Mayordomo, S., Peña, J. I. & Romo, J. (2014). Testing for statistical arbitrage in credit derivatives markets. *Journal of Empirical Finance, vol. 26*, pp. 59–75.

DOI: 10.1016/j.jempfin.2014.02.002

Testing for statistical arbitrage in credit derivatives markets ☆

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A R T I C L E I N F O

Article history:
Received 8 March 2013
Received in revised form 6 November 2013
Accepted 4 February 2014

Keywords:
Credit derivatives
Credit spreads
Persistent mispricings
Subsampling

A B S T R A C T

This paper studies statistical arbitrage opportunities in credit derivatives markets using strategies combining Credit Default Swaps (CDSs) and Asset Swap Packages (ASPs) by means of an improved statistical arbitrage test. Using four different databases (GFI, Reuters, CMA, and J.P. Morgan) from 2005 to 2009, we find persistent mispricings between the CDS and ASP spreads of individual firms, which should be priced similarly, before and during the 2007–2009 financial crisis. These mispricings are more frequent in low credit quality bonds and appear to offer arbitrage opportunities. We also aggregate the firms' CDS and ASP in a portfolio and still find persistent deviations, mainly in the lower rated bonds. In aggregate terms the deviations from the parity relation can be explained from systematic factors such as financing costs, counterparty risk, and global risk. However, after considering realistic estimations of funding and trading costs, all these mispricings are unlikely to provide profitable arbitrage opportunities.

1. Introduction

In this paper we analyze statistical arbitrage opportunities from a strategy involving two credit derivatives contracts: Credit Default Swaps (CDSs) and Asset Swap Packages (ASPs). A CDS is a credit derivative designed to transfer the credit exposure of fixed income products between two parties. The purchaser of the CDS makes periodic payments (CDS premium or spread) to the seller until the maturity date of the contract or until a credit event materializes. In the latter case the seller pays off compensation to cover the purchaser's losses. An ASP contain a defaultable coupon bond and an interest rate swap (IRS) that swaps the bond's coupon into Euribor rate plus the asset swap spread rate. CDS premiums and ASP spreads are market-based measures of credit risk for a given reference name. Investing in an ASP, funded with a loan at the Euribor rate, has the same economic risk profile as selling protection through a CDS. As a result, no-arbitrage arguments imply that the CDS premium should be similar to the asset swap spread. Statistical arbitrage represents a zero cost, self-financing trading opportunity that has positive expected cumulative trading profits with a declining time-averaged variance and a probability of loss that converges to zero. The statistical arbitrage analysis is designed to detect persistent anomalies.

☆ The authors acknowledge Óscar Arce, Max Bruche, Álvaro Cartea, Antonio Diez de los Ríos, Abel Elizalde, Javier Gil-Bazo, Enrique ter Horst, Oliver Linton, José Penalva, Joaquín Poblet, María Rodríguez-Moreno, Eduardo Schwartz, Jesús Saurina, Pedro Serrano, Javier Suárez, Antoni Vaello, and seminar participants at Carlos III University, CNMV, University of Navarra, University of Cambridge, Universitat de les Illes Balears, XVI Foro de Finanzas, XXXIII Symposium of Economic Analysis, 2010 Financial Management Association (FMA) European Conference, and 2010 European Financial Management Association (EFMA) Annual Meeting for all their comments and suggestions. Sergio Mayordomo acknowledges financial support from PIUNA (University of Navarra) and the Spanish Ministry of Economy and Competitiveness (grant ECO2012-32554). Juan Ignacio Peña acknowledges financial support from MCI grant ECO2012-35023. Any errors and omissions are the responsibility of the authors.
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The statistical arbitrage test was introduced by Hogan et al. (2004) (HJTW henceforth) and later improved in Jarrow et al. (2012) (JTTW henceforth). These authors test statistical arbitrage on stock markets on the basis of the increment in cumulative trading profits associated with the corresponding strategies. HJTW analyzes momentum and value trading strategies while JTTW extends the analysis to stock liquidity and industry momentum strategies. Both studies find that these strategies generate statistical arbitrage opportunities even after adjusting for market frictions such as transaction costs, margin requirements, liquidity buffers for the marking-to-market of short-sales, and borrowing rates.

The investment strategy to be analyzed in this study is the equivalence relation between the credit spreads obtained from CDS and ASP. The strategy is based on the equivalence relation arising from a cash-and-carry strategy in which a given investor trades two self-financing portfolios based on credit derivatives. The first portfolio contains a long position in a CDS while the second contains a long position in an ASP funded at Euribor. This second portfolio is equivalent to a synthetic short position in a CDS. For this reason, there should be an equivalence relation between the payoffs of both portfolios, which are given by the CDS premium and the asset swap spread, respectively. Thus, contrary to previous statistical arbitrage tests, ours is employed to find persistent mispricings.

The analysis of the equivalence relation between credit spreads has been traditionally done on the basis of the cointegration test proposed by Engle and Granger (1987). For instance, Blanco et al. (2005) and Zhu (2006) analyze this equivalence relation for CDS and bond spreads and find support, in general, for the parity relation as a long-run equilibrium condition. Zhu (2006) also analyzes the determinants of the basis, defined as the difference between the CDS and bond spreads and shows that both spreads respond differently to credit conditions such as rating events. Trapp (2009) analyzes trading opportunities that arise from differences between the bond and the CDS market and show that the basis size is closely related to measures of company-specific credit risk and liquidity, and to market conditions. Bai and Collin-Dufresne (2011) test several possible explanations for the violation of the arbitrage relation between cash bond and CDS contract and find several drivers related to funding risk, counterparty risk, and collateral quality that force the individual CDS-bond basis into negative territory at different phases of the crisis.

Previous literature has addressed other arbitrage strategies in fixed income markets such as swap spread, yield curve, mortgage, volatility, and capital structure arbitrages (see Duarte et al., 2007). These authors find that all the five previous strategies yield positive excess returns which are positively skewed. Jarrow et al. (2009) explore arbitrage opportunities in the term structure of CDS spreads and point out potential for arbitrage in this term structure on the basis of the Sharpe ratios obtained. Yu (2006) uses the HJTW procedure to detect statistical arbitrage in monthly capital structure arbitrage returns generated with CDS and stock price data. Capital structure arbitrage is based on strategies trading equity instruments against CDSs. Nevertheless, the analysis of statistical arbitrage in the context of the CDS–ASP basis had not been addressed before.

Our paper contributes to the literature in three dimensions. The first contribution is that, to the best of our knowledge, ours is the first paper that applies the statistical arbitrage methodology to study the relation between two credit derivatives (CDS and ASP) whose spreads, or prices for credit risk, should be similar. The use of asset swap spreads should allow a more precise analysis of the parity relation between CDS and bond spreads.[1] We apply the statistical arbitrage test to the CDS and ASP spreads of individual firms and also to portfolios of firms. To take into account the effects of the 2007–2009 financial crisis, we analyze two different sub-samples covering the periods before and during the crisis. The empirical evidence suggests that there is one key factor that determines the existence of statistical arbitrage: the issuer's credit risk. Thus, the lower the bond's credit quality, the higher the probability of persistent deviations between CDSs and ASPs spreads.

