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Pairs Trading In The Index Options Market

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Abstract

We test the Index options market efficiency by means of a statistical arbitrage strategy, i.e. pairs trading. Using data on five Stock Indexes 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 positive returns, thus providing evidence in support of Index Option market efficiency. The time-to-maturity of the options involved in the trade as well as financial market turbulence have a marginal effect on the eventual strategy returns, which are instead mostly driven by the moneyness of the options traded. Our results remain qualitatively unchanged if a stricter definition of reversion to the equilibrium is applied or when the long-run relationship is estimated on an (artificially derived) time series of options prices rather than on options' implied volatilities.

Keywords: pairs trading, option market efficiency

JEL Codes: G10, G12, C44, C5

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1. Introduction

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Market efficiency is a core assumption in financial theories and, not surprisingly, is one of the most investigated financial market characteristics. Indeed, a fundamental assumption in financial modelling is that agents are rational and seek to maximize their own profits, using all available information to continuously update their expectations on asset prices. Due to the large number of agents competing concurrently, any mispricing is exploited immediately so that the market equilibrium is restored. This process, according to which all the information available to market participants is always reflected in securities prices, is known as market efficiency.

The notion of market efficiency was formalized, first, in the 1960s, in the so-called Efficient Market Hypothesis (EMH). Fama (1965) states that, in efficient markets, 'on average, competition will cause the full effects of new information on intrinsic values to be reflected "instantaneously" in actual prices'. In the same period, Samuelson (1965) reaches a similar conclusion, recognizing the randomness of price variations, and explains price unpredictability as a consequence of market competition. An EMH milestone is the publication of Fama's 1970 article 'Efficient capital markets: A review of theory and empirical work'. The main takeaway from this work is that abnormal returns cannot be obtained from a market based on full information disclosure. In practice, only a few agents will be able to profit from identification of mispriced securities, thus, ensuring that arbitrage opportunities disappear quickly from the market and guaranteeing that all assets will be priced at the present values of their expected future cash flows, accounting for volatility, liquidity and default risk.¹ Therefore, the EMH is relatively easy to test and can be disproved if it is possible, systematically, to identify and exploit arbitrage opportunities in order to obtain profits.

In this Essay, we investigate the efficiency of the index option market by exploiting a specific statistical arbitrage strategy. In detail, we test market efficiency by verifying the absence of arbitrage opportunities using pairs trading, which we test on front-month at-the-money call options. If we find significant profitability, associated to frequent and long-lasting mispricing, we can conclude that the market is inefficient in terms of the relative pricing of similar risks/assets. However, if strategy employed is unable to identify and exploit arbitrage opportunities, this cannot be interpreted as proof of market efficiency; rather, it indicates simply that the strategy fails to produce significant profits.

This approach, which requires identification of pairs of assets whose prices commove and setting a trading rule to profit from price divergences, is typically applied to stocks. Therefore, the first step is to adapt pairs formation to options, which are assets with different characteristics. This is done using two different methods: one based on the Implied Volatility of at-the-money one-month maturity options; and, as robustness check, one based on an (artificial) series of at-the-money front-month Option Prices (OP). Once pairs of index options

¹ 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).

are formed, we can establish a stationary and mean-reverting relationship between them and implement a simple trading strategy whenever this relationship appears to be violated.

This paper is novel in being the first study to apply cointegration-based pairs trading to options to test the efficiency of the index options market, and contributes to work on both option market efficiency and pairs trading. Another distinguishing feature of the present study is that it relies on a customized dataset, which includes all dead call options on five European stock indexes during the period May 2007 to end 2017. 2

The paper is organized as follows: Section 2 reviews the relevant market efficiency and statistical arbitrage literature; Section 3 describes the methodology and the arbitrage strategy employed to test market efficiency; Section 4 presents the empirical application and provides some details on the dataset and the results; Section 5 outlines our main conclusions.

2. Literature review

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This work lies at the intersection between two distinct literature streams on testing for index option market efficiency and implementing statistical arbitrage strategies, such as pairs trading. The work in this area, so far, uses stocks and other kinds of assets, but not options.

Two different types of arbitrage strategies are identified in the literature. A '*Pure Arbitrage Opportunity* is a zero-cost trading strategy that offers the possibility of a gain with no possibility of a loss', whereas a '*Statistical Arbitrage Opportunity* 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' (Bondarenko, 2003). In both cases, the average payoff in each final state must be non-negative and the main difference between them is the possibility of negative payoffs in the statistical, but not in the pure arbitrage opportunity.

Previous tests of index options market efficiency typically rely on pure arbitrage strategies.³ The seminal paper by Stoll (1969) paved the way to many contributions testing these relationships, especially for US stock option markets. For instance, Evnine and Rudd (1985) observe significant violations of put-call parity and boundary conditions for the S&P 100 options market, which suggest market inefficiency. Several years later and working with S&P 500 index options, Ackert and Tian (2001) reach the opposite conclusion. Tests of 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, Cavallo and Mammola (2000) and Brunetti and Torricelli (2005) on Italian index (Mib30) option market,

²In constructing the dataset, all price anomalies were reported to the data provider Thomson Reuters DataStream, so that most of the corrections are embedded in the series available on its platform and, thus, have been ameliorated.

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

highlight the pivotal role of market frictions. Violations are frequent, but disappear almost completely once transaction costs are taken into account, which supports index option market efficiency.⁴ One advantage of this type of test for market efficiency is that it avoids the so called 'joint hypothesis problem' highlighted Fama (1998). Indeed, when model-based tests are used, market efficiency and the appropriateness of the pricing model are tested jointly, so that potential violations may be due to use of the (wrong) pricing model rather than rejection of the EMH.

Statistical arbitrage has the very same advantage, since it does not rely on an equilibrium pricing model. The idea behind this approach consists of identifying potential anomalies in asset prices and exploiting them: if it is possible to profit systematically from these mispricings, then market efficiency can be disproved. However, statistical arbitrage is applied, mostly, to the stock (and a few other) markets.⁵

Among the many statistical arbitrage methodologies, the best known is pairs trading, which dates back to the 1980s and, specifically, to the work of Nunzio Tartaglia at Morgan Stanley. In a nutshell, pairs trading is aimed at identifying assets whose prices show similar historical behaviour, and deriving profit from short-term deviations from this long-run mean-reverting relationship, based on the expectation that history will repeat itself. Pairs trading can be implemented using a variety of approaches (Krauss, 2017), including the distance, cointegration, time series and stochastic control methods, which vary in how the pairs are selected and how their relationship is modelled. The methodologies most relevant for the current study are the distance and cointegration approaches. In the distance approach, pairs formation relies, usually, on minimizing the Sum of Squared Deviations (SSD) between normalized prices, and the equilibrium is determined as the difference between the normalized prices. In the cointegration approach, selection is based on cointegration testing and the long-term relationship is identified through the Error Correction Representation (Engle & Granger, 1987).

Regardless of which of these methods is applied, the relevant literature focuses mostly on stock markets and, especially, the US stock market (Gatev, Goetzmann, & Rouwenhorst, 2006; Avellaneda & Lee, 2010; Do & Faff, 2010; Miao, 2014; Jacobs & Weber, 2015; Rad, Low, & Faff, 2016). However, there are also some applications to other markets, such as the European (Dunis & Lequeux, 2000), Japanese (Huck, 2015), Brazilian (Perlin, 2009; Caldeira & Moura, 2013), Chinese (Li, Chui, & Li, 2014) and Taiwanese (Andrade, Di Pietro, & Seasholes, 2005) stock markets.⁶

⁴ Parallel investigations have been conducted on derivatives on the same underlying, for instance options and futures, see, e.g., Lee and Nayar (1993) and Fung and Mok (2001).

⁵ See Hogan *et al*. (2004) for a review of statistical arbitrage applications to test market efficiency.

 6 The only paper among those cited here that uses neither the distance nor cointegration approach, is Avellaneda and Lee (2010), who propose two approaches for stock returns decomposition based on principal component analysis and exchange traded funds sector returns and use a relative value model for stock performance, assuming that residuals are distributed as an Ornstein–Uhlenbeck process.

The few works that investigate securities other than stocks, apply pairs trading methodologies to future commodity markets: Girma and Paulson (1999) and Cummins and Bucca (2012) focus on the 'crack spread', that is, the difference between the petroleum price and the prices of its refined product futures; Simon (1999) works on the 'crush spread', which is the difference between soybean and its manufactured goods futures prices; Emery and Liu (2002) use the 'spark spread', i.e. the difference between the prices of natural gas and electricity futures. In all these applications, the authors apply unit root testing to verify that prices are integrated of order one series, and check for the presence of cointegration between them before directly modelling the spread on futures prices via different methods. By exploiting the spread mean-reverting property, they obtain positive results for pairs trading profitability. Only Cummins and Bucca (2012) propose a different methodology that belongs to the time series approach; they apply it empirically to a large dataset, modelling the spread of energy futures as an Ornstein–Uhlenbeck process.

