.53	48.35	41.84	287.46	120.70	93.50	152.62
		DAX30	253.73	76.39	105.80	494.50	236.40	196.70	302.70
		ESTOX50	94.68	36.81	30.60	243.50	87.40	68.10	113.30
		FTSE100	179.80	79.05	52.51	476.55	159.77	123.14	212.97
		FTSEMIB	796.20	287.58	256.00	2245.00	752.00	616.00	905.00
	Maturity	CAC40	46.15	9.16	31	65	46	38	53
		DAX30	46.10	9.51	31	65	45	38	53
		ESTOX50	45.87	9.30	31	65	45	38	53
		FTSE100	46.22	9.19	31	65	46	38	53
		FTSEMIB	46.03	9.25	31	65	45	38	53
At trade closing	Price	CAC40	130.16	81.62	0.01	627.85	111.81	75.14	165.56
		DAX30	257.47	149.58	0.10	1302.40	233.60	165.10	322.70
		ESTOX50	94.19	57.06	0.10	369.10	80.60	56.40	118.85
		FTSE100	185.79	122.40	0.57	970.50	159.51	106.86	231.41
		FTSEMIB	788.00	483.36	1.00	3551.00	707.00	467.00	1015.00
	Maturity	CAC40	38.78	12.57	2	64	39	31	49
		DAX30	38.07	13.51	2	64	39	30	49
		ESTOX50	38.96	12.64	2	64	39	31	49
		FTSE100	38.38	13.27	2	64	39	30	49
		FTSEMIB	38.36	13.01	2	64	39	31	49
	In the money	CAC40	0.23	0.42	0	1	0	0	0
		DAX30	0.22	0.41	0	1	0	0	0
		ESTOX50	0.22	0.41	0	1	0	0	0
		FTSE100	0.28	0.45	0	1	0	0	0
		FTSEMIB	0.28	0.45	0	1	0	0	0
	Out of the money	CAC40	0.18	0.38	0	1	0	0	0
		DAX30	0.17	0.38	0	1	0	0	0
		ESTOX50	0.19	0.39	0	1	0	0	0
		FTSE100	0.12	0.33	0	1	0	0	0
		FTSEMIB	0.23	0.42	0	1	0	0	0

Notes: the table reports the mean, standard deviation, minimum, maximum, median, first and third quartiles of the main characteristics of the options included into the trades, by underlying stock price index. The summary statistics refer to the market price and the time to maturity (in days left before maturity) at the day the trade is opened as well as at the day the trade is closed, and to moneyness, as measured by the dummies for being in the money and out of the money as defined in equation (4), at the time the trade is closed (at opening all options are by construction at the money).

Table 5 reports the estimates of various specifications of regression model (5) using the entire sample of the realized trades. In line with expectations, the strategy payoffs are poorly associated to the time to maturity: despite the effect is statistically significant in specification (1), where only the option characteristics are considered, the estimated effect is negligible in magnitude. Moreover, when market factors are taken into account, as in the last specification, the estimated effect for time to maturity is no longer statistically significant. As for the moneyness, again consistently with expectations, the payoffs are on average higher whenever the option sold is OTM and/or the option on which a long position is taken is ITM, and on average lower when the sold option is ITM and/or the option bought is OTM. Besides, the results suggest that moneyness is the element contributing the most to explain the returns variability (even though most of this variability remains unexplained) and are robust to the inclusion of all other controls considered. We also find that the strategy payoffs are positively (negatively) correlated to the variance risk premium of the short (long) option, albeit the estimates are no longer statistically significant when other factors are taken into account. Finally, in the most complete specification, the payoffs do not significantly correlate with any of the conventional risk factors, nor seem to be statistically different during periods of financial turbulence.

These results are fully confirmed when the analysis is repeated focusing on the subset of trades involving the pairs that actually produced average positive and significant payoffs only (see Table 6).

Table 5 – Drivers of the pair-trading final payoffs.

	(1)	*(2)*	*(3)*	*(4)*
Constant	30.221***	25.181***	8.688	26.579
	(4.384)	(4.896)	(6.079)	(16.690)
τ_{it}	-0.621***	-0.607***		-0.585
	(0.096)	(0.096)		(0.370)
$ITM_{i,short}ITM_{i,long}$	16.503***	15.585***		21.957*
	(3.365)	(3.461)		(12.020)
$ITM_{i,short}ATM_{i,long}$	-95.843***	-98.563***		-93.512***
	(4.357)	(4.388)		(15.373)
$ITM_{i,short}OTM_{i,long}$	-151.157***	-144.436***		-138.991***
	(49.670)	(49.671)		(22.771)
$OTM_{i,short}ITM_{i,long}$	566.428***	564.540***		567.658***
	(31.537)	(31.523)		(134.194)
$OTM_{i,short}ATM_{i,long}$	83.527***	79.151***		75.582***
	(5.989)	(6.091)		(13.687)
$OTM_{i,short}OTM_{i,long}$	3.872	3.440		-1.177
	(3.831)	(4.176)		(6.499)
$ATM_{i,short}ITM_{i,long}$	138.945***	140.206***		143.010***
	(6.359)	(6.379)		(30.490)
$ATM_{i,short}OTM_{i,long}$	-40.953***	-38.240***		-40.834***
	(7.225)	(7.261)		(6.549)
$VRP_{it,short}$		1.138***		1.122
		(0.230)		(0.730)
$VRP_{it,long}$		-1.014***		-1.013
		(0.211)		(0.670)
MKT_t			0.459	-0.656
			(3.903)	(3.613)
SMB_t			3.931	1.074
			(7.985)	(7.212)
HML_t			-9.514	-7.527
			(6.516)	(6.231)
RMW_t			20.912**	9.199
			(9.686)	(8.844)
CMA_t			4.551	-0.205
			(11.724)	(10.160)
MOM_t			-3.467	1.075
			(3.814)	(3.508)
$Crisis_t$			0.450	-5.041
			(6.863)	(7.359)
Observations	10,605	10,605	10,605	10,605
R-squared	0.145	0.148	0.009	0.152