The second contribution is an enhanced version of the JTTW test that allows for non-normal, autocorrelated and heteroskedastic innovations of the incremental trading profits. Our test is based on the subsampling methodology developed in Politis et al. (1995, 1997, 1999a, 1999b). This technique is based on asymptotic inference and provides an asymptotically valid test under weak assumptions. Our results suggest that, for the data employed in the empirical exercise, the new test finds potential arbitrage opportunities with lower downside risk than existing alternatives.

Our third contribution is methodological. We present a procedure which is more appropriate for misprice testing than traditional alternatives. The analysis of the equivalence relation between credit spreads has been traditionally done on the basis of the cointegration test. The validity of the cointegration methodology is based on the assumption that bonds or ASPs can be shorted to guarantee that the equivalence relation holds. A cointegration test cannot isolate by itself strategies in which an ASP short sale is involved because it is based on both types of deviations from the equivalence relation. Nevertheless, according to Schonbucher (2003) and Mengle (2007) shorting a corporate bond with a required maturity, even years, is not always a feasible option.[2] It implies that traders might not be able to exploit deviations in the equivalence relation when the CDS premium is higher than the asset swap spread and so, ASP short positions are necessary. However, our test allows us to study the existence of statistical arbitrage whenever only long positions in ASPs are needed. Thus, our methodological proposal overcomes two problems that arise from the use of the cointegration analysis (i) bonds or ASPs short sales restrictions and (ii) the actual risk incurred to obtain arbitrage profits. Hence, we focus our analysis to testing the cases in which only long positions in CDSs and ASPs are needed. This trading strategy is known as a long basis trade. Additionally, and for the sake of completeness, we extend the study to test the strategies that are based on taking short position in ASPs and CDSs, which are known as short basis trades.

Using four different CDS databases (GFI, CMA, Reuters, and J.P. Morgan) and a sample of 55 bonds from November 2005 to August 2007, we find 16 persistent mispricings in which the long bases are persistently positive. A persistent positive long basis implies that the CDS spreads are too low in comparison with asset swap spreads. Employing a sample of 46 cases covering the

[1] This finding has been documented by Mayordomo et al. (2011), among others.

[2] The short sale of bonds or ASPs could be done via a repurchase agreement (repo) but the repo market for corporate bonds is illiquid and even if it was possible to short a bond via a repo, the tenor of the agreement would be short.

crisis period from August 2007 to June 2009, we find eight persistent positive long bases. We also aggregate the firms' CDS and ASP in a portfolio and still find persistent deviations. The empirical evidence suggests that higher the bond's (or bond portfolio's) credit risk, the higher the probability of persistent deviations between CDSs and ASPs spreads. In aggregate terms the deviations from the parity relation can be explained from systematic factors such as funding costs, counterparty risk, and global risk. Once realistic assessments of the funding costs are included, all these mispricing are unlikely to provide profitable arbitrage opportunities. As far as we know, ours is the first paper showing formally the effect of the trading and funding costs in arbitrage opportunities in credit markets and more especially, the effect of their increase due to the credit squeeze of the recent financial crisis.

The paper is divided into eight sections. In Section 2 we address the concept of statistical arbitrage and its implementation. In Section 3 we introduce the new test. Section 4 includes the empirical application of the new test. Section 5 describes the dataset. In Section 6 we report the results. Section 7 contains several robustness checks and extensions and Section 8 concludes the paper.

2. Statistical arbitrage: Definition, implementation and hypothesis testing

Following JTTW's definition, statistical arbitrage is a zero initial cost, self-financing trading strategy with a cumulative discounted trading profits $v(t)$ such that:

i. $v(0) = 0$,
ii. $\lim_{t\to\infty} E[v(t)]>0$,
iii. $\lim_{t\to\infty} P[v(t)<0] = 0$, and
iv. $\lim_{t\to\infty} Var[\Delta v(t)|\Delta v(t)<0] = 0$.

Statistical arbitrage requires that the expected cumulative discounted profits, $v(t)$, are positive, the probability of loss converges to zero, and the variance of the incremental trading profits $\Delta v(t)$ also converges to zero. The fourth condition suggests that investors are only concerned about the variance of a potential decrease in wealth. Whenever the incremental trading profits are nonnegative, their variability is not penalized.

Although statistical arbitrage is defined over an infinite time horizon, there is a finite timepoint t^* such that the probability of a loss is arbitrarily small, $P[v(t^*) < 0] = \varepsilon$. Standard arbitrage requires that at the time point t^* $P[v(t^*) < 0] = 0$. Thus, statistical arbitrage converges to standard arbitrage in the limit (as t tends to infinity).

The methodology for analyzing the existence of statistical arbitrage opportunities is based on HJTW, later improved in JTTW. This methodology is based on the incremental discounted cumulative trading profits Δv_i measured at equidistant time points.[3] Firstly, we employ a process denoted as the unconstrained mean (UM) model where Δv_i is assumed to evolve over time as:

$$\Delta v_i = \mu i^\theta + \sigma i^\lambda z_i \text{ for } i = 1, 2, \ldots, n \tag{1}$$

where z_i are the innovations such that $z_0 = 0$ and so, both $v(t_0)$ and Δv_0 are zero. Parameters θ and λ indicate whether the expected trading profits and the volatility, respectively, are decreasing or increasing over time and their intensity. Under the assumption that innovations z_i are *i.i.d.* $N(0,1)$ random variables, the expectation and variance of the discounted incremental trading profits in Eq. (1) are $E[\Delta v_i] = \mu i^\theta$ and $Var[\Delta v_i] = \sigma^2 i^{2\lambda}$.

The discounted cumulative trading profits generated by a given strategy are:

$$v(t_n) = \sum_{i=1}^n \Delta v_i \sim N\left(\mu \sum_{i=1}^n i^\theta, \sigma^2 \sum_{i=1}^n i^{2\lambda}\right) \tag{2}$$

while the log likelihood function for the increments in Eq. (2) is:

$$\log L\left(\mu,, \sigma^2, \theta, \lambda | \Delta v\right) = -\frac{1}{2}\sum_{i=1}^n \log\left(\sigma^2 i^{2\lambda}\right) - \frac{1}{2\sigma^2}\sum_{i=1}^n \frac{1}{i^{2\lambda}}\left(\Delta v_i - \mu i^\theta\right)^2. \tag{3}$$

The cash-and-carry strategy generates statistical arbitrage opportunities if incremental trading profits satisfy simultaneously all the following hypotheses:

H1. $\mu > 0$.

H2. $\lambda < 0$ or $\theta > \lambda$.

H3. $\theta > \max\left\{\lambda - \frac{1}{2}, -1\right\}$.