To sum up, the efficiency of the index options market has been investigated by testing for the profitability of pure arbitrage strategies, while statistical arbitrage and, pairs trading in particular, has been used mostly to examine the stock market. The contribution of this paper is to test index option market efficiency using pairs trading.

To our knowledge, there is only one other paper, which is by Ammann and Herriger (2002), that adopts a statistical arbitrage methodology to investigate the efficiency of the index options market. 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. After selecting indexes with highly correlated returns, the methodology estimates a relationship between index returns and then, based on linearity, assumes that the estimated relationship is valid also for implied volatilities. 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. Our work differs in that, as shown below, we estimate the mean-reverting relationship on implied volatility directly, not on index returns.

3. Methodology

To test index option market efficiency using pairs trading, we employ the cointegration approach, given its superiority in terms of profitability with respect to distance approach (Huck & Afawubo, 2015; Rad, Low, & Faff, 2016; Blázquez, De la Orden, & Román, 2018). The baseline structure of the cointegration approach, which is described in Vidyamurthy (2004), distinguishes a formation and a trading period. In the former, the test for cointegration is run on all possible stock price pairs, with the aim of selecting couples that share a long-term equilibrium that is stationary and mean-reverting. In the trading period, a simple trading strategy that exploits deviations from the equilibrium relationship is implemented.

In our application, we use at-the-money (hereafter ATM) index options with the shortest maturity, imposing at least 10 days before expiration.⁷ There are two main reasons for this choice: these options are the most liquid in the market, so to ensure that recorded prices are close to the price at which a trade could actually occur; and ATM options are the most informative in terms of volatility since most of their value is driven by this component.

However, applying cointegration to index options can be difficult since, by their nature, options have a finite life. This implies that we may not have enough data to train the classical cointegration approach: in most applications the length of the formation period employed to test for cointegration is 1 year. To overcome this issue, Ammann and Herriger (2002) rely on the returns from the underlying indexes. Specifically, they select pairs of indexes with highly correlated daily returns. Then, after checking for stationarity of returns, they estimate the long-run relationship linking the indexes returns and apply the estimates obtained to the corresponding relationship between the respective volatilities. The idea is that, if the quotations related to the underlying indexes are highly correlated and the market is efficient at pricing similar risks, the volatilities of the options on those indexes should also be related. If violations of the equilibrium-relationship between volatilities are observed systematically and allow significant profit, then market efficiency is disproved.

We differ from Ammann and Herriger (2002) since we identify the potential mispricing based on the relationship estimated directly between the implied volatilities of the ATM options, rather than estimating the relation between the returns from the underlying indexes, and then applying it to the volatilities. This approach is based on the concept of long-term equilibrium, which is fundamental to the cointegration methodology, but, in practice, there is no need for a cointegration test due to the characteristics of the series considered.

The proposed methodology is structured as follows:

- 1. Check for stationarity: using data over the full sample, we run an Augmented Dickey Fuller (ADF) test to check for stationarity of the implied volatilities (IV);
- 2. Using 1-year observations in the estimation period, we regress the IV_Y^{ATM} on the IV_{X}^{ATM} , for all options written on the pairs of indexes (Y,X) , to obtain the estimates required to derive the *Spread*;
- 3. In the following 6-month trading period, we compute the *Spread* and implement a simple trading strategy whenever a misprice is suspected, that is, if the *Spread* diverges considerably from its zero mean;
- 4. Rolling regression: steps 2 to 3 are repeated, shifting the sample one month ahead. This scheme, which updates the information set as time passes, generates 6 overlapping trading periods for each month.

 7 For each day, we compute the difference between the current date and the expiration date of all call options on the index considered. We then select all call options with the minimum difference, excluding those with only 10 or fewer days left before expiration. Finally, we identify among them the ATM option, which is the option whose strike price is closest to the value of the Index.

We evaluate the profitability profile per transaction by looking at the total number of trades, the average number of days a position is kept open and the average returns.⁸ The analysis concludes by focusing on the profitability drivers and a brief overview of the average monthly returns per pair, computed as mean values first across overlapping portfolios and then across pairs.

The following subsections describe steps 2 and 3 in more detail.

3.1 Estimation period

Using 1-year data, we estimate the following regression via Ordinary Least Squares (OLS):

$$
IV_{t,Y}^{ATM} = \beta_0 + \beta_1 IV_{t,X}^{ATM} + \varepsilon_t
$$
\n(1)

where:

- \bullet $IV^{ATM}_{t,Y}$ is the implied volatility of the one-month maturity ATM option written on Index Y observed at day t
- \bullet $IV^{ATM}_{t,X}$ is the implied volatility of the one-month maturity ATM option written on Index X observed at day t
- ε_t is the error term at time t
- \cdot β_0 is the intercept coefficient, which, in this case, acts simply as a scale parameter
- θ β_1 is the proportionality factor, measuring the relationship between the two implied volatilities

The estimate is repeated monthly and executed for all possible pairs of indexes (Y, X) .

Notice that using implied volatilities, which are stationary time series, allows correct measurement of their association via OLS regression without the need for further tests. Instead, stock prices, typically, are $I(1)$ time series, so the long-term relationship must be determined by means of cointegration tests.

The estimation is done in a rolling window fashion, using observations in one calendar year (estimation period) and shifting the sample one calendar month ahead at each repetition.⁹ This scheme is employed to evaluate the methodology, regardless of the start point, and to update the information set as time passes, and generates six overlapping trading periods for each month.

3.2 Trading period

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Each estimation period is followed by a six-month trading period, in which the market efficiency in pricing relative risks is tested. The idea is that a potentially profitable trading opportunity emerges whenever one of the ATM options has an observed implied volatility

⁸ Averages are computed across all trades, aggregating the 6 overlapping portfolios.

⁹ For each month, we consider observations going from the first to the last day of that interval.

that deviates sufficiently from the relationship estimated in model (1). When such divergence is detected, the agent sells the relatively overpriced asset and buys the relatively underpriced asset. The position is then closed when the equilibrium is restored. If this strategy is able to generate non-negative expected payoffs, we conclude that the market is inefficient.

We use a statistical approach to provide a definition of 'sufficient deviation'. Based on the estimates obtained in the estimation period, the *Spread¹⁰* is computed as:

$$
Spread_t = IV_{t,Y}^{ATM} - \hat{\beta}_0 - \hat{\beta}_1 IV_{t,X}^{ATM}
$$
\n(2)

and represents the out-of-sample residual of the model (1). Under stationarity of both of the variables involved in the simple linear regression model, in-sample residuals are a stationary process and mean-reverting towards 0. We take advantage of this characteristics out-of-sample and identify a significant deviation of the Spread_t from its long-run value of 0 as a violation of the following condition:

$$
2\hat{\sigma} \geq \text{Spread}_t \geq -2\hat{\sigma} \tag{3}
$$

where $\hat{\sigma}$ is the standard deviation of the regression residuals from the estimation period. All departures of the *Spread* from these boundaries is interpreted as a misalignment of the ATM options implied volatilities from the relationship estimated in model (1), and signals a potentially profitable mispricing, which leads the agent to trigger a trade. Figure 1 provides a graphical example.

Figure 1 - Example of implied volatilities and Spread time series

First panel: implied volatility time-series for one-month maturity ATM call options written on CAC40 and ESTOX50 Indexes, between 1st July and 31st December 2012. *Second panel*: Spread and statistical trigger boundaries.

 10 This definition is in line with the definition in Vidyamurthy (2004) and includes the estimated intercept.

We set up two types of trading strategies: the first with zero net capital investment (i.e., the 'self-financing strategy') and the second where the traded quantities are determined by the estimated regression slope (i.e., the 'beta-arbitrage strategy').

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, in the self-financing strategy, 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. In the beta-arbitrage strategy, 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 β_1 (the idea here is that the amount spent in euros for the option written on X is equal to $\hat{\beta_1}$ times the price of option Y). The position is closed when the *Spread* reverts to within the estimated boundaries (or at maturity of the option and/or the end of the trading period).