Notes: The dependent variable is the final payoff obtained implementing the pairs trading strategy, closing the positions when the Spread reverts to within the boundaries. τ stands for time to maturity. ITM stands for in-the-money, ATM for at-the-money and OTM for out-of-the-money, while VRP for variance risk premium. MKT, SMB,HML, RMW, and CMA are the Fama-French 5 factors, MOM is the momentum factor, and $Crisis$ is a dummy for the transaction closing during a period of financial turbulence. Clustered standard errors in parenthesis. $**$significant at 5% level. $***$significant at 1% level.

Table 6 – Drivers of the pair-trading payoff: subsample of significantly positive final payoff.

	(1)	*(2)*	*(3)*	*(4)*
Constant	60.972***	48.387***	27.637***	48.076
	(8.121)	(9.434)	(10.197)	(31.674)
τ_{it}	-1.157***	-1.103***		-1.047
	(0.176)	(0.176)		(0.674)
$ITM_{i,short}ITM_{i,long}$	36.035***	33.805***		43.707**
	(6.119)	(6.261)		(20.772)
$ITM_{i,short}ATM_{i,long}$	-83.825***	-88.838***		-80.511***
	(8.496)	(8.529)		(26.061)
$ITM_{i,short}OTM_{i,long}$	-205.160**	-186.186*		-189.295***
	(102.799)	(102.522)		(44.129)
$OTM_{i,short}ITM_{i,long}$	408.229***	410.965***		423.020***
	(59.555)	(59.356)		(99.526)
$OTM_{i,short}ATM_{i,long}$	92.486***	86.643***		84.353***
	(10.584)	(10.640)		(23.716)
$OTM_{i,short}OTM_{i,long}$	2.711	3.842		-6.998
	(6.819)	(7.386)		(12.118)
$ATM_{i,short}ITM_{i,long}$	150.921***	154.513***		159.698***
	(11.337)	(11.328)		(39.884)
$ATM_{i,short}OTM_{i,long}$	-39.542***	-34.310***		-40.582***
	(12.491)	(12.499)		(10.817)
$VRP_{it,short}$		2.539***		2.320**
		(0.451)		(1.154)
$VRP_{it,long}$		-2.254***		-1.908*
		(0.410)		(1.082)
MKT_t			-0.611	-2.518
			(6.248)	(6.030)
SMB_t			7.063	6.378
			(13.694)	(12.730)
HML_t			-7.398	-5.324
			(10.715)	(11.307)
RMW_t			21.556	9.275
			(17.125)	(16.919)
CMA_t			1.391	-2.656
			(18.627)	(16.957)
MOM_t			-9.025	-1.908
			(6.226)	(5.958)
$Crisis_t$			-4.427	-10.039
			(11.685)	(11.950)
Observations	4,322	4,322	4,322	4,322
R-squared	0.118	0.124	0.007	0.130

Notes: The dependent variable is given by the payoffs of all the trades involving those pairs that actually produced positive and significant profits, closing the positions when the Spread reverts to within the boundaries. τ stands for time to maturity. ITM stands for in-the-money, ATM for at-the-money and OTM for out-of-the-money, while VRP for variance risk premium. MKT, SMB,HML, RMW, and CMA are the Fama-French 5 factors, MOM is the momentum factor, and $Crisis$ is a dummy for the transaction closing during a period of financial turbulence. Clustered standard errors in parenthesis. $**$significant at 5% level. $***$significant at 1% level.

5. Robustness

In this section we check the robustness of our results. First, we implement a stricter definition of reversion to the equilibrium, by closing the trades when the Spread converges back to exactly 0, rather than when it returns to within the estimated $\pm 2\hat{\sigma}$ boundaries, as in equation (3). Then, we address the potential concern that the relationship between implied volatilities, which we use to estimate the long-run equilibrium, might not be extended directly to options prices.