The first hypothesis (H_1) is due to condition ii. of the statistical arbitrage definition while H_2 and H_3 are due to conditions iv. and iii., respectively. H_3 can be divided into two hypotheses: H3.a: $\theta - \lambda + \frac{1}{2} > 0$ and H3.b: $\theta + 1 > 0$.

As in JTTW, a more restrictive version of model (1) is also considered in the analysis. It is based on constant expected profits over time and it implies that the parameter θ in Eq. (1) is set to zero. This model is defined as the constrained mean (CM) model.

[3] We use the notation Δv_i instead of $\Delta v(i)$ to avoid any misunderstanding with the later use of the time points i.

Thus, the required hypotheses to be satisfied for the existence of statistical arbitrage opportunities under the CM model are: H_1: $\mu > 0$ and H_2: $\lambda < 0$.

In this paper we allow innovations z_i to be non-normal, auto correlated, and heteroskedastic but stationary. Thus, we construct an asymptotically valid test for UM and CM models based on test statistics which are formed from the quasi-maximum likelihood (QML) estimators in Eq. (3). The parameters are estimated by maximizing the previous quasi-log likelihood function from a nonlinear optimization method based on a Quasi-Newton-type algorithm.

Under the assumption that the trading profits evolve as a UM model, all the previous hypotheses must be satisfied simultaneously in order to provide a statistical arbitrage opportunity. The existence of statistical arbitrage is thus based on an intersection of subhypothesis. On the other hand, the absence of statistical arbitrage is based on a union of four subhypotheses which are given by the complementary of the previous hypotheses. We set the null hypothesis as the absence of statistical arbitrage and then, the hypotheses for the UM model become:

H_1^c. $\mu \leq 0$ *or*

H_2^c. $\lambda \geq 0$ and $\theta - \lambda \leq 0$ *or*

H_3^c. $\theta - \lambda + \frac{1}{2} \leq 0$ or

H_4^c. $\theta + 1 \leq 0$.

If one of the previous restrictions is satisfied (necessary and sufficient condition), we conclude that no statistical arbitrage opportunities exist. For the CM model the complementary hypotheses are: H_1^c:$\mu \leq 0$ or H_2^c:$\lambda \geq 0$.

3. A new test of statistical arbitrage

The Bonferroni approach employed by HJTW for hypothesis testing presents a low statistical power to reject an incorrect null hypothesis in every case. JTTW overcome these limitations by introducing the Min-t test methodology[4] and employing the stationary bootstrap procedure proposed by Politis and Romano (1994), which allows for innovations z_i to follow a stationary weakly dependent process, to estimate the *p*-values corresponding to each hypothesis. Our test relies on the subsampling method developed in Politis et al. (1995, 1997, 1999a, and 1999b) and allows innovations z_i to be nonnormal, autocorrelated and heteroskedastic. In this more general situation, the use of the stationary bootstrap could be not advisable for estimating the *p*-values for the *Min-t* statistics.[5] The remainder of this section is devoted to an exposition of the statistical methodology employed in our paper to test for statistical arbitrage.

Let $(x_1,\ldots,x_n)$ be a sample of *n* observations that are distributed in a sample space *S*. The common unknown distribution generating the data is denoted by *P*, the null hypothesis H_0 asserts $P \in P_0$, and the alternative hypothesis H_1 is $P \in P_1$, where $P_j \subset P$ for $j = 0,1$, and $P_0 \cup P_1 = P$. Our purpose is to create an asymptotically valid test based on a given test statistic for the case in which the null hypothesis translates into a null hypothesis about a real-valued parameter $\xi_i(P)$. The test statistic is defined as:

$$T_{i,n} = \tau_n t_{i,n}(X_1,\ldots,X_n) = \tau_n\left(\hat{\xi}_{i,n}(X_1,\ldots,X_n) - \xi_{i,0}\right) \ \textit{for} \ \ i = (1,2,3,4) \qquad (5)$$

where τ_n is a normalizing constant and, as in regular cases, we set $\tau_n = n^{1/2}$, $\hat{\xi}_{i,n} = \hat{\xi}_{i,n}(X_1,\ldots,X_n)$ is the estimator of $\xi_{i,n}(P_i) \in \mathbb{R}$, which is the parameter of interest, P_i denotes the underlying probability distribution of the *i*th statistic and $\xi_{i,0}$ is the value of $\xi_{i,n}$ under the null hypothesis. Each of the four statistics is defined from the hypotheses H_i^c in Section 2 which lead to four contrasts of hypothesis based on real-valued parameters such that:

$$\begin{cases} H_0 : \xi_i(P) \leq \xi_{i,0} \\ H_1 : \xi_i(P) > \xi_{i,0} \end{cases} \ \text{for} \ \ i = (1,2,3,4) \qquad (6)$$

where $\xi_{i,0}$ is equal to zero in our analysis. The test is applied to the union of hypotheses H_i^c and so, the non-rejection of one of the four null hypotheses automatically confirms the absence of statistical arbitrage.

The distribution of the *i*th statistic $T_{i,n}$ under P_i can be denoted by:

$$G_{i,n}(x,P_i) = Prob_{P_i}\left\{T_{i,n}(X_1,\ldots,X_n) \leq x\right\} \qquad (7)$$

where $G_{i,n}(.,P_i)$ converges in distribution at least for $P_i \in P_{i,0}$, where $P_{i,0}$ denotes the probability distribution under H_0.

[4] Min-t test considers separately the t-statistics associated with the four hypotheses H_1^c, H_2^c, $H_3^c$and H_4^c and uses the minimum of their associated *t*-statistics serves as a rejection criterion.

[5] Stationary bootstrap is generally applicable for stationary weakly dependent time series. Subsampling allows for a more general structure in the innovations. Thus, in Politis et al. (1997), it is shown that in the presence of heteroskedasticity in residuals, subsampling gives better results for the right choice than moving block bootstrap methods. This choice is not affected materially by the degree of dependence in the residuals. Moreover, one should obtain better information about the sampling distribution of the statistic using the subsampling methodology. The reason is that, while the subsample statistics are always generated from the true model, bootstrap data come from an approximation to the true model. Another advantage of subsampling is that it has been shown to be valid under very weak assumptions.

Because P_i is unknown, $G_{i,n}(.,P_i)$ is unknown and the sampling distribution of $T_{i,n}$ is approximated by:

$$\hat{G}_{i,n,b}(x) = \frac{1}{n-b+1}\sum_{t=1}^{n-b+1} 1\left|\left\{\tau_b t_{i,n,b,t}(X_1,\ldots,X_n) \le x\right\}\right. \quad (8)$$

where $1\!\!1$ is an indicator function, $\tau_b = b^{1/2}$ such that $\frac{\tau_b}{\tau_n} \to 0$ as $n \to \infty$, $n - b + 1$ indicates the number of subsets of $(X_1,\ldots,X_n)$ and $t_{i,n,b,t}(X_1,\ldots,X_n)$ is the statistic evaluated at the block of data $(X_1,\ldots,X_{t+b-1})$ which is defined as:

$$t_{i,n,b,t}(X_1,\ldots,X_n) = \hat{\xi}_{i,n,b,t}(X_t,\ldots,X_{t+b-1}) - \hat{\xi}_{i,n,t} \quad (9)$$

where $\hat{\xi}_{i,n,b,t}$ is the estimator of $\xi_{i,n}(P_i) \in \mathbb{R}$ based on the subsample $(X_1,\ldots,X_{t+b-1})$ and $\hat{\xi}_{i,n,t}$ is the estimator of $\xi_{i,n}$ for the whole sample.