Conversely, if $Spread_t < -2\hat{\sigma}$, the option on Y is suspected to be underpriced with respect to the option on X , and the trading scheme is reversed. In the self-financing strategy, one unit of the option written on X is sold and an amount of the option on Y is bought using the proceeds from the sale. In the beta-arbitrage strategy, one unit of the option on X is sold and the quantity of the option written on Y will be the same as the amount bought in the self-financing strategy divided by $\hat{\beta_1}.$ As above, the position is closed when the *Spread* reverts to within the estimated boundaries (or is closed forcibly at option maturity and/or at the end of the trading period). 11

To reduce the sensitivity of our results to the decline in option prices as they approach expiration, all positions are closed forcibly two trading days before maturity. Transaction payoffs and returns are computed once the initial trade is unwound and depend on the relative prices of the traded options. Notice that returns can be interpreted as excess returns only in the self-financing strategy since no initial investment in needed in this case. In the beta-arbitrage strategy, the payoff when the trade is initiated depends on $\hat{\beta}_1$ and affects the final outcome of the transaction.

4. Empirical application

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In this section, we describe the dataset employed for the empirical application and the total and average results obtained using the methodology presented in Section 3.

¹¹ As a robustness check (Section 4.5), we implement a stricter methodology where trades are closed when the *Spread* reverts to zero.

4.1 Data

The empirical application relies on daily data for the period $1st$ May 2007 to 31 st December</sup> 2017, and refers to five Euro area stock indexes:

- 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).

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.

For each index, we use the following data, retrieved from Thomson Reuters DataStream:¹²

• Stock index prices:

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- Options prices for all call options written on the indexes, along with their maturities and strike prices;¹³
- Implied volatilities of the ATM 1-month maturity call options written on the indexes.

For each date and each underlying index in our sample, we select the ATM call option with shortest maturity, excluding those with a residual life of less than 10 days. The selection is performed, first, identifying all call options with the minimum distance between the current date and the expiration date, excluding options with less than 10 days before expiration. Thus, the number of days before expiration ranges between 11 days (corresponding to at least 7 trading days) and 46 days (corresponding to at least 32 trading days). Second, for each day, we select the ATM option with strike price as close as possible to the value of the index (i.e. the ATM option), among the call options with the shortest maturity. If two series have the same absolute distance between the strike and the index price, we exclude the one with the higher strike price, to maintain the more conservative one in terms of final payoff.

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

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

The selection process excludes all call options with non-standard maturity, 14 that is, the third Friday of the month, and some calls presenting two series for the same strike price.¹⁵ For each ATM option, we store the entire price series and obtain 2784 series per underlying index, that is, one ATM call option for each trading day in our sample. Price series are entirely stored because every position is opened on the call option that is ATM that day and, to close it, we need to trade exactly the same option, which may not coincide with the ATM option at closure date.

Implied volatilities series of one-month maturity ATM call options for each underlying Index.

Figure 2 depicts implied volatility time series of one-month maturity ATM options, written on the selected indexes. The behaviour is similar across the underlying indexes, suggesting a strong relationship among these variables. The implied volatilities appear to be fairly stable around their means, across the whole sample, and are affected by two major common shocks: the global financial crisis and the sovereign debt crisis, which caused instability (i.e., higher volatility) on the European financial markets.

¹⁴ Call options with non-standard maturity are those assets in our sample with a maturity date different from the third Friday in the month. Since our ATM-options selection process is based on considering first maturity and then moneyness, call options with non-standard maturity would be selected for some dates as those with the shortest maturity even if they have a strike price that is far from the underlying Index value. We excluded one option on the CAC 40, one option on the ESTOX 50 and four options on the FTSE 100.

¹⁵ We found only two call options on the FTSE 100 with this problem. In detail, we found two series of call options with same maturity and strike price: one presenting just one observation while the other containing the entire price series. We excluded the series with just one observation.

4.2 Preliminary analyses

Before proceeding to the empirical test for market efficiency, we performed a complete statistical analysis of the variables used in the regressions. We began with the ADF test for stationarity of the implied volatilities, run by 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.¹⁶

Table 1 reports the descriptive statistics for the implied volatility of the one-month maturity ATM call options. The implied volatilities present similar characteristics: for all the underlying indexes, the average value is near to 21.5, and the standard deviation is around 8.75, with fairly well aligned minimum (maximum) values, ranging between 4.62 and 10.36 (76.24 and 91.41).

Table 1 - IV of the one-month ATM Call Options: descriptive statistics, by underlying Index

Notes: main descriptive statistics for the IV series of the one-month maturity ATM call options over the entire sample period, by underlying index.

This result is further confirmed by the correlations in Table 2. The implied volatilities are highly correlated for all index pairs: the correlation coefficients range between 0.75 and 0.98, with minima for all pairs containing options on the FTSE MIB.

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Notes: Pearson correlation coefficients for the IV series of the one-month maturity ATM call options for each pair of underlying indexes, using the entire data sample.

This preliminary descriptive analysis suggests that the implied volatilities of these options are strongly related; we exploit this relation in our test for option market efficiency based on statistical arbitrage.

¹⁶ Among all the specifications considered, the maximum pValue is equal to 0.0083 for the implied volatility related to the underlying FTSE 100 (model with drift-only and lag-length set at 14).

4.3 Main Results

This section presents the results of the trading strategy described in Section 3.2. Specifically, we evaluate the number of trades and their final returns, and test their statistical significance by means of the Newey-West statistics (Newey & West, 1987) for a two-tailed test.

The results are presented for both the self-financing and the beta-arbitrage strategies; only in the self-financing case, the results can be interpreted as excess returns since the strategy does not require any initial investment. In all cases, the trading period runs from 1st May 2008 to 31st December 2017, since the first year of data is used for the first estimation period. All the results are computed by aggregating all of the trades triggered in the considered samples and without considering transaction costs. Including transaction costs would further reduce the profitability of the strategies and our aim is to evaluate market efficiency under the most conservative conditions.¹⁷

In many pairs trading applications, the initial set of potential pairs is artificially narrowed (for instance, Miao, 2014, and Ammann & Herriger, 2002, pre-select pairs with correlations greater than 0.9 and 0.95, respectively); in our case, no pairs are excluded in order to avoid the need for arbitrary thresholds, and this allows us to assess *ex-post* the effects of weak correlation.

Table 3 shows that the overall number of trades realized exceeds 11,000 in 116 months, meaning that, during the period analysed, the *Spread* violated condition (3) on several occasions, signalling potential mispricings. Since we are dealing with six overlapping portfolios, some trades will be similar across portfolios, with the result that the actual number of mispricing is lower than the total number of trades. The vast majority (88%) of the trades, which remains open for 4 days on average, closes because the *Spread* reverts to within the boundaries; the remainder are non-convergent trades which are closed forcibly either because the options expire (8%) or because the end of the trading period is reached.

Despite the high number of suspected mispricings, the average returns from the self-financing strategy are around 0.8% and not statistically significant. By splitting the results based on the pairs of underlying indexes on which the options are written, we find that the strategy is significantly profitable for 6 out of the possible 20 couples. For these pairs, the excess returns range from 4.3% (for the couple FTSEMIB-CAC40, corresponding to €15.60 in terms of average profit) to 13.6% (for the FTSEMIB-DAX30 couple, corresponding to an average profit of €56.60). In all the other cases, the strategy does not provide significant returns and in four cases, all of which include the FTSE100 (CAC40-FTSE100, ESTOX50-FTSE100, FTSE100-CAC40, FTSE100-ESTOX50), it resulted in statistically significant negative returns due, most likely, to the additional friction imposed by exchange rate conversion to euros.

The beta-arbitrage strategy differs from the self-financing strategy only in terms of traded quantities; the number of transactions and the reasons for closure remain the same. However, since the beta-arbitrage strategy requires an initial investment, the returns cannot

 17 Tables 12 and 14 in the Appendix provide more results on strategy profitability.

Table 3 – Results for the IV-based pairs trading strategies

Notes: results of the pairs trading strategies implemented over the sample from May 2008 to December 2017, with May 2007 to April 2008 data activated whenever the implied volatilities of the one-month maturity ATM call options deviate from the relationship in model (1), estimate between the indicated underlying Indexes as X and the second as Y, and closed when the *Spread* reverts to within the boundaries. Columns 1-3 r the self-financing strategy. Columns 4-6 refer to the returns from the beta-arbitrage strategy, which differ only in terms of the quantities trad average, the standard deviation and t-statistics computed using the Newey-West heteroskedasticity and autocorrelation robust standard errors can be interpreted as excess returns, since the strategy does not require any initial investment. ***, **, and * are significance at the 1%, 5%, a the share of closed trades due to Spread reversion to within the boundaries, option expiration and reaching the end of the trading period. Colum number of days a trade remains open, and the total number of trades.

be interpreted as excess returns. The average return observed across all pairs is still positive, but is much higher than in the case of the self-financing strategy (7.3% against 0.8%). This is likely due to the estimates of beta, which, in most cases, are close to 1. This in turn leads to an initial investment close to zero, which works to inflate the final returns. Nonetheless, consistent with the above findings, the average return is not statistically significant. Also, considering the results by pairs, the returns are significantly positive only for the pairs written on FTSEMIB and the ESTOX50.