5.1 Spread reaching the zero

A stricter definition of convergence to equilibrium is applied, by closing the trades when the *Spread* reverts to zero, rather than just re-entering the boundaries (or at the end of the trading period or when the options reach maturity). Table 7 reports the results obtained in terms of profitability. As the condition for closing the trade is now much more restrictive, the average life is now much longer (on average 19 days compared to the 4 observed in the previous application). Moreover, the percentages of transactions closed due to expiry of the options or end of the trading period increase, at the expense of a reduction in the number of closures due to *Spread*'s convergence to zero which now accounts for the 44% of the total. The option pairs trading arbitrage strategy still does not produce a significantly positive payoff. Dissecting the results by pairs of underlying indexes, we now observe significant profits at the 5% confidence level for only 2 out of 20 possibile couples, namely the 2 possibile involving both ESTOX50 and FTSEMIB, with average profits slightly higher than 30€. In 8 cases out of 20 the strategy now leads to statistically significant losses, with maximum average loss of 52.60€ for the DAX30-FTSE100 pair, and the remaining cases lead to non significant profits. All in all, our main conclusion in favor of index option market efficiency remains thus unchanged, if not reinforced. Similarly, the results concerning the profitability drivers, reported in Table 8, remain qualitatively unchanged.

Table 7 – Results for the option pairs trading self-financing strategy, by pairs of underlying indexes: closing when the Spread reaches 0.

	Average Profits (or losses)	**NW stat**	**Closing**			**Average life**	**Total number of trades**
			Convergence	**Maturity**	**Trading period**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
CAC40-DAX30	10.54	1.09	0.36	0.41	0.23	20.29	233
CAC40-ESTOX50	-6.90***	-3.39	0.54	0.32	0.14	15.39	259
CAC40-FTSE100	-31.04***	-3.05	0.62	0.23	0.16	16.24	268
CAC40-FTSEMIB	-32.91	-0.77	0.42	0.42	0.16	18.92	257
DAX30-CAC40	6.33	0.70	0.32	0.45	0.23	20.94	215
DAX30-ESTOX50	10.95*	1.83	0.40	0.42	0.18	19.89	240
DAX30-FTSE100	-52.60***	-3.57	0.33	0.46	0.21	21.93	272
DAX30-FTSEMIB	81.95*	1.76	0.30	0.49	0.21	21.14	236
ESTOX50-CAC40	-5.91**	-2.57	0.46	0.38	0.16	17.68	242
ESTOX50-DAX30	11.35*	1.65	0.32	0.47	0.21	21.46	228
ESTOX50-FTSE100	-46.11***	-5.96	0.50	0.33	0.17	18.70	248
ESTOX50-FTSEMIB	36.80**	2.38	0.38	0.43	0.19	19.30	282
FTSE100-CAC40	-12.78*	-1.65	0.56	0.27	0.17	17.07	255
FTSE100-DAX30	-31.53**	-2.57	0.31	0.48	0.21	22.10	296
FTSE100-ESTOX50	-28.62***	-3.66	0.50	0.35	0.16	17.99	258
FTSE100-FTSEMIB	-76.80	-1.38	0.36	0.44	0.20	20.15	261
FTSEMIB-CAC40	-15.91	-0.50	0.54	0.34	0.12	15.30	275
FTSEMIB-DAX30	57.38	1.46	0.38	0.43	0.19	19.29	274
FTSEMIB-ESTOX50	33.50**	2.31	0.62	0.25	0.13	14.03	344
FTSEMIB-FTSE100	-64.43	-1.15	0.45	0.37	0.18	17.78	247
ACROSS ALL PAIRS	-7.72	-0.02	0.44	0.38	0.18	18.67	5190

Notes: the table reports the results, by pair of underlying indexes, of the self-financing pairs trading strategy implemented over the sample from May 2008 to December 2017, and refers to the trades triggered whenever the implied volatilities of the one-month maturity ATM call options deviate from the relationship in model (1), estimated based on the regression which uses the first between the indicated underlying Indexes as X and the second as Y, and closed when the *Spread* reaches the zero level. Specifically, the table reports the average profits (if positive) or losses (if negative), whose statistical significance is tested based on the Newey-West heteroskedasticity and autocorrelation robust t-statistics (Newey & West, 1987). The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 3 to 5 report the shares of closed trades due to the Spread reversion to within the boundaries, option expiration and reaching the end of the trading period, respectively. The last two columns report the average number of days the trades remained opened, and the total number of trades observed.

Table 8 – Drivers of the pair-trading payoffs: closing when the Spread reaches 0.