The only assumptions that will be needed to consistently estimate the cumulative distribution function $G_{i,n}(x,P_i)$ are the following:

a. The estimator, properly normalized, has a limiting distribution.
b. For large n, the distribution function of the normalized estimator based on the subsamples will be, on average, close to the distribution function of the normalized estimator based on the entire sample.

Using this estimated sampling distribution, we can compute the critical value for the test at least under the null hypothesis. It is obtained as the $1 - \alpha$ quantile of $\hat{G}_{i,n,b}(x)$:

$$g_{i,n,b}(1-\alpha) = inf\left\{x : \hat{G}_{i,n,b}(x) \ge 1-\alpha\right\}. \quad (10)$$

Our purpose is to test if T_n is rejected at a level of significance α depending on whether the statistic exceeds the exact $1 - \alpha$ quantile of the true sampling distribution $G_n(x,P)$, that is $g_n(1 - \alpha,P)$. Of course, P is unknown and so is $g_n(1 - \alpha,P)$. However and according to Politis et al. (1999a), the asymptotic power of the subsampling test against a sequence of contiguous alternatives $\{P^n\}$ to P with P in P_0 is the same as the asymptotic power of this fictitious test against the same sequence of alternatives. For this reason and given that there is no loss in efficiency in terms of power, we test the statistic T_n against the $1 - \alpha$ quantile under P_0, $g(1 - \alpha,P_0)$.

The steps in which the subpsampling technique is applied in this study are as follows:

1. Once the parameters have been estimated by QML, we calculate the test statistic for the whole sample:

$$T_{i,n} = \tau_n\left(\hat{\xi}_{i,n}(\Delta v_1,\ldots,\Delta v_n) - \xi_{i,0}\right) \; for \; i = (1,2,3,4) \quad (11)$$

and the estimated residuals $\hat{z}_i$[6]:

$$\hat{z}_i = \frac{\Delta v_i - \hat{\mu} i^{\hat{\theta}}}{\hat{\sigma} i^{\hat{\lambda}}} \; for \; i = 1,\ldots,n \quad (12)$$

2. We create subsamples of consecutive blocks of data with length b such that the first subsample of residuals is defined by $(\hat{z}_1,\ldots,\hat{z}_b)$, and so on.
3. We generate $n - b + 1$ successive subsamples of trading profits $(\Delta v_i^*,\ldots,\Delta v_{i+b-1}^*)$ from the corresponding residuals $(\hat{z}_i,\ldots,\hat{z}_{i+b})$ for $i = 1,\ldots, n - b$. The trading profits are calculated with the parameters under the null hypothesis such that their values bind the restrictions. Thus, the parameter values are $(\mu,\sigma,\theta,\lambda) = \left(-10^{-6},\hat{\sigma},-1,-0.5\right)$ for the UM model and $(\mu,\sigma,\lambda) = 0,\hat{\sigma},0)$ for the CM model[7]:

$$\Delta v_i^* = \mu i^{\theta} + \hat{\sigma} i^{\lambda} \hat{z}_i \quad (13)$$

4. We estimate $n - b + 1$ times by QML the parameters for the successive blocks and for every block we calculate the statistic $t_{i,n,b,t}$ such that we have $n - b + 1$ statistics.
5. Finally we approximate the sampling distribution of $T_{i,n}$ by means of the estimated sampling distribution $\hat{G}_{i,n,b}(x)$ as in Eq. (8) and compute the critical values $g_i(1 - \alpha,P_0)$ as in Eq. (10) under the null hypothesis. We reject the null hypothesis at a degree of significance of α if and only if $T_{i,n}$ exceeds the corresponding critical value $g_i(1 - \alpha,P_0)$.

There is not a universal prescription for the choice of the optimal block size. Moreover, Politis et al. (1999a) show that subsampling works quite well even with a data-driven choice of block size. Block sizes should not be too large or small but the effect of different choices of b diminishes as the sample size increases. In the correct range of b, the confidence intervals should be stable when

6 We find that the residuals follow ARMA processes and, in some cases, they even present heteroskedasticity. These facts suggest that it is unduly restrictive to impose any process for z_i.

7 We used other values of μ such as -0.0001 or -10^{-8} to have θ in the equation, but results are similar in the three cases. The values of parameters θ and λ bind the third restriction and we employ them due to their good properties in JTTW. Parameter $\hat{\sigma}$ does not appear in the restrictions and we use the value of the QML estimator for σ in the whole sample.

considered as a function of the block size. For this reason, we use the method defined by Politis et al. (1999a) as the Minimum Volatility Method to select the optimum b:

1. Compute a subsampling quantile $g_{n,b}(1-\alpha)$ for $b = b_{small} = n^{4/10}$ to $b = b_{big} = n^{9/10}$.
2. For each b compute a volatility index as the standard deviation of the quantiles in a neighborhood of b, $VI(g_{n,b-k}(1-\alpha), g_{n,b}(1-\alpha), g_{n,b+k}(1-\alpha))$ with $k = 2$.
3. Pick the value b^* corresponding to the smallest volatility index and use $g_{n,b^*}(1-\alpha)$ as the critical value of the test.

We obtain that the optimum block size is such that the ratio block size/sample size is between 0.15 and 0.6.[8]

4. Empirical application: The cash-and-carry arbitrage strategy

A combined long position in a CDS (buy protection) and an ASP is hedged against a bond's default risk and should therefore trade close to the price of an equivalent default free bond. This is the intuition behind the cash-and-carry arbitrage pricing of CDSs. From cash-and-carry strategies, we construct two equivalent portfolios which should produce the same payments at the same time. Then, we analyze the existence of possible mispricings that could derive in arbitrage opportunities.

Portfolio I

- Long position in a CDS with an annual full running premium equals $\bar{s}$ that is paid quarterly.

The CDSs employed in our analysis trade on a full running format (i.e. no upfront defrayal) and so, the CDS contract is unfunded. For this reason, the investors do not make an upfront payment (ignoring dealer margins and transaction costs). The traded CDS premium is an at-market annuity premium rate such that the market value of the CDS is zero at origination.