Overall, despite frequent signals of potential mispricing, the statistical arbitrage strategy does not produce statistically significant positive returns; namely, there is no evidence suggesting that the index option market is inefficient.

4.4 Profitability drivers

The results of the arbitrage strategy present a variegated scenario, with some pairs showing a positive and significant profitability. In this section, we investigate the potential drivers of this performance. First, we investigate the role of options characteristics. The value of an option is function of: its moneyness, that is, the closeness between the option strike price and the price of the underlying asset; its time to maturity, that is, time before expiration; the volatility of the underlying quotations and the interest rate. Since the last two are (supposed to be) common across all options traded in the market, we focus on time to maturity and moneyness. Notice that, even if the options are ATM when a position is opened, they may not be ATM at closure. Therefore, we regress the strategy's per-transaction returns (either self-financing or beta-arbitrage) on the time to maturity and a measure of moneyness of both the options included in the trade, that is, the bought (long) option and the sold (short) option.

We include in the regression model dummies for whether the options are at-the-money (ATM_i), in-the-money (ITM_i) or out-of-the-money (OTM_i) at trade closure, considering all possible combinations of long and short positions.¹⁸ In our sample, the distribution of the strike-price ratio at closure $\left((K/S)_i\right)$ ranges in the interval [0.8 - 1.36] for the options sold (in the short leg of the trade) and [0.85 - 1.62] for the options bought (in the long leg of the trade), with mean and median of approximately 1. We thus classify the options as follows¹⁹:

$$
\begin{cases}\nITM_i & \text{if } \left(\frac{K}{S}\right)_i < 0.98 \\
OTM_i & \text{if } \left(\frac{K}{S}\right)_i > 1.02 \\
ATM_i & \text{otherwise}\n\end{cases} \tag{4}
$$

where K is the option strike and S is the underlying index price of the closing transaction i .

¹⁸ $ATM_{t,long} - ATM_{t,short}$ is the reference category.

 19 Table 20 in the Appendix reports the distribution of the trades according to option classification, and shows that, in most cases, the transactions involve options belonging to the same moneyness category. We tried to use alternative classifications, setting the thresholds for the ITM/OTM equal to the mean value \pm 0.01, 0.03, 0.04 and 0.05 and the results are qualitatively unchanged.

The regression model is the following:

 $r_i = \beta_0 + \beta_1 \tau_{i, short} + \beta_2 \tau_{i, long} +$ $\beta_3 I T M_{i, short} I T M_{i, long} + \beta_4 I T M_{i, short} A T M_{i, long} + \beta_5 I T M_{i, short} O T M_{i, long}$ $\beta_6 O T M_{i, short} I T M_{i, long} + \beta_7 O T M_{i, short} A T M_{i, long} + \beta_8 O T M_{i, short} O T M_{i, long} +$ $\beta_9ATM_{i,short}ITM_{i,long} + \beta_{10}ATM_{i,short}OTM_{i,long} + \beta_{11}Crisis_i + \epsilon_i$ (5)

where r_i is the strategy return realized on the trade closed by the transaction i . $\tau_{i,short}$ and $\tau_{i, long}$ are the respective times to maturity of the options sold and bought, measured by the number of trading days before expiry of the option. ITM_i , OTM_i and ATM_i are dummies capturing whether, at closure, the call option is respectively in-the-money, out-of-the-money or at-the-money and are differentiated for long and short positions. Finally, Crisis_i is a dummy variable for whether the trade is closed in a 'period of crisis', that is, during the global financial crisis (October 2007 to May 2009) or the stock market 'selloff' (June 2015 to June 2016).

Table 4 reports the results of the regressions for the self-financing and the beta-arbitrage strategies. The intercept represents the expected return and, in the specifications that include moneyness dummies (2, 4, 6, 8), is interpreted as the return from a trade of two options that are both ATM when the position is closed. It is positive in all the self-financing strategy specifications, and significant only if the moneyness dummies are excluded; it is negative, but never statistically significant for the beta-arbitrage strategy. Also, periods of crisis have a significantly negative effect on returns only in the self-financing application. The R-squared of the beta-arbitrage strategy is fairly low compared to the self-financing strategy, which reaches a maximum of 0.24 in the specifications that include dummies for options being ITM, OTM or ATM.

The results show that the returns are related significantly to the time to maturity of the options involved, with the exception of the self-financing strategy specification that includes all the regressors (4). In particular, the returns are negatively (positively) associated to the time to maturity of the option sold (bought), which is consistent with the price of the option being related positively to the time to expiration. The estimates of time to maturity for the two legs are almost identical in magnitude, because the options used in the sample have standardized maturities.

As expected, the returns of the strategy are related positively to the options sold being OTM and the options bought being ITM. Conversely, the relation is negative for short positions in ITM options and long positions in OTM options. The lower is the strike-price ratio (i.e. the more the underlying price is higher than the strike price), the higher is the intrinsic value of the call option and, as a result, the higher are the chances of making a profit when a long position is taken on a call (and the higher are the chances of a loss if the option is sold short). If the price of the underlying is lower than the strike price, the reverse applies. The parameters are almost always statistically significant in the self-financing strategy and in four cases in the beta-arbitrage strategy. Notice that if both options are OTM (ITM) at closure, the short (long) leg positive relation prevails over the long (short) leg negative relation, generating a positive parameter that is significant only in the self-financing strategy.

Notes: regression estimates for the four alternative model specifications of equation (5). The dependent variable is the return obtained implementing the pairs trading (self-financing or beta-arbitrage) strategy. τ is the time to maturity. ITM is a dummy for the option being in-the-money, ATM is a dummy for the option being at-the-money and OTM is a dummy for the option being out-of-the-money; all are defined for both the option bought (long) and the option sold (short) in the transaction. Crisis is a dummy for trade closure being in a period of crisis. ***, **, and * are significance at the 1%, 5%, and 10% levels, respectively. pValue is in parentheses.

When only trades that produce statistically significant positive returns are considered (Table 5), the results are fairly similar to the previous analysis, with some differences: the returns appear to be generally unrelated to the time to maturity; the intercept for the self-financing strategy specification that includes all the regressors (4) becomes statistically significant; the moneyness parameters in the beta-arbitrage specifications 6 and 8 present less extreme values, with $ITM_{i,short}OTM_{i,long}$ which turn out to be not significant and $OTM_{i,short} OTM_{i,long}$ which turn significant. Notice that the number of observations differs considerably between the two strategies.

Figure 3 depicts the average monthly number of trades, number of wins (i.e., transactions with positive final payoff) and returns per pair from the self-financing (upper panel) and beta-arbitrage (bottom panel) strategies. The results are obtained by first computing the average monthly results for each trading period, then averaging them over the six overlapping trading periods and, finally, taking the mean across all pairs.²⁰

 20 The full results are provided in Tables 13 and 15 in the Appendix.

		Self-financing strategy				Beta-arbitrage strategy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	$0.07***$	0.01	$0.04***$	$0.04***$	0.35	0.31	$0.55***$	0.05
	(0.00)	(0.37)	(0.00)	(0.00)	(0.34)	(0.15)	(0.00)	(0.90)
	$-0.03*$			0.002	0.01			0.02
$\tau_{i,short}$	(0.09)			(0.87)	(0.65)			(0.29)
	0.02			-0.003	N/A			
$\tau_{i,long}$	(0.12)			(0.82)				N/A
		$0.07***$		$0.07***$		0.34		0.43
$ITM_{i,short}ITM_{i,long}$		(0.00)		(0.00)		(0.41)		(0.31)
		$-0.31***$		$-0.32***$		$-1.94***$		$-2.00***$
$ITM_{i, short}ATM_{i, long}$		(0.00)		(0.00)		(0.00)		(0.00)
		$-0.69***$		$-0.73***$		0.00		0.00
$ITM_{i, short}$ $OTM_{i, long}$		(0.00)		(0.00)		(0.00)		(0.00)
		$0.77***$		$0.77***$		4.03		3.95
$OTM_{i, short} ITM_{i, long}$		(0.00)		(0.00)		(0.29)		(0.30)
		$0.20***$		$0.20***$		$1.79**$		$1.68**$
$OTM_{i, short}ATM_{i, long}$		(0.00)		(0.00)		(0.01)		(0.02)
		0.01		$0.03*$		$0.91**$		$1.10**$
$OTM_{i, short} OTM_{i, long}$		(0.40)		(0.05)		(0.03)		(0.01)
		$0.71***$		$0.71***$		$2.53***$		$2.62***$
$ATM_{i, short}ITM_{i, long}$		(0.00)		(0.00)		(0.00)		(0.00)
		$-0.12***$		$-0.11***$		-1.23		-1.21
$ATM_{i, short} OTM_{i, long}$		(0.00)		(0.00)		(0.22)		(0.23)
$Crisis_i$			$-0.03***$	$-0.06***$			-0.11	-0.38
			(0.01)	(0.00)			(0.73)	(0.23)
Ordinary R-squared	0.004	0.212	0.001	0.217	0.000	0.030	0.000	0.032
Num. of observations	5132	5132	5132	5132	1366	1366	1366	1366