	(1)	*(2)*	*(3)*	*(4)*
Constant	2.075	5.430	-17.271	9.955
	(10.745)	(12.535)	(37.269)	(23.152)
τ_{it}	0.685***	0.856***		1.047
	(0.240)	(0.251)		(1.059)
$ITM_{i,short}ITM_{i,long}$	-69.019***	-66.894***		-64.917**
	(11.617)	(11.660)		(30.665)
$ITM_{i,short}ATM_{i,long}$	-213.999***	-214.360***		-220.194***
	(15.377)	(15.380)		(25.546)
$ITM_{i,short}OTM_{i,long}$	-443.860***	-438.826***		-427.538***
	(46.268)	(46.295)		(109.749)
$OTM_{i,short}ITM_{i,long}$	608.990***	616.670***		581.869***
	(42.064)	(42.540)		(90.105)
$OTM_{i,short}ATM_{i,long}$	116.286***	117.365***		110.666***
	(20.713)	(20.878)		(25.016)
$OTM_{i,short}OTM_{i,long}$	-19.442	-11.113		-12.271
	(12.409)	(13.317)		(20.368)
$ATM_{i,short}ITM_{i,long}$	349.157***	350.464***		351.833***
	(18.960)	(18.961)		(66.680)
$ATM_{i,short}OTM_{i,long}$	-86.210***	-83.800***		-90.750***
	(18.600)	(18.616)		(16.589)
$VRP_{it,short}$		1.117		1.664
		(0.724)		(3.177)
$VRP_{it,long}$		-1.506**		-3.021
		(0.648)		(3.203)
MKT_t			23.232	19.347
			(20.470)	(18.263)
SMB_t			5.299	-5.483
			(21.913)	(21.727)
HML_t			-31.529	-37.280
			(53.253)	(52.513)
RMW_t			31.332	-2.490
			(23.955)	(19.820)
CMA_t			69.047	51.600
			(82.556)	(83.937)
MOM_t			36.767	43.057
			(34.088)	(33.979)
$Crisis_t$			3.687	20.554
			(33.533)	(46.093)
Observations	5,190	5,190	5,190	5,190
R-squared	0.185	0.186	0.029	0.213

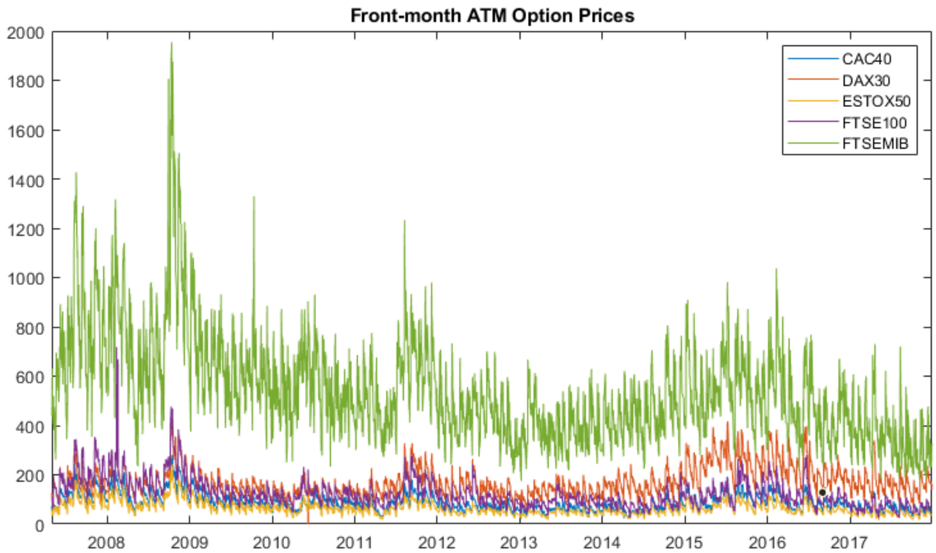
Notes: The dependent variable is given by the final payoff of all the trades and closing the positions when the Spread reaches the value of 0. τ stands for time to maturity. ITM stands for in-the-money, ATM for at-the-money and OTM for out-of-the-money, while VRP for variance risk premium. MKT, SMB,HML, RMW, and CMA are the Fama-French 5 factors, MOM is the momentum factor, and $Crisis$ is a dummy for the transaction closing during a period of financial turbulence. Clustered standard errors in parenthesis. $**$significant at 5% level. $***$significant at 1% level.

5.2 Spread estimated based on option prices

In our baseline analysis, each potential mispricing of options is spotted based on a long-run relationship estimated on options' implied volatilities (rather than on underlying indexes' returns, as in Ammann and Herriger, 2002). Then, the statical arbitrage strategy is implemented on the options. A potential concern with this approach might be that the long-run equilibrium relationship estimated on the implied volatilities might not extend directly to options prices. To address this issue, we thus repeat the analysis estimating the long-run equilibrium relationship based on the time series of options prices (OP here on).

Given the short-term nature of options, the time series of options prices used for this exercise is obtained selecting for each trading day, the price of the option (written on each underlying index) that is at-the-money and front-month at that point in time. Figure 4 and Table 9 report a graphical representation and the main descriptive statistics of the OP time-series obtained, respectively. Despite the degree of correlation is generally lower compared to the series of the implied volatilities, the association is still relevant, ranging between 0.56 to as high as 0.95 (see Panel B of Table 9). Moreover, as in the baseline case, the 95% confidence level of the ADF test confirms that the OP series are stationary, regardless of the specification employed (see Panel C of Table 9).

Figure 4 – Option prices time-series of the daily one-month-maturity ATM option, by underlying index.