Portfolio II:

- Long position in an ASP that contains a defaultable coupon bond and an interest rate swap (IRS) that swaps the bond's coupon (c) into the 3-month Euribor rate (E_{3m}) plus the asset swap spread rate (s^A). The asset swap's fixed leg (c) represents the buyer's periodic fixed rate payments, while the floating leg ($E_{3m} + s^A$) represents the seller's potential payment. The quarterly payment dates (floating leg) coincide with the CDS premium payment dates.[9] The cost of the ASP is equal to the bond's par value.[10]
- Loan (principal equals the bond's face value) at 3-month Euribor. Interest payment dates coincide with both CDS premium and ASP floating leg payment dates.

Portfolio II is equivalent to a synthetic short position in a CDS and so, there should be an equivalence relation between CDS and asset swap spreads. Otherwise and ignoring the effects of potential market frictions, arbitrage opportunities could appear. We first assume that the investor can borrow money at Euribor flat for the entire duration of the trade and we relax after this assumption and estimate the critical level of average funding costs which delimits the existence/absence of statistical arbitrage.

At origination the cost of both portfolios is zero, and so the net payoff is also zero. The investor pays the CDS premium ($\bar{s}_t$), receives the floating leg payment of the ASP ($E_{3m,t} + s_t^A$) and pays the interest associated with the loan ($E_{3m,t}$). The net payment is equal to the difference between ASP and CDS spreads $(s_t^A - \bar{s}_t)$ converted into quarterly terms using an actual/360 day count convention. The previous difference is known as the long basis. This payment is repeated every quarter up to maturity or default, whichever comes first. The existence of funding costs (F) would transform the net payment into $(s_t^A - \bar{s}_t - F)$.

At the coupon payment dates, the investor receives the coupon (c) from the underlying bond and delivers it to the asset swap counterparty as the fixed leg payment. Thus, net payoff at the coupon payment date is zero. At the bond's maturity, the investor receives the bond's face value plus the final coupon payment. The coupon is delivered to the ASP counterparty as the IRS fixed leg payment while the bond's face value is employed to refund the loan's principal. From the IRS floating leg, the investor receives a 3-month Euribor rate plus the ASP spread. The former is employed to pay the loan's interest. Finally, the investor must pay the CDS spread, which is the price for credit risk protection. Then, the net payoff is also equal to the long basis. The strategy's payments are equal to the long basis unless there is default. In that case the payments could slightly differ from the long basis unless one assumes, for simplicity, that the asset swap is a perfect asset swap and the future cash flows disappear upon default.[11] To avoid any bias due to potential future defaults we restrict our sample to investment grade firms.

[8] We require that the selected block size, b, can also be obtained from the expression $b = n^x$ with $x < 1$. It guarantees that the required assumption stating that $b \to \infty$ as $n \to \infty$ and $\frac{b}{n} \to 0$ as $n \to \infty$ is fulfilled.

[9] According to the California Debt and Investment Advisory Commission (2007), floating-rate payment intervals in an IRS need not coincide with fixed-rate payment intervals, although they often do. Thus, the ASP investors could make the fixed rate payments dates to coincide with the defaultable bond's coupon payments dates while the floating payments, Euribor plus asset swap spread, could be made quarterly.

[10] The ASP spread is chosen such that the value of the whole package is the par value of the defaultable bond. Thus, an upfront payment must be added to the bond's price at the investment period to ensure that the value of the whole package is the bond face value. The upfront payment represents the net present value of the swap.

[11] The net payment at default also consists of: (i) the value of the IRS included in the ASP that remains alive after default and must be serviced or unwound at market value; (ii) the payment of the CDS accrued premium from the last payment date to the credit event; (iii) the payment of the loan accrued interest from the last payment date to the credit event; and (iv) the value of the cheapest-to-deliver option.

We analyze the existence of profitable arbitrage opportunities in a realistic setting and therefore we consider the potential restrictions that a given investor could face in the market. For this reason, we employ CDSs with a notional equal to €500,000 and assume that the strategy stops if the total investment in a given bond exceeds 25% of the bond's issued amount.[12] As an additional restriction, the strategy stops if the total expected future losses exceed €25,000. Finally, the strategy also stops if there are two downgrades that place the firm in BBB-Rating category. The payment on a given date is added to the cumulative trading profits from the first investment date to the day before, which were invested or borrowed at the risk-free rate a day ago. The cumulative trading profits obtained at every period are discounted up to the initial date. Then, we obtain the increment in the discounted cumulative trading profits at a given date t, $\Delta v(t)$, as the difference between the discounted cumulative trading profits at t and at $t-1$.

The profitability of the long basis trading lies on potential mispricings which lead to deviations in the equivalence relation that should exist between the CDS and the ASP/bond spreads on the same underlying reference name. In fact, basis trades represent one of the closest trading techniques in the credit market to an arbitrage free trade given that the investor is not exposed to risk but still receives the difference between the ASP and CDS spreads. We employ a long-run investment strategy to detect the existence of possible persistent anomalies instead of punctual deviations between credit spreads. For this reason, the same self-financing strategy based on the same individual bond should be repeated across time, maintaining all the terms and conditions. In spite of the restrictions in the bond/ASP short-positions and the non-viability for the arbitrageurs to exploit positive short bases, we also analyze the existence of persistent positive short bases (the CDS spread is persistently higher than the ASP spread) that are based on taking short position in ASPs and CDSs.

Besides the statistical arbitrage analysis at the individual firm level, we construct two portfolios (indexes) to check the existence of statistical arbitrage at the aggregated level. The portfolios' profits are obtained as an equally-weighted average of the trading profits of all the individual firm CDS–ASP pairs included in the portfolio (55 pairs before the crisis and 46 pairs during the crisis).

5. Data

Our database contains daily data on Eurobonds and ASPs denominated in Euros and issued by nonfinancial companies that are collected from Reuters and Datastream and on CDSs also denominated in Euros, whose underlying firms are the same nonfinancial companies. CDS data are obtained from four different databases: GFI, Reuters, CMA, and J.P. Morgan.

We employ four different CDS databases to have more robust results and to minimize the possibility that measurement errors could affect our results. This variety of sources also serves as a check of the reliability of our data. The first source we employ is GFI which is a major inter-dealer broker (IDB) specializing in the trading of credit derivatives. GFI data contain single name CDS market prices for 1, 2, 3, 4, and 5 year maturities. These prices correspond to actual trades, or firm bids and offers where capital is actually committed and so, they are not consensus or indications. Thus, these prices are an accurate indication of where the CDS markets traded and closed for a given day. For some companies and for maturities of two and four years, the data availability is scarce and in these cases, whenever there exist data on CDSs' actual market prices for the maturity of five years, we employ mid-price quotes from a credit curve also reported by GFI. We take advantage of the range of CDS maturities to fit a CDS curve using a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) algorithm that permits us to match ASP and CDS maturities. This method is also used in Levin et al. (2005).

The second source is Reuters. Reuters takes CDS quotes each day from several contributors around the world and offers end of day data for single name CDSs. Before computing a daily composite spread, it applies a rigorous screening procedure to eliminate outliers or doubtful data. The third source is Credit Market Analysis (CMA) DataVision(™). CMA DataVision is consensus data sourced from 30 buy-side firms, including major global Investment Banks, Hedge Funds, and Asset Managers which offers quoted CDS prices (bid, ask and mid). Our fourth database contains mid-market data provided by J.P. Morgan which is one of the leading players and most active traders in the CDS market.