Table 5 - Drivers of significantly positive trades returns: time-to-maturity, moneyness and crisis periods

Notes: regression estimates for the four alternative model specifications of equation (5). The dependent variable is the return obtained implementing the pairs trading (self-financing or beta-arbitrage) strategy, considering only trades where it is significantly positive. τ is the time to maturity. ITM is a dummy for the option being in-the-money, ATM is a dummy for the option being at-the-money and OTM is a dummy for the option being out-of-the-money; all are defined for both the option bought (long) and the option sold (short) in the transaction. Crisis is a dummy for trade closure being in a period of crisis. ***, **, and * are significance at the 1%, 5%, and 10% levels, respectively. pValue is in parentheses. 'N/A' in specifications (5) and (8) is because the $\tau_{i, short}$ and $\tau_{i, long}$ series are identical and, thus, the variables are collinear.

The mean of the average number of transactions per month is equal to 0.8, implying that trades per pair are both short and infrequent. The average number of wins is close to 0.42 and 0.41 in the self-financing and beta-arbitrage strategies, respectively, which is just slightly higher than 50% of total trades. However, the characteristics of the returns differ considerably between the strategies considered. On average, the self-financing strategy provides excess returns equal to 0.67%, while the beta-arbitrage strategy provides returns of 5.88%. Notice that, in this second case, the returns are more volatile , which is due, in part, to $\hat{\beta_1}$ being very close to 1, with the result that the amounts traded when the position is opened are so similar between the two options considered, that the initial investment is almost zero. Consequently, the final payoff divided by the initial investment is either extremely high or extremely low, depending on whether it is positive or negative.

Figure 3 - Pairs trading monthly results (average values)

Average results across pairs in the trading strategies implemented over the sample from May 2008 to December 2017: average number of transactions per month, average number of wins per month (i.e., trades with a positive final payoff) and average monthly returns. Trades are activated 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. The first and the second panels refer to the results of the self-financing and beta-arbitrage strategies, respectively. Notice that, in the first case, returns can be interpreted as excess returns since the strategy does not require any initial investment.

4.5 Robustness

Our results are robust to several checks. First, we implemented a stricter definition of convergence by closing the trades when the *Spread* reverts to zero, rather than when it returns to within the boundaries. The results are qualitatively unchanged in terms of both profitability and its drivers, as shown in Tables 6 and 7. However, trade characteristics and returns differ from the baseline methodology.

		Self-financing strategy returns			Beta-arbitrage strategy returns		Closing			
	Mean	Std	NW stat	Mean	Std	NW stat	Boundary	Maturity		
CAC40-DAX30	0.036	0.49	0.93	0.522	13.69	0.60	0.24	0.61		
CAC40-ESTOX50	-0.040	0.29	$-1.81*$	-9.136	70.49	$-1.97**$	0.40	0.50		
CAC40-FTSE100	-0.116	0.74	$-2.52**$	-2.084	22.27	$-1.94*$	0.45	0.43		
CAC40-FTSEMIB	-0.009	0.59	-0.25	-0.480	22.24	-0.37	0.28	0.62		
DAX30-CAC40	0.031	0.47	0.96	1.316	21.03	1.15	0.20	0.64		
DAX30-ESTOX50	0.057	0.44	$1.94*$	5.137	77.35	1.03	0.28	0.60		
DAX30-FTSE100	-0.137	0.81	$-2.60***$	-1.203	99.93	-0.29	0.17	0.68		
DAX30-FTSEMIB	0.100	0.82	$1.80*$	-3.810	67.51	-0.78	0.20	0.66		
ESTOX50-CAC40	-0.047	0.31	$-1.92*$	-4.643	30.38	$-2.44**$	0.33	0.56		
ESTOX50-DAX30	0.079	0.48	$2.76***$	0.227	15.53	0.28	0.18	0.68		
ESTOX50-FTSE100	-0.228	0.84	$-5.27***$	-1.935	31.30	$-2.00**$	0.33	0.55		
ESTOX50-FTSEMIB	0.082	0.57	$2.11**$	0.519	13.94	0.74	0.28	0.60		
FTSE100-CAC40	-0.037	0.72	-0.81	1.202	48.97	0.56	0.39	0.49		
FTSE100-DAX30	-0.057	0.81	-1.27	-0.253	28.57	-0.17	0.16	0.69		
FTSE100-ESTOX50	-0.193	0.84	$-3.65***$	-9.652	133.72	-1.64	0.34	0.55		
FTSE100-FTSEMIB	-0.030	1.11	-0.44	-0.348	39.59	-0.12	0.21	0.66		
FTSEMIB-CAC40	-0.017	0.57	-0.52	-0.699	15.51	-0.99	0.42	0.48		
FTSEMIB-DAX30	0.094	0.92	$1.74*$	1.269	37.32	1.21	0.26	0.62		
FTSEMIB-ESTOX50	0.109	0.56	$2.73***$	2.556	28.19	$1.73*$	0.47	0.44		
FTSEMIB-FTSE100	-0.059	1.18	-0.82	0.983	83.24	0.26	0.31	0.56		
ACROSS ALL PAIRS	-0.018	0.73	-0.02	-0.966	55.22	-0.02	0.29	0.58		

Table 6 – Results for the IV-based pairs trading strategies: closing when the Spread reaches 0

Notes: results of the pairs trading strategies implemented over the sample from May 2008 to December 2017, with May 2007 to April 2008 data activated whenever the implied volatilities of the one-month maturity ATM call options deviate from the relationship in model (1), estimate between the indicated underlying Indexes as X and the second as Y, and closed when the *Spread* reaches its zero mean. Columns 1-3 refer to self-financing strategy. Columns 4-6 refer to the returns from the beta-arbitrage strategy, which differ only in terms of the quantities traded. For the standard deviation and t-statistics computed using the Newey-West heteroskedasticity and autocorrelation robust standard errors (Newey West, 1987). interpreted as excess returns, since the strategy does not require any initial investment. ***, **, and * are significance at the 1%, 5%, and 10% le of closed trades due to Spread reversion to zero, option expiration and reaching the end of the trading period. Columns 10 and 11 report the a remains open, and the total number of trades.

Compared to the previous application, the total number of trades is roughly halved and the average life is more than tripled. Also, the percentage of transactions closed due to expiry of the options or end of the trading period increases, at the expense of a reduction in the number of closures due to *Spread* convergence to zero. These results suggest that, in most the cases, the long-run equilibrium, in its stricter interpretation, cannot be re-established, leading the profitability to be not really dependent on the theoretical basis of the methodology. Consequently, in both the self-financing and beta-arbitrage strategies, average returns generally assume more extreme values, leading to negative total profitability and higher standard deviations. Overall, the find that the pairs trading strategy provides no evidence of market inefficiency remains unchanged.

Also, the results for the drivers of profitability (Table 7) are mostly coherent with our baseline methodology, except for time-to-maturity parameters, which, in this case are never statistically significant, regardless of the specification. Finally, the monthly analysis (Figure 4) shows that, although the average number of transactions per pair is smaller (around 0.47) and the average monthly returns are more volatile (with means close to -0.85% and -45.36%), the behaviour over time of both series is similar to the baseline application.

Notes: regression estimates for the four alternative model specifications of equation (5). The dependent variable is the return obtained implementing the pairs trading (self-financing or beta-arbitrage) strategy. τ is the time to maturity. ITM is a dummy for the option being in-the-money, ATM is a dummy for the option being at-the-money and OTM is a dummy for the option being out-of-the-money; all are defined for both the option bought (long) and the option sold (short) in the transaction. Crisis is a dummy for trade closure being in a period of crisis. ***, **, and * are significance at the 1%, 5%, and 10% levels, respectively. pValue is in parentheses.