Front-month ATM call option prices series for each underlying Index (the series are constructed considering for each trading day the price of the option that is front-month and at-the-money at that point in time).

Table 9 - Descriptive statistics, correlation and ADF test: one-month ATM options prices, by underlying Index.

	CAC 40	DAX 30	ESTOX 50	FTSE 100	FTSE MIB
	Panel A – Option Prices				
	CAC 40	**DAX 30**	**ESTOX 50**	**FTSE 100**	**FTSE MIB**
Mean	87.86	173.46	65.65	124.95	544.53
St. Deviation	280.72	451.80	243.50	718.12	1955.00
Min	21.61	0.10	16.50	24.84	173.00
Median	81.04	161.25	60.30	110.81	505.00
Max	35.79	61.64	27.34	59.74	217.10
	Panel B – Correlation across Option Prices				
	CAC 40	**DAX 30**	**ESTOX 50**	**FTSE 100**	**FTSE MIB**
CAC 40	1	0.72	0.95	0.88	0.85
DAX 30		1	0.68	0.61	0.56
ESTOX 50			1	0.90	0.87
FTSE 100				1	0.83
FTSE MIB					1
	Panel C – ADF tests on Option Prices				
	CAC 40	**DAX 30**	**ESTOX 50**	**FTSE 100**	**FTSE MIB**
ADF (drift)					
test statistics	-4.8912	-5.3718	-4.7900	-4.7662	-4.9473
pvalue	0.0010	0.0010	0.0010	0.0010	0.0010
ADF (drift and trend)					
test statistics	-5.6381	-5.4974	-5.7925	-6.2240	-6.6759
pvalue	0.0010	0.0010	0.0010	0.0010	0.0010

Notes: the table reports the main descriptive statistics for the option prices time series obtained selecting, for each trading day, the price of the front-month maturity ATM call option (panel A), the Pearson Correlation Coefficient across the option prices time series (panel B), and the t-statistics, and associated p-values, of the ADF test with drift only and with trend and drift run setting a maximum lag length equal to 15, by underlying Index.

We use the derived OP series to estimate the following OLS regression:

$$OP_{t,Y} = \gamma_0 + \gamma_1 OP_{t,X} + \varepsilon_t \tag{6}$$

where $OP_{t,Y}$ and $OP_{t,X}$ are the respective prices at day t of the front-month maturity at-the-money option written on indexes Y and X. Then, the Spread is computed as:

$$Spread_t = OP_{t,Y} - \hat{\gamma}_0 - \hat{\gamma}_1 OP_{t,X} \tag{7}$$

and, as above, the self-financing trading strategy is implemented whenever a mispricing is suspected, that is, whenever the spread violates the same condition in equation (3), i.e. when $2\hat{\sigma} \geq Spread_t \geq -2\hat{\sigma}$.

Table 10 reports the results obtained. The total number of transactions remains of the same order of magnitude, while the average life is halved, and again the reversion to within the boundaries is by far the most common reason for a trade to be closed. In terms of profits, we again observe quite a high degree of variability among the pairs. For instance, option pairs trading provides significant and positive profits in most cases (13 out of 20), although within a much closer range: from a 1.85€ (for the couple CAC40-ESTOX50) to a maximum of 36.63€ for the pair involving the CAC40 and the FTSEMIB). In the remaining cases, the strategy does not provide significant returns, and in two cases (DAX30-FTSE100 and FTSE100-ESTOX50) it even leads to statistically significant negative excess returns. Nonetheless, despite the high number of suspected mispricing, the strategy does not lead to significant profits overall, again providing evidence in favor of the index option market efficiency.

The analysis of the profitability drivers produces results that are largely in line with our baseline methodology, in terms of both the signs and magnitude of the parameters (Table 11). The overall effect of maturity is negligible, if any, moneyness correlates in the expected direction: the final payoffs are on average higher for those trades in which the long position is taken on an option that, at the closure of the trade, is in-the-money and the short position is taken on an option that is at-the-money. On the other hand, the combination leading to the worst outcome in terms of final payoff is the one entailing a short and a long position respectively on the options that are in-the-money and out-of-the-money at the end of the trade. Again, the obtained payoffs do not correlate with traditional risk factors and are not significantly different in periods of financial turbulence.

Table 10 – Results for the option pairs trading self-financing strategy, by pairs of underlying indexes: spread estimated based on Option Prices.