Given the four different data sources on CDS spreads, we cross-check the data using all the sources to confirm the validity of any CDS price. Due to liquidity restrictions and to require that investments take place whenever there is trading activity, these investments are restricted to dates when we observe 5-year CDS actual trades or firm bids and offers where capital is actually committed according to GFI data.[13] The results that we report in the paper are the ones obtained with GFI data.

Our sample contains fixed-rate senior unsecured Euro denominated bonds whose issued quantity exceeds €300 million. These straight bonds are neither callable nor convertible and have constant coupons with a fixed frequency. For each bond we use information on both bid and ask prices, the swap spread, the asset swap spread, the rating history, the issuance date and the amount issued, the coupon and coupon dates, and the maturity. We use bonds whose maturity at the investment dates is lower than five years. Several bonds issued by the same company are used whenever they satisfy all the required criteria. Due to liquidity considerations, bonds with time to maturity equal to or less than twelve months in the date corresponding to their last observation are excluded. We also cross-check the data on bonds with the equivalent data obtained from Datastream.

The data span from November 1st, 2005 to June 29th, 2009. However, we split the data into two subperiods to take into account the possible effects of the ongoing financial crisis. The first subperiod covers the period from November 1st, 2005 to

[12] The CDS typical notional amount is €10–20 million for investment grade credits and €1–5 million for high yield credits. Successive repetitions of the strategy might lead to a bond demand that could exceed the issued amount. For this reason, we employ CDSs with a notional equal to €500,000. This notional is high enough to deal with fixed costs and is of adequate size to guarantee that a substantial number of investments can be made.

[13] Even when CDS quotes, from any of the data sources, are available at a given date, we do not employ them unless we observe 5-year CDS data from GFI. Thus, these dates do not indicate missing observations in a given source of data, but lack of trading activity.

August 8th, 2007 while the second one spans from August 9th, 2007 to June 29th, 2009. We consider all the bonds issued by nonfinancial European companies but due to the imposed requirements the final sample consists of 49 nonfinancial companies and 64 bonds. In the first subsample we employ 55 bonds and 41 companies while in the second one we use 46 bonds and 36 companies. The sample size is comparable to others in the literature on CDS and bond spreads, both in terms of length and number of companies.[14] Table 1 presents information about ASPs, bonds, and CDSs in the two different periods under study. As shown in Table 1, there is a great deal of variation in the amount issued and, in the first period, in the sample size.

6. Results

6.1. Individual firm level analysis

6.1.1. Individual firm level analysis using the new test

Panels A and B of Table 2 contain information on the profitability of the trading strategy joint with the results for the analysis of statistical arbitrage for the pre-crisis and crisis periods, respectively. The results that we report in this table are obtained under the UM model on the basis of GFI data.[15] Under the baseline specification (long positions and no market frictions) our test finds 16(8) persistent anomalies at 5% confidence level in the period before (during) the crisis in which the long basis is persistently positive (the ASP spread is higher than the CDS spread).[16,17] The previous analysis has been implemented on a total of 12,940 and 13,125 trades in the pre-crisis and crisis periods, respectively. The results obtained with the other data sources (Reuters, CMA, and J.P. Morgan) are similar to the ones reported in Table 2 although some small differences exist.[18] The average of the strategy relative profits, which are defined as the ratio of the profits relative to the notional amount of each investment (€500,000), is noticeably higher during the subprime crisis. This could lead to the appearance of more potential statistical arbitrage opportunities given that the deviation between the ASP and CDS spreads persists over time. However, the minimum and the volatility in the relative profits have also increased considerably during the crisis and as a consequence, profitable arbitrage opportunities are less likely (because of the non-rejection of the hypothesis H_2^c). In fact, the coefficient of variation for these profits during the crisis doubles the one obtained in the pre-crisis period.

The previous results ignore market frictions involved in entering the trade in the real world. For this reason, we cannot assure that the mispricings we find are profitable statistical arbitrage opportunities. One of these market frictions are trading costs. We employ the ASP and CDS quote-level data to evaluate the effect of trading costs, which are measured by means of the bond and CDS bid–ask spread, to the strategy's profits. When trading costs are included, the CDS–ASP pairs with persistent positive long bases before the crisis decreases to 14. During the crisis, we find that the number of the persistent positive long bases decreases to 4 confirming that the effect of trading costs on statistical arbitrage is more relevant during the crisis.[19]

Additionally, one should have in mind that to retain self-financing the investor would need to fund drawdowns through additional leverage. We consider that the cost for this additional leverage is higher than the rate at which the profits are invested (3-month T-bill rate) and use as a proxy for this cost the 3-month commercial paper rate. The results from the statistical arbitrage test obtained when we consider higher costs for financing additional leverage jointly with trading costs are similar to ones in which we only use trading costs, that is, we end up with the same statistical arbitrage opportunities. For sure, as shown in Table 2 the trading profits are lower when considering the extra financing costs. This result is explained because there are no large drawdowns in the cases in which we find statistical arbitrage opportunities. In fact, we are analyzing deviations from an equivalence relationship. Moreover, even in the presence of drawdowns the strategy stops whenever losses exceed a given threshold. The reason is that, in the cases in which we find statistical arbitrage opportunities, the deviations from the equivalence relation are persistently higher than zero and the cumulated profits are enough to compensate for any large loss. The results are robust to the use of higher costs such as the case in which we add additional borrowing spreads to the commercial paper rate.

The most important market friction is the funding cost or borrowing spread faced by the investor when borrowing money through the loan in Portfolio II. Elizalde and Doctor (2009) estimate that the costs for funding long risk positions in investment grade bonds were quite low during the period prior to the crisis (around 3 basis points (b.p.) for AAA-rated reference entities). Nevertheless, the situation changes after the summer of 2007 and funding costs for the same long risk positions increase

[14] Longstaff et al. (2005) include 68 firms from March 2001 to October 2002, Blanco et al. (2005) use 33 American and European companies from January 2001 to June 2002, and Zhu (2006) uses 24 investment grade companies from January 1999 to December 2002.

[15] We only report the results obtained for the UM model because it presents smaller Akaike Information Criteria (AIC) and Schwarz Information Criteria (SC) than the CM model and because the parameter θ is significantly higher than zero according to its t-statistic.

[16] Before the crisis, we find statistical arbitrage opportunities for the following bonds/firms: Altadis, British AM Tob. II, Casino I, Casino II, Compass Group, Edison, Louis Vuitton I, Louis Vuitton II, PPR, Renault, Repsol YPF, Reuters, Saint Gobain II, Sodexho, Technip, and Tesco II. The notation is the one employed in Table 1 that summarizes all the bonds employed in our study.