Figure 4 - Pairs trading monthly results (average values): closing when the Spread reaches 0

Average results across pairs in the trading strategies implemented over the sample from May 2008 to December 2017: average number of transactions per month, average number of wins per month (i.e., trades with a positive final payoff) and average monthly returns. Trades are activated 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 its zero mean. The first and the second panels refer to the results of the self-financing and beta-arbitrage strategies, respectively. Notice that, in the first case, returns can be interpreted as excess returns since the strategy does not require any initial investment.

As further robustness, we repeat the analysis using an artificially constructed series of front-month ATM options prices (hereafter OP), in place of the one-month ATM options implied volatilities. This allows us to take account of the possibility that the relationship between implied volatilities might not extend directly to options prices. More specifically, the OP series is constructed by selecting, for each trading day and for each underlying index, the price of the option that is front-month and at-the-money at that point in time. This provides a synthetic index that tracks the evolution over time of the front-month ATM options prices sequence for a given underlying asset.

Then, we use the OP series to estimate the following OLS regression:

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

where $OP_{t,Y}^{ATM}$ and $OP_{t,X}^{ATM}$ are the respective prices at day t of the front-month maturity ATM option written on indexes Y and X. All other elements are defined as in regression (1) so that the *Spread* eventually is computed as:

$$
Spread_t = OP_{t,Y}^{ATM} - \hat{\gamma}_0 - \hat{\gamma}_1 OP_{t,X}^{ATM}
$$
\n(7)

As above, the self-financing and the beta-arbitrage trading strategies are implemented whenever a mispricing is suspected, that is, whenever the *Spread* violates the same condition in equation (3), i.e. $2\hat{\sigma} \geq \text{S}{\text{pread}}_t \geq -2\hat{\sigma}$.

Figure 5 and Table 8 show that the levels of the OP series and their standard deviations are considerably higher than the implied volatilities, but that, also in this case, the 95% confidence level of the ADF test confirms that they are stationary, regardless of the specification employed.²¹ Also, even if OP generally show lower correlations (Table 9) and, in particular, for couples including options written on the DAX 30, they still remain relevant, ranging between 0.56 to as high as 0.95.

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

²¹ As in the IV application, we used the ADF test for stationarity, run on the OP series, setting the maximum lag length equal to 15 and with both drift-only and drift and trend specifications.

Notes: main descriptive statistics for the OP series of the front-month ATM call options over the entire sample period, by underlying index (series constructed considering the price of the option that is front-month and at-the-money at that point in time, for each trading day).

Notes: Pearson correlation coefficients for the OP series of the front-month ATM call options for each pair of underlying indexes, using the entire data sample (series constructed considering the price of the option that is front-month and at-the-money at that point in time, for each trading day).

Table 10 reports the results obtained for both the self-financing and the beta-arbitrage strategies. With respect to the baseline approach, the total number of the transactions is slightly higher (albeit it has same order of magnitude), while the average life is halved, becoming approximately 2 trading days. It should be remarked that, in almost all cases, trades close due to reversion to within the boundaries.

In terms of returns, again we observe quite high levels of variability among the pairs. For instance, for the self-financing strategy, in most cases (13 out of 20), pairs trading provides significant and positive returns, although within a much closer range: from 1.4% (for the pair ESTOX50-CAC40) to a maximum of 7.3% (pair involving the FTSEMIB and DAX30). In the remaining cases, the self-financing strategy does not provide significant returns, and in one case (FTSE100-ESTOX50) it leads to statistically significant negative excess returns. In the beta-arbitrage strategy, this single case of a significantly negative return is confirmed, while the overall profitability is much reduced; in this instance, option pairs trading leads to significant returns in only 7 out of 20 cases. Thus, the beta-arbitrage strategy seems to deliver generally higher, but more volatile returns. However, despite the high number of suspected mispricings, signalled by trade frequency, the average returns from both strategies, across all pairs, are not statistically significant, which further supports index option market efficiency. In other words, although an individual trader might earn a significantly positive return on one options pair, on average, the pairs trading strategy will not provide a profit to the hedge fund that trades on the entire market.²²

 22 Further profitability and monthly results are provided in Tables 16 to 19 in the Appendix.

Table 10 - Results for the OP-based pairs trading strategies

Notes: results of the pairs trading strategies implemented over the sample from May 2008 to December 2017, with May 2007 to April 2008 data activated whenever the OP of the front-month maturity ATM call options deviate from the relationship in model (6), estimated based on tl indicated underlying Indexes as X and the second as Y, and closed when the Spread reverts to within the boundaries. Columns 1-3 refer t self-financing strategy. Columns 4-6 refer to the returns from the beta-arbitrage strategy, which differ only in terms of the quantities traded. For the standard deviation and t-statistics computed using the Newey-West heteroskedasticity and autocorrelation robust standard errors (Newey West, 1987). interpreted as excess returns, since the strategy does not require any initial investment. ***, **, and * are significance at the 1%, 5%, and 10% le of closed trades due to Spread reversion to within the boundaries, option expiration and reaching the end of the trading period. Columns 10 and of days a trade remains open, and the total number of trades.

		Self-financing strategy					Beta-arbitrage strategy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	$0.05***$	$0.05***$	$0.03***$	$0.05***$	$0.34***$	0.01	0.01	$0.29***$
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.67)	(0.72)	(0.00)
	0.00			$0.00***$	-0.01			0.00
$\tau_{i,short}$	(0.87)			(0.00)	(0.20)			(0.90)
	0.00			$0.00***$	0.00			-0.01
$\tau_{i,long}$	(0.56)			(0.01)	(0.81)			(0.25)
		$0.08***$		$0.07***$		0.01		0.00
$ITM_{i, short}ITM_{i, long}$		(0.00)		(0.00)		(0.88)		(0.98)
		$-0.18***$		$-0.18***$		-0.13		$-0.16*$
$ITM_{i\;short}ATM_{i\;long}$		(0.00)		(0.00)		(0.13)		(0.08)
		$-0.65***$		$-0.69***$		$-1.04**$		$-1.19***$
$ITM_{i, short}$ $OTM_{i, long}$		(0.00)		(0.00)		(0.01)		(0.01)
		$0.76***$		$0.76***$		0.00		0.00
$OTM_{i, short} ITM_{i, long}$		(0.00)		(0.00)		(0.00)		(0.00)
		$0.09***$		$0.07***$		0.11		0.06
$OTM_{i, short}ATM_{i, long}$		(0.00)		(0.00)		(0.61)		(0.80)
		$-0.02**$		$-0.02**$		0.02		0.00
$OTM_{i, short} OTM_{i, long}$		(0.02)		(0.02)		(0.84)		(0.98)
		$0.40***$		$0.40***$		$1.49***$		$1.44***$
$ATM_{i,short}ITM_{i,long}$		(0.00)		(0.00)		(0.00)		(0.00)
		$-0.13***$		$-0.13***$		-0.01		0.02
$ATM_{i, short} OTM_{i, long}$		(0.00)		(0.00)		(0.91)		(0.83)
			$0.02***$	0.00			0.06	0.02
$Crisis_i$			(0.00)	(0.98)			(0.24)	(0.75)
Ordinary R-squared	0.000	0.182	0.002	0.183	0.003	0.014	0.000	0.016
Num. of observations	7706	7706	7706	7706	5499	5499	5499	5499

Table 11 - Drivers of OP-based trades returns: time-to-maturity, moneyness and crisis periods

Notes: regression estimates for the four alternative model specifications of equation (5). The dependent variable is the return obtained implementing the pairs trading (self-financing or beta-arbitrage) strategy. τ is the time to maturity. ITM is a dummy for the option being in-the-money, ATM is a dummy for the option being at-the-money and OTM is a dummy for the option being out-of-the-money; all are defined for both the option bought (long) and the option sold (short) in the transaction. Crisis is a dummy for trade closure being in a period of crisis. ***, **, and * are significance at the 1%, 5%, and 10% levels, respectively. pValue is in parentheses.

Finally, notice that the analysis of the profitability drivers (Table 11) produces results that generally are in line with our baseline methodology, in terms of both the signs and magnitude of the parameters. There are some small differences related to: the time-to-maturity parameter, which is statistically significant only in specification 4; the *Crisis* dummy, which is no longer significant in specification 4; the intercept, which is significantly positive in most cases; and the parameter associated to the moneyness dummies in the beta-arbitrage strategy, which is significant only for two combinations.