	Average Profits (or losses)	NW stat	Closing			Average life	Total number of trades
			Convergence	Maturity	Trading period		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAC40-DAX30	12.62***	5.79	0.98	0.00	0.02	3.23	591
CAC40-ESTOX50	1.85***	6.17	1.00	0.00	0.00	1.30	683
CAC40-FTSE100	2.61	1.54	0.99	0.00	0.01	2.47	495
CAC40-FTSEMIB	36.63***	5.57	1.00	0.00	0.00	1.28	715
DAX30-CAC40	6.83***	3.80	0.97	0.02	0.01	3.06	467
DAX30-ESTOX50	3.02	1.44	0.98	0.00	0.02	2.93	541
DAX30-FTSE100	-7.56***	-2.58	0.97	0.01	0.02	3.05	587
DAX30-FTSEMIB	23.67***	3.31	0.99	0.00	0.00	1.69	619
ESTOX50-CAC40	1.96***	5.15	1.00	0.00	0.00	1.19	554
ESTOX50-DAX30	6.00***	4.01	0.98	0.00	0.02	3.19	616
ESTOX50-FTSE100	-2.22	-1.13	0.99	0.00	0.01	2.39	530
ESTOX50-FTSEMIB	28.25***	3.98	1.00	0.00	0.00	1.22	641
FTSE100-CAC40	1.69	1.05	0.99	0.00	0.01	2.17	501
FTSE100-DAX30	-1.60	-0.61	0.97	0.00	0.02	3.27	798
FTSE100-ESTOX50	-3.47***	-2.86	0.99	0.00	0.01	2.18	547
FTSE100-FTSEMIB	21.23***	2.63	0.99	0.00	0.01	1.41	756
FTSEMIB-CAC40	27.31***	4.62	1.00	0.00	0.00	1.63	748
FTSEMIB-DAX30	34.43***	7.12	0.98	0.01	0.02	2.88	704
FTSEMIB-ESTOX50	25.91***	4.59	0.99	0.00	0.01	1.68	739
FTSEMIB-FTSE100	23.04***	4.30	0.98	0.00	0.02	2.51	549
ACROSS ALL PAIRS	13.18	0.11	0.99	0.00	0.01	2.20	12,381

Notes: the table reports the results, by pair of underlying indexes, of the pairs trading strategy implemented over the sample from May 2008 to December 2017, where the *Spread* used to spot the mispricing is estimated based on option prices time series rather than on Implied Volatilities. The results are based on the estimates of model (6) where the first between the indicated underlying Indexes enters as X and the second as Y, and trades are closed when the Spread reverts to within the boundaries. Specifically, the results reported include the average profits (if positive) or losses (if negative), whose statistical significance is tested based on the Newey-West heteroskedasticity and autocorrelation robust t-statistics (Newey & West, 1987). The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns 3 to 5 report the shares of closed trades due to the Spread reversion to within the boundaries, option expiration and reaching the end of the trading period, respectively. The last two columns report the average number of days the trades remained opened, and the total number of trades observed.

Table 11 – Drivers of the pair-trading payoff with Spread estimated based on Option Prices.

	(1)	*(2)*	*(3)*	*(4)*
Constant	12.465***	-8.605**	8.432**	-2.611
	(3.893)	(4.260)	(3.365)	(14.902)
τ_{it}	0.000	-0.047		-0.047
	(0.084)	(0.083)		(0.256)
$ITM_{i,short}ITM_{i,long}$	37.480***	29.007***		27.051**
	(2.974)	(3.087)		(11.278)
$ITM_{i,short}ATM_{i,long}$	-41.849***	-46.872***		-44.583***
	(3.117)	(3.140)		(9.725)
$ITM_{i,short}OTM_{i,long}$	-241.831***	-252.395***		-250.020***
	(68.769)	(68.384)		(11.415)
$OTM_{i,short}ITM_{i,long}$	-	-		-
$OTM_{i,short}ATM_{i,long}$	45.787***	37.246***		31.490**
	(8.534)	(8.523)		(13.622)
$OTM_{i,short}OTM_{i,long}$	-2.095	-17.257***		-18.721
	(3.525)	(3.734)		(15.193)
$ATM_{i,short}ITM_{i,long}$	179.509***	174.380***		175.544**
	(6.648)	(6.701)		(76.746)
$ATM_{i,short}OTM_{i,long}$	-34.803***	-37.883***		-40.840***
	(3.280)	(3.351)		(10.211)
$VRP_{it,short}$		1.383***		1.360**
		(0.169)		(0.605)
$VRP_{it,long}$		-0.265*		-0.542
		(0.156)		(0.451)
MKT_t			-12.358	-14.285
			(12.714)	(12.587)
SMB_t			-35.772	-31.892
			(29.718)	(26.738)
HML_t			-0.204	1.419
			(7.450)	(7.137)
RMW_t			-16.951	-11.323
			(14.022)	(12.399)
CMA_t			-40.202	-37.228
			(29.029)	(27.209)
MOM_t			-3.372	-0.674
			(5.094)	(5.282)
$Crisis_t$			8.594	2.836
			(6.715)	(5.957)
Observations	12,381	12,381	12,381	12,381
R-squared	0.096	0.106	0.038	0.131

Notes: The dependent variable is the final payoff of the pairs trading strategy implemented when the $Spread$ used to spot the mispricing is estimated based on option prices rather than on Implied Volatilities, and closed when the Spread reverts to within the boundaries. τ stands for time to maturity. ITM stands for in-the-money, ATM for at-the-money and OTM for out-of-the-money, while VRP for variance risk premium. MKT, SMB,HML, RMW, and CMA are the Fama-French 5 factors, MOM is the momentum factor, and $Crisis$ is a dummy for the transaction closing during a period of financial turbulence. Clustered standard errors in parenthesis. $**$significant at 5% level. $***$significant at 1% level.