[17] During the crisis, we find statistical arbitrage opportunities for the following bonds/firms: Bayer, British AM Tob. II, Casino III, Edison, SES, Telecom Italia II, Telekom Austria, and Teliasonera.

[18] Before the crisis, we find an additional persistent positive long basis or mispricing using the CMA and the J. P. Morgan databases: Stora Enso. In the crisis period, we find that Edison (Telecom Italia II) does not show mispricings in the Reuters and CMA databases (Reuters and J.P. Morgan databases) but it does in the J. P. Morgan database (CMA database).

[19] Counterparty risk could also have a role on the deviations from the CDS–ASP equivalence relation. The baseline analysis is implemented from the long basis and so, the profits are defined as the ASP minus the CDS spread. In principle, the higher the counterparty risk of the seller of protection via CDS is, the lower should be the CDS spread charged as a result of the lower quality of the protection (see the discussion in Choudhry (2006), pages 66–71). Thus, when counterparty risk is high the basis could be even wider leading to more statistical arbitrage opportunities.

Table 1
Descriptive statistics This table details the bonds/firms employed in our analysis. The second column reports the bonds/firms rating for the pre-crisis (November 2005–August 2007) and crisis (August 2007–June 2009) periods. The third and fourth columns report the bond amount issued and coupon. The last two columns contain the number of observations for each bond employed in the statistical arbitrage analysis.

Issuer	Rating	Amount issued (millions of euros)	Coupon (%)	Observations Nov 05–Aug 07	Aug 07–Jun 09
Akzo Nobel I	A−/BBB+	750	4.250	220	396
Akzo Nobel II	A−/BBB+	1000	5.625	286	–
Altadis	BBB/–	600	4.250	330	–
Astrazeneca	–/AA−	750	4.625	–	157
Auchan	–/A	600	3.000	–	169
BASF	–/A+	1400	3.375	–	290
Bayer	–/A−	2000	6.000	–	347
Belgacom	–/A+	775	4.125	–	38
BMW	A+/A	750	3.875	295	393
Bouygues I	BBB+/BBB+	750	4.625	197	260
Bouyges II	BBB+/BBB+	1000	5.875	221	–
British AM Tob. I	BBB+/BBB+	1700	4.875	338	–
British AM Tob. II	BBB+/BBB+	1000	4.375	232	300
Carrefour I	A/A	1100	4.375	221	324
Carrefour II	A/A	1000	6.125	314	324
Casino G. P. I	BBB−/BBB−	400	4.750	148	304
Casino G. P. II	BBB−/BBB−	500	5.250	195	304
Casino G. P. III	BBB−/BBB−	700	6.000	–	304
Compass Group	BBB+/−	300	6.000	121	–
Edison	BBB+/BBB+	700	5.125	339	338
Enel	A−/A−	750	4.125	91	206
Energias de Portugal I	A−/A−	1000	6.400	184	258
Energias de Portugal II	A−/A−	747	5.875	162	251
E.ON	A+/−	4250	5.750	200	–
France Telecom I	A−/A−	750	4.625	119	298
France Telecom II	A−/A−	1000	4.375	100	298
France Telecom III	A−/A−	1000	3.000	294	298
Iberdrola I	A/A−	750	4.375	234	291
Iberdrola II	A/A−	600	4.500	195	–
Kingfisher	BBB−/BBB−	500	4.500	270	146
Louis Vuitton I	BBB+/BBB+	600	4.625	251	368
Louis Vuitton II	BBB+/BBB+	750	5.000	352	369
Philips	–/A−	750	6.125	–	237
PPR	BBB−/BBB−	800	5.250	289	339
Reed Elsevier	A−/–	500	5.000	208	–
Renault	BBB+/−	1000	6.125	249	–
Repsol YPF	BBB+/BBB+	1175	6.000	298	358
Reuters	A−/–	500	4.625	229	–
Saint Gobain I	BBB+/BBB+	1000	4.750	316	–
Saint Gobain II	BBB+/BBB+	1100	4.250	261	384
Saint Gobain III	BBB+/BBB+	1000	5.000	337	384
Scania	A−/–	600	3.625	219	–
Schneider	–/A−	900	3.125	–	110
SES	BBB/BBB	500	3.875	52	119
Siemens	AA−/A+	2000	5.750	72	228
Sodexho	BBB+/−	1000	5.875	350	–
Stora Enso	BBB−/–	500	3.250	316	–
Technip	BBB/BBB	650	4.625	112	194
Telecom Italia I	BBB+/BBB	750	4.500	300	299
Telecom Italia II	BBB+/BBB	2000	7.250	269	299
Telefonica	BBB+/A−	2250	3.750	317	272
Telekom Austria	BBB+/BBB+	500	3.375	137	255
Teliasonera	–/A−	500	3.625	–	383
Tesco I	A/A−	750	4.750	347	276
Tesco II		500	3.875	303	286
Thales	A−/A−	500	4.375	111	298
Thyssenkrupp	BBB+/BBB−	750	5.000	235	358
Union Fenosa	A−/A−	500	5.000	317	288
Veolia Environ.	BBB+/−	2000	5.875	239	–
Vinci	BBB+/−	1025	5.875	158	–
Vivendi	BBB/−	630	3.625	97	–
Vodafone	A−/–	1900	5.125	311	–
Volkswagen	A−/BBB+	1000	4.125	255	400
Volvo	A−/BBB+	300	5.375	324	327

Table 2
Statistical arbitrage opportunities at firm level. This table contains information on (i) the profitability of the trading strategy that is applied firm by firm and (ii) the existence of statistical arbitrage (SA) opportunities. Panel A refers to the pre-crisis period (Nov 05–Aug 07) and is constructed from a total of 55 CDS–ASP pairs. Panel B refers to the crisis period (Aug 07–Jun 09) and is constructed from 46 CDS–ASP pairs. The first column denotes the positions taken in the CDS and ASP contracts (Long or Short), the market frictions faced by the investor (Liq or FLiq), and the rating category of the underlying firms (A Rating or BBB Rating). Liq refers to the existence of trading costs while FLiq refers to the existence of trading and financing costs when additional leverage is needed to retain self-financing due to drawdowns. A Rating denotes that the firms have rating category between AA− and – while BBB Rating firms have rating category between BBB+ and BBB−. The second, third, and fourth columns contain the total number of daily investments in CDS–ASP pairs and the percentage of days in which the strategy leads to either losses or gains, respectively. The next four columns contain the average, maximum, minimum, and standard deviation of the strategy daily relative profits that are defined as the ratio of the profits relative to the notional amount of each investment (€500,000). Total Profit refers to the total profits obtained over all the firm CDS–ASP pairs. The column % Pairs Stop includes the percentage of pairs in which the strategy stops because the total losses for that pair exceed the threshold of €25,000. The last column reports the number of pairs in which our test finds SA opportunities at 5% significance level over the total number of cases in the pre-crisis (55) and crisis (46) periods.