5. Conclusions

According to the EMH, in efficient markets, no arbitrage opportunities should arise and no systematic mispricings can be exploited. In this essay, we tested options market efficiency using a statistical arbitrage trading strategy, through an application on front-month ATM call options, written on five European indexes.

The methodology consists of identifying highly correlated options through their one-month maturity implied volatilities and establishing a stationary and mean-reverting relationship between them. This relationship allow us to identify possible relative mispricings, that is, to determine whether one asset is not 'correctly' priced with respect to the other asset. We employ a simple trading strategy to systematically exploit these suspected mispricings in the expectation of a positive profit when the relationship is re-established. As a robustness check, we used an artificially constructed series of the front-month ATM options prices (in place of the IV) to perform pairs identification and establish the equilibrium relationship.

The results show that the European option market is not always perfectly efficient since some of the pairs considered provide positive and significant profitability. However, the number of trades is relatively small; overall, less than one round-trip transaction per month for each pair of options. In addition, market forces are able quickly to identify and reabsorb the mispricing, which is reflected in the fact that the average time a trade remains open is four days in the IV application and two days in the OP-based strategy. This suggests that although arbitrage windows occur, they are short-lived, which is consistent the with the mean-reverting property of the equilibrium relationship.

Due to the high level of volatility associated to the outcomes of the trading strategies, we also analyse the relation between profitability and some determinants of the options prices. The results confirmed our thesis that returns are related strongly to moneyness and time to maturity, which contribute depending on the trader's long or short position on the option. We found, also, that these variables cannot completely explain how the strategies perform. Since both the price of the underlying index and the volatility of the options play a central role in determining the transaction payoffs, we can conclude that the profitability of options pairs trading is affected by many more factors than in case of its application to the stock market, which might explain the variability in our results.

Since our analysis does not allow any definite conclusions, we call for further investigation into the application of pairs trading strategies in the options market. To our knowledge, this is an unexplored area of research, which might help to verify whether the options market is efficient in terms of relative pricing. Empirical applications should be conducted on much larger datasets and, ideally, should consider different categories of options in terms of contract type, maturity and moneyness.

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Appendix

		Profit & Losses											
		Mean	Std	Min	Max	Skew.	Kurtosis	NW stat	pValue	Mean	Std	Min	M
	CAC40-DAX30	3.77	56.64	-281.16	327.30	1.81	16.99	1.21	0.23	0.003	0.32	-1.59	1 ₁
	CAC40-ESTOX50	-1.06	10.51	-56.20	49.27	-0.01	10.41	-2.19	0.03	-0.004	0.13	-0.54	0.
	CAC40-FTSE100	-6.51	53.68	-191.57	328.26	1.63	14.85	-3.33	0.00	-0.042	0.49	-1.46	з.
	CAC40-FTSEMIB	31.02	167.73	-882.44	812.63	0.73	10.31	4.21	0.00	0.044	0.30	-1.32	1 ₁
	DAX30-CAC40	5.18	54.13	-186.49	331.96	2.79	17.35	1.85	0.06	0.007	0.33	-1.25	2.
	DAX30-ESTOX50	1.35	35.27	-148.27	205.06	1.21	12.03	0.89	0.38	0.005	0.30	-1.10	1.
	DAX30-FTSE100	-5.91	74.86	-331.68	381.21	0.14	9.46	-2.29	0.02	-0.022	0.44	-1.57	2.1
	DAX30-FTSEMIB	39.66	272.89	-857.28	1643.89	2.42	14.85	3.44	0.00	0.059	0.46	-1.36	2.
	ESTOX50-CAC40	0.34	10.94	-39.40	90.52	1.79	14.45	0.66	0.51	0.006	0.13	-0.57	0.
	ESTOX50-DAX30	3.89	36.62	-134.25	205.06	1.66	14.26	2.23	0.03	0.023	0.30	-1.07	1.
	ESTOX50-FTSE100	-12.34	50.24	-230.74	217.57	-0.46	10.05	-5.95	0.00	-0.094	0.50	-2.19	2.
	ESTOX50-FTSEMIB	30.37	148.74	-810.63	994.46	1.81	17.57	5.14	0.00	0.051	0.24	-1.19	1.
	FTSE100-CAC40	-2.32	53.62	-166.93	328.26	1.85	16.15	-1.10	0.27	-0.037	0.50	-1.50	3.
	FTSE100-DAX30	-4.05	72.47	-353.35	402.70	0.21	10.43	-1.61	0.11	-0.013	0.41	-1.57	1 ₁
	FTSE100-ESTOX50	-4.70	47.62	-230.74	295.99	1.13	17.45	-2.86	0.00	-0.065	0.53	-2.19	2.
	FTSE100-FTSEMIB	16.64	297.78	-2497.80	1768.17	0.46	18.69	1.21	0.23	0.008	0.61	-3.81	3.
	FTSEMIB-CAC40	15.60	116.49	-504.57	626.51	0.68	9.32	2.96	0.00	0.043	0.25	-0.94	0.
	FTSEMIB-DAX30	56.60	246.60	-687.19	1814.14	3.52	24.41	5.35	0.00	0.136	0.47	-1.10	2.
	FTSEMIB-ESTOX50	19.67	98.65	-454.03	578.78	0.43	8.00	5.00	0.00	0.054	0.22	-1.19	0.
	FTSEMIB-FTSE100	-9.77	243.27	-1572.92	1748.80	0.26	15.27	-0.82	0.41	-0.024	0.61	-4.03	3.
	ACROSS ALL PAIRS	9.30	142.09	-2497.80	1814.14	2.59	51.53	0.06	0.95	0.008	0.40	-4.03	3.

Table 12 - Profitability per transaction: IV-based self-financing strategy

Notes: analysis of Profit&Loss and Returns for the self-financing strategy implemented on the implied volatilities of one-month maturity ATM December 2017; underlying Indexes are used as row headings where the regressor is mentioned firstly and positions are closed when the Spread are tested to be significantly positive using Newey-West heteroskedasticity and autocorrelation robust standard errors (Newey & West, 1987) are reported.

Table 13 - Results per month: IV-based self-financing strategy

Notes: monthly results (average values across months and overlapping portfolios) for the self-financing strategy implemented on the implied vol over the sample from May 2007 to December 2017; underlying Indexes are used as row headings where the regressor is mentioned firstly and within the boundaries. Num. of trades is the average number of trades per month; Num. of Wins (Losses), average profit (loss) and average number of transactions closing with a gain (loss), and the corresponding average profit (loss) and return; Average P&L (Return) is the average and Returns are tested to be significantly positive using Newey-West heteroskedasticity and autocorrelation robust standard errors (Newey & pValues are reported.

Table 14 - Profitability per transaction: IV-based beta-arbitrage strategy

Notes: analysis of Profit&Loss and Returns for the beta-arbitrage strategy implemented on the implied volatilities of one-month maturity ATM December 2017; underlying Indexes are used as row headings where the regressor is mentioned firstly and positions are closed when the Spread are tested to be significantly positive using Newey-West heteroskedasticity and autocorrelation robust standard errors (Newey & West, 1987) are reported.

Table 15 - Results per month: IV-based beta-arbitrage strategy

Notes: monthly results (average values across months and overlapping portfolios) for the beta-arbitrage strategy implemented on the implied vo over the sample from May 2007 to December 2017; underlying Indexes are used as row headings where the regressor is mentioned firstly and within the boundaries. Num. of trades is the average number of trades per month; Num. of Wins (Losses), average profit (loss) and average number of transactions closing with a gain (loss), and the corresponding average profit (loss) and return; Average P&L (Return) is the average and Returns are tested to be significantly positive using Newey-West heteroskedasticity and autocorrelation robust standard errors (Newey & pValues are reported.