6. Conclusions

This paper represents one among the few attempts of testing the index options market efficiency by means of a statistical arbitrage strategy, namely pairs trading.

Using data on at-the-money call options written on five European Indexes, over the 2007-2017 period, we find that arbitrage opportunities, despite frequent, are short-lived and mostly lead to non-significant final profits. Market forces are thus able to quickly identify and reabsorb potential mispricing, which is confirmed by the fact that the average trade closes within 4 days. Our final conclusion is thus in favor of index option market efficiency even during the most recent periods characterized by unprecedented crises, such as the Global Financial Crisis and the European Debt Crisis. Notice that all the results presented are computed without taking transaction costs into account. Indeed, their inclusion is likely to further reduce the profitability of the strategies, so our conclusion about index option market efficiency is reached under the most conservative condition.

We also provide an investigation of the main drivers of options' pairs trading performance, finding that the realized profits are not correlated to options' maturity, variance risk premium, or any other of the conventional risk factors. On the other hand, we find a significant and strong association with the moneyness of both the options involved, although most of the variability of the observed profits remains unexplained. Finally, profits are not statistically different during periods of financial turbulence.

Our results are proved to be robust to a stricter definition of reversion to the equilibrium, by having the positions closed whenever the estimated spread between implied volatilities converges back to exactly 0, rather than just re-entering within the significance boundaries. Then, we address the potential concern that the relationship between implied volatilities, which we use to spot options mispricing, might not directly extended to options prices. We thus repeat the analysis estimating the long-run equilibrium relationship based on the time series of options prices constructed collecting the price of the front-month at-the-money option for each day. Also in this case, the results remain qualitatively unchanged.

The application of pairs trading strategies to the options market is still scant, so that our analysis lends itself to several potential extensions, including the enlargement to options with different contract type, maturity and moneyness, which are thus left to further research.

References

Ackert, L. F., & Tian, Y. S. (2001). Efficiency in index options markets and trading in stock baskets. *Journal of banking & finance*, 1607-1634.

Ammann, M., & Herriger, S. (2002). Relative Implied-Volatility Arbitrage with Index Options. *Financial Analysts Journal*, 42-55.

Andrade, S., Di Pietro, V., & Seasholes, M. (2005). Understanding the profitability of pairs trading. *Unpublished working paper, UC Berkeley, Northwestern University*.

Avellaneda, M., & Lee, J. H. (2010). Statistical arbitrage in the US equities market. *Quantitative Finance, 10*(7), 761-782.

Bali, T. G., H. Beckmeyer, M. Moerke, and F. Weigert. (2021). Option return predictability with machine learning and big data. Available at SSRN 3895984.

Barry, C. B., & Brown, S. J. (1984). Differential information and the small firm effect. *Journal of Financial Economics*, 283-294.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *The journal of political economy*, 637-654.

Blázquez, M. C., De la Orden, D. C., & Román, C. P. (2018). Pairs trading techniques: An empirical contrast. *European Research on Management and Business Economics, 24*(3), 160-167.

Bondarenko, O. (2003). Statistical Arbitrage and Securities Prices. *The Review of Financial Studies*, 875-919.

Brunetti, M., & Torricelli, C. (2005). Put-call parity and cross-markets efficiency in the index options markets: evidence from the Italian market. *International Review of Financial Analysis,Elsevier, 14*(5), 508-532.

Caldeira, J. F., & Moura, G. V. (2013). Selection of a portfolio of pairs based on cointegration: a statistical arbitrage strategy. *Brazilian Review of Finance, 11*(1), 49-80.

Capelle-Blancard, G., & Chaudhury, M. (2001). Efficiency tests of the French index (CAC 40) options market. *In EFMA 2002 London Meetings.*

Cavallo, L., & Mammola, P. (2000). Empirical tests of efficiency of the Italian index options market. *Journal of Empirical Finance, 7*(2), 173-193.

Clarke, J., Jandik, T., & Mandelker, G. (2001). The efficient markets hypothesis. *Expert financial planning: Advice from industry leaders*, 126-141.

Clegg, M., Krauss, C. (2018). Pairs trading with partial cointegration, *Quantitative Finance*, 18(1), 121-138.

Cummins, M., & Bucca, A. (2012). Quantitative spread trading on crude oil and refined products markets. *Quantitative Finance, 12*(12), 1857-1875.

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of finance*.

Do, B., & Faff, R. (2010). Does simple pairs trading still work? *Financial Analysts Journal, 66*(4), 83-95.

Duffie, D. (2010). *Dynamic asset pricing theory.* Princeton University Press.

Dunis, C., & Lequeux, P. (2000). Intraday data and hedging efficiency in interest spread trading. *The European Journal of Finance, 6*(4), 332-352.

Elyasiani, E., Gambarelli, L., & Muzzioli, S. (2021). The skewness index: uncovering the relationship with volatility and market returns. *Applied Economics*, 53(31), 3619-3635.

Emery, G. W., & Liu, Q. W. (2002). An anlysis of the relationship between electricity and natural-gas futures prices. *Journal of Futures Markets, 22*(2), 95-122.

Engelberg, J., Gao, P., & Jagannathan, R. (2009). An anatomy of pairs trading: the role of idiosyncratic news, common information and liquidity. *Proceedings of the 3rd Singapore International Conference on Finance.*

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correcton: Representation, estimation, and testing. *Econometrica, 55*(2), 251-276.

Evnine, J., & Rudd, A. (1985). Index options: The early evidence. *The Journal of Finance*, 743-756.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, 34-105.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 383-417.

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance*, 1575-1617.

Fama, E. F. (1995). Random walks in stock market prices. *Financial analysts journal*, 75-80.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of financial economics*, 283--306.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics, 33*(1), 3-56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics, 116(*(1), 1-22.

Fung, J. K., & Chan, K. C. (1994). On the arbitrage-free pricing relationship between index futures and index options: A note. *Journal of Futures Markets*, 957-962.

Fung, J. K., & Mok, H. M. (2001). Index options-futures arbitrage: A comparative study with bid/ask and transaction data. *The Financial Review*, 71-94.

Gambarelli, L., & Muzzioli, S. (2019). Risk-asymmetry indices in Europe. DEMB working paper No. 0157

Gatev, E., Goetzmann, W. N., & Rouwenhorst, K. G. (2006). Pairs trading: perfomance of a relative-value arbitrage rule. *Review of Financial Studies, 19*(3), 797-827.

Girma, P. B., & Paulson, A. S. (1999). Risk arbitrage opportunities in petroleum future spreads. *Journal of Futures Markets, 19*(8), 931-955.

Hogan, S., Jarrow, R., Teo, M., & Warachka, M. (2004). Testing market efficiency using statistical arbitrage with applications to momentum and value strategies. *Journal of Financial economics*, 525-565.

Huck, N. (2015). Pairs trading: does volatility timing matter? *Applied economics, 47*(57), 6239-6256.

Huck, N., & Afawubo, K. (2015). Pairs trading and selection methods: is cointegration superior? *Applied Economics, 47*(6), 599-613.

Jacobs, H., & Weber, M. (2015). On the determinants of pairs trading profitability. *Journal of Financial Markets, 23*, 75-97.

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of financial economics*, 95-101.

Krauss, C. (2017). Statistical arbitrage pairs trading strategies; review and outlook. *Journal of Economic Surveys, 31*(2), 513-545.

Lee, J. H., & Nayar, N. (1993). A transactions data analysis of arbitrage between index options and index futures. *Journal of Futures Markets*, 889-902.

Li, M. L., Chui, C. M., & Li, C. Q. (2014). Is pairs trading profitable on China AH-share markets? *Applied Economics Letters, 21*(16), 1116-1121.

Londono, J. M. (2015). The variance risk premium around the world. Available at SSRN 2517020.

López-Martín, C., Benito Muela, S. & Arguedas, R. (2021). Efficiency in cryptocurrency markets: new evidence. *Eurasian Economic Review*, 11, 403–431.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *The Journal of Economic Perspectives*, 59-82.

Miao, G. J. (2014). High frequency and dynamic pairs trading based on statistical arbitrage using a two stage correlation and cointegration approach. *International Journal of Economics and Finance, 6*(3), 96-110.

Mittnik, S., & Rieken, S. (2000). Put-call parity and the informational efficiency of the German DAX-index options market. *International review of financial analysis, 9*(3), 259-279.

Newey, W., & West, K. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica, 55*(3), 703-708.

Olbrys, J. (2021). The Global Financial Crisis 2007-2009: A Survey. *SSRN Working Paper*, available at: https://ssrn.com/abstract=3872477 or http://dx.doi.org/10.2139/ssrn.3872477

Perlin, M. S. (2009). Evaluation of pairs-trading strategy at the Brazilian financial market. *Journal of Derivatives & Hedge Funds, 15*(2), 122-136.

Rad, H., Low, R. K., & Faff, R. W. (2016). The profitability of pairs trading strategies: distance, cointegration and copula methods. *Quantitative Finance, 16*(10), 1541-1558.

Ross, S. A. (2009). *Neoclassical Finance.* Princeton University Press.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randoml. *Industrial Management Review*, 41-49.

Shiller, R. J. (1981). The use of volatility measures in assessing market efficiency. *The Journal of Finance*.

Simon, D. P. (1999). The soybean crush spead; empirical evidence and trading strategies. *Journal of Futures Markets, 19*(3), 271-289.

Stoll, H. R. (1969). The Relationship between Put and Call Option Prices. *Journal of Finance, 24*(5), 801-824.

Thaler, R. H. (1987). Amomalies: The january effect. *The Journal of Economic Perspectives*, 197-201.

Vidyamurthy, G. (2004). *Pairs Trading: Quantitative Methods and Analysis.* Hoboken, NJ: John Wiley & Sons.