Strategy	Total Inv	Days_Loss	Days_Gain	Av_Ret	Max_Ret	Min_Ret	SD_Ret	Total profit	% Pairs stop	SA (5%)
Panel A. Pre-crisis (55 CDS–ASP pairs)										
Long	12,940	27%	73%	0.021%	0.161%	−0.067%	0.031%	1,465,811	49%	16
Long_Liq	12,940	33%	67%	0.015%	0.151%	−0.080%	0.029%	931,449	56%	14
Long_Liq&Fund	12,940	33%	67%	0.015%	0.151%	−0.080%	0.029%	931,774	56%	14
Long_ARating	5654	42%	58%	0.008%	0.112%	−0.067%	0.024%	206,307	68%	2
Long_BRating	7286	19%	81%	0.028%	0.161%	−0.067%	0.032%	1,259,504	33%	14
Short	12,940	55%	45%	0.003%	0.182%	−0.052%	0.024%	205,666	73%	3
Panel B. Crisis (46 CDS–ASP pairs)										
Long	13,125	37%	63%	0.048%	1.638%	−0.939%	0.158%	3,270,781	70%	8
Long_Liq	13,125	41%	59%	0.036%	1.523%	−0.844%	0.151%	2,248,989	80%	3
Long_Liq&Fund	13,125	41%	59%	0.036%	1.523%	−0.844%	0.151%	2,248,989	80%	3
Long_ARating	6320	44%	56%	0.031%	0.608%	−0.231%	0.093%	820,347	79%	2
Long_BRating	6805	32%	68%	0.060%	1.638%	−0.939%	0.188%	2,450,435	59%	6
Short	13,125	53%	47%	0.026%	2.424%	−0.518%	0.142%	1,556,178	85%	8

remarkably being between 6 and 25 b.p. in July 2008, 51 and 101 b.p. in October 2008 and 14 and 44 b.p. in July 2009. To analyze the persistence of statistical arbitrage opportunities after considering the previous funding costs we estimate the critical level of average funding costs which delimits the existence/absence of persistent mispricings. We find that when the annualized average funding cost associated to each investment before the crisis is greater than 2 b.p., the persistent positive long basis is not profitable in 7 cases in which there was statistical arbitrage opportunities when market frictions were ignored. When the transaction costs are greater than 3 b.p., no profitable persistent mispricing is found in the remaining 9 cases.[20] In view of the estimation of funding costs by Elizalde and Doctor (2009), it is hard to believe that the mispricings observed in CDS and ASP markets are profitable statistical arbitrage opportunities. Regarding the crisis period, if the annualized average funding cost associated to each investment is greater than 1 b.p., the profitable persistent positive long basis disappears in 3 cases. When the strategy's cost is greater than 2 b.p. (3 b.p.), the persistent positive long basis disappears in 2 (2) cases. In view of the funding costs, we conclude that no statistical arbitrage opportunity remains during the crisis.

Although shorting a corporate bond or ASP is not always a feasible option, for the sake of completeness we also apply the statistical arbitrage test to the strategy based on short positions both in Portfolio I and Portfolio II for the whole sample of entities. We find three additional mispricings before the crisis and eight during the crisis.[21] This result suggests that there are noticeable differences between both subperiods that could be explained because during the crisis the ASPs' short-positions are less feasible and most costly than under a normal regime.[22]

These results suggest the following conclusions. First, in the short-run the basis could temporarily deviate from zero to a considerable extent. Second, there are persistent mispricings from the CDS–ASP equivalence relation in 34.5% and 34.8% of the cases in the pre-crisis and crisis periods, respectively, when market frictions are not taken into account. These deviations suggests that the arbitrage forces find some obstacles, probably related with funding and trading costs or the unfeasibility to take short-positions in ASPs. These obstacles are particularly relevant during periods of financial distress. In sum, although some persistent mispricings in credit spreads are found, market frictions prevent them from becoming profitable statistical arbitrage opportunities.

6.1.2. Individual firm level analysis using alternative statistical arbitrage tests

In this section we use the HJTW and the JTTW tests to study the existence of statistical arbitrage opportunities in our sample. We find that both HJTW and JTTW tests offer similar results. A total of 27 (11) persistent positive long bases at 5% confidence level

[20] We are considering average constant funding costs for the corresponding period although it is likely that an investor would have to renew their funding at regular intervals and so, would be somewhat exposed to changes in the levels of funding. To have a better perspective of these average costs, the average ASP, bond, and CDS spread during the period before the crisis is around 25 b.p. and, so, a cost of 3 b.p. is around 12% of the credit spread.

[21] The three additional mispricings before the crisis are: Carrefour II, British AM Tob. I, and France Telecom III. The eight additional mispricings during the crisis are: Astrazeneca, BASF, Enel, France Telecom III, Iberdrola I, PPR, Thyssenkrupp, and Volkswagen.

[22] Trapp (2009) finds that during the crisis the short basis (constructed from bond short-sales) becomes relatively more profitable than the long basis (based on bond long positions) compared to the pre-crisis period.

are found before (during) the crisis. Thus, before the crisis, HJTW/JTTW tests find persistent positive long bases in eleven cases in which our test rejects the existence of such persistent deviations. Regarding the crisis period, HJTW/JTTW tests find three persistent positive long bases more than our test. The differences between those tests and ours are due mainly to the estimators and the corresponding *p*-values associated with restrictions H_1^c and H_2^c which are defined in Section 2.[23] To clarify the economic difference between HJTW/JTTW test versus our test and for a better view of the characteristics of statistical arbitrage opportunities found by both tests, we show a measure of the downside risk in the losses or lower payments in Fig. 1. This measure is the Fisher's skewness of the payments when they are below the 33rd percentile. All the potential statistical arbitrage opportunities found by our test have positive skewness except in one case (−0.04). On the other hand, all the potential arbitrage opportunities discarded by our test but accepted by the HJTW/JTTW test have negative skewness ranging from (−0.08,−2.36). During the crisis and using our test, all the potential statistical arbitrage opportunities have positive skewness except in one case (−0.05). On the other hand, the potential arbitrage opportunities discarded by our test but accepted by the JTTW test all have negative skewness ranging from (−1.45,−2.24). Therefore, there is a salient economic implication of this result: arbitrage opportunities detected by JTTW's test (but not detected by our test) exhibit substantially larger downside risk that is even more extreme during the crisis period. This discrepancy between both tests may be due to the differences between subsampling and bootstrap given that in fact, one should obtain better information about the sampling distribution of the statistic using the subsampling methodology. The reason is that, while the subsample statistics are always generated from the true model, bootstrap data come from an approximation to the true model. This would explain why our test deals better with the downside risk observed in the increments of the discounted cumulative trading profits. For this reason, we choose to employ our test as the baseline tool in the remainder of the study due to its better properties in this specific context.[24]

6.2. Portfolio level analysis

In this section we construct two profit portfolios (indexes) to check the existence of statistical arbitrage. In the first case we compute the portfolio's incremental profits as an equally-weighted average of the increment in the discounted cumulative trading profits of all the CDS–