		Profit & Losses											
		Mean	Std	Min	Max	Skew.	Kurtosis	NW stat	pValue	Mean	Std	Min	M
	CAC40-DAX30	7.83	53.89	-195.11	309.59	1.74	12.68	3.09	0.00	0.020	0.21	-0.64	0.
	CAC40-ESTOX50	1.43	7.66	-24.53	42.23	1.29	6.82	3.76	0.00	0.015	0.09	-0.20	0.
	CAC40-FTSE100	1.29	29.23	-129.81	183.76	0.08	10.94	1.20	0.23	0.016	0.20	-0.65	0.
	CAC40-FTSEMIB	47.99	165.40	-264.80	1469.19	5.12	42.36	6.04	0.00	0.064	0.20	-0.45	0.
	DAX30-CAC40	2.88	37.45	-119.51	131.90	0.40	5.55	1.74	0.08	0.004	0.20	-0.64	0.
	DAX30-ESTOX50	5.47	44.22	-112.81	243.03	1.96	11.96	2.02	0.04	0.007	0.20	-0.52	0.
	DAX30-FTSE100	-1.01	75.02	-342.69	461.22	0.60	17.90	-0.33	0.74	0.001	0.34	-1.16	2.
	DAX30-FTSEMIB	50.65	230.40	-569.00	2368.15	5.80	52.24	4.29	0.00	0.073	0.25	-0.72	1.
	ESTOX50-CAC40	1.31	7.31	-23.11	42.23	1.47	10.69	4.53	0.00	0.014	0.07	-0.18	0.
	ESTOX50-DAX30	6.78	40.10	-112.81	243.03	2.47	15.15	3.46	0.00	0.033	0.21	-0.52	1 ₁
	ESTOX50-FTSE100	-2.52	37.71	-206.50	256.53	0.60	18.34	-1.50	0.13	-0.004	0.24	-0.98	1 ₁
	ESTOX50-FTSEMIB	51.16	170.11	-256.92	1299.83	4.20	28.02	5.74	0.00	0.069	0.20	-0.32	1 ₁
	FTSE100-CAC40	0.05	24.83	-197.13	85.64	-0.81	10.98	0.04	0.97	0.001	0.20	-1.07	0.
	FTSE100-DAX30	-1.04	83.45	-342.69	402.70	-0.10	10.01	-0.24	0.81	0.000	0.34	-1.14	1.
	FTSE100-ESTOX50	-4.59	27.39	-133.58	68.81	-0.90	5.87	-3.43	0.00	-0.034	0.25	-1.06	0.
	FTSE100-FTSEMIB	39.90	227.97	-651.46	1562.98	2.72	19.65	3.86	0.00	0.039	0.29	-1.10	0.
	FTSEMIB-CAC40	31.22	157.58	-263.74	1469.19	6.32	52.65	4.75	0.00	0.053	0.24	-1.10	1.
	FTSEMIB-DAX30	27.22	138.84	-569.00	1120.90	3.00	31.25	4.43	0.00	0.062	0.25	-1.06	0.
	FTSEMIB-ESTOX50	30.02	143.22	-215.83	1299.83	5.75	47.42	4.47	0.00	0.058	0.19	-0.61	1 ₁
	FTSEMIB-FTSE100	33.32	189.54	-731.52	1562.98	4.49	38.49	2.65	0.01	0.046	0.30	-1.23	1.
	ACROSS ALL PAIRS	17.85	125.28	-731.52	2368.15	6.70	85.00	0.11	0.91	0.029	0.23	-1.23	2.2

Table 16 - Profitability per transaction: OP-based self-financing strategy

Notes: analysis of Profit&Loss and Returns for the self-financing strategy implemented on the OP of front-month maturity ATM call options ove (series constructed considering the price of the option that is front-month and at-the-money at that point in time, for each trading day); underly regressor is mentioned firstly and positions are closed when the Spread reverts to within the boundaries. Excess returns are tested heteroskedasticity and autocorrelation robust standard errors (Newey & West, 1987); the t-statistics and the corresponding pValues are report

Table 17 - Results per month: OP-based self-fiancing strategy

Notes: monthly results (average values across months and overlapping portfolios) for the self-financing strategy implemented on the OP of f sample from May 2007 to December 2017 (series constructed considering the price of the option that is front-month and at-the-money at that Indexes are used as row headings where the regressor is mentioned firstly and positions are closed when the *Spread* reverts to within the boun trades per month; Num. of Wins (Losses), average profit (loss) and average positive (negative) return refer to the average number of transactions average profit (loss) and return; Average P&L (Return) is the average result of a trade in euros (in percentages); P&L and Returns are tested heteroskedasticity and autocorrelation robust standard errors (Newey & West, 1987); t-statistics and the corresponding pValues are reported.

	Profit & Losses											
	Mean	Std	Min	Max	Skew.	Kurtosis	NW stat	pValue	Mean	Std	Min	N
CAC40-DAX30	13.96	75.61	-193.50	342.55	1.61	8.79	4.24	0.00	0.250	1.77	-5.50	21
CAC40-ESTOX50	2.36	17.00	-39.11	100.60	1.74	7.65	3.03	0.00	0.050	0.40	-0.61	$\overline{2}$
CAC40-FTSE100	1.46	29.13	-130.56	174.89	0.11	9.99	1.33	0.18	-0.636	22.49	-266.1	14
CAC40-FTSEMIB	161.74	1040.25	-2023.74	7741.66	4.01	26.51	3.72	0.00	0.071	0.34	-0.68	1
DAX30-CAC40	8.63	127.06	-333.02	895.90	2.33	13.31	1.47	0.14	-0.008	0.53	-1.82	3
DAX30-ESTOX50	42.47	234.14	-644.70	1185.78	1.67	9.66	3.60	0.00	0.086	0.57	-1.54	2
DAX30-FTSE100	-2.14	117.23	-511.60	826.06	1.58	21.82	-0.43	0.67	-0.170	3.87	-59.62	33
DAX30-FTSEMIB	93.74	618.90	-1297.53	6625.03	7.84	76.97	3.00	0.00	0.106	0.47	-1.60	1
ESTOX50-CAC40	1.93	13.18	-37.14	91.65	2.36	16.08	3.52	0.00	0.131	0.74	-3.48	
ESTOX50-DAX30	27.67	132.56	-435.91	896.08	2.20	13.21	4.23	0.00	0.070	5.63	-39.60	91
ESTOX50-FTSE100	-4.30	54.93	-274.99	352.03	0.66	15.55	-1.62	0.11	-0.036	0.81	-4.00	5
ESTOX50-FTSEMIB	231.39	1323.25	-3224.35	10721.34	3.35	23.94	4.06	0.00	0.092	0.33	-0.56	1
FTSE100-CAC40	0.29	45.26	-236.89	254.38	0.61	12.04	0.14	0.89	-0.036	0.58	-3.57	
FTSE100-DAX30	0.02	85.11	-416.67	481.92	-0.87	10.68	0.00	1.00	-2.116	32.22	-308.1	2 ₀
FTSE100-ESTOX50	-11.53	52.47	-202.26	144.56	-0.54	4.48	-4.74	0.00	-0.124	0.54	-2.92	Ω
FTSE100-FTSEMIB	57.49	395.14	-1075.91	2169.22	1.77	10.25	3.86	0.00	0.046	0.52	-2.55	
FTSEMIB-CAC40	151.65	1468.66	-7564.80	12397.97	3.32	28.84	2.78	0.01	0.013	0.45	-3.30	3
FTSEMIB-DAX30	17.13	444.87	-1164.36	5029.38	7.56	82.69	0.88	0.38	-0.001	0.37	-1.35	1
FTSEMIB-ESTOX50	268.16	1688.22	-3749.55	11170.75	2.63	13.85	3.46	0.00	0.012	0.41	-2.77	$\overline{2}$
FTSEMIB-FTSE100	60.16	713.37	-1795.76	4112.14	2.41	13.67	1.29	0.20	0.006	0.38	-1.03	1
ACROSS ALL PAIRS	61.35	728.66	-7564.80	12397.97	6.33	80.86	0.07	0.94	-0.108	8.93	-308.1	20

Table 18 - Profitability per transaction: OP-based beta-arbitrage strategy

Notes: analysis of Profit&Loss and Returns for the beta-arbitrage strategy implemented on the OP of front-month maturity ATM call options over (series constructed considering the price of the option that is front-month and at-the-money at that point in time, for each trading day); underly regressor is mentioned firstly and positions are closed when the Spread reverts to within the boundaries. Excess returns are tested heteroskedasticity and autocorrelation robust standard errors (Newey & West, 1987); the t-statistics and the corresponding pValues are report

Table 19 - Results per month: OP-based beta-arbitrage strategy

Notes: monthly results (average values across months and overlapping portfolios) for the beta-arbitrage strategy implemented on the OP of f sample from May 2007 to December 2017 (series constructed considering the price of the option that is front-month and at-the-money at that Indexes are used as row headings where the regressor is mentioned firstly and positions are closed when the *Spread* reverts to within the boun trades per month; Num. of Wins (Losses), average profit (loss) and average positive (negative) return refer to the average number of transactions average profit (loss) and return; Average P&L (Return) is the average result of a trade in euros (in percentages); P&L and Returns are tested heteroskedasticity and autocorrelation robust standard errors (Newey & West, 1987); t-statistics and the corresponding pValues are reported.

Notes: the table stratifies transactions based on the moneyness of each call option forming the pair at the close of the trade, depending on whether the position is long or short .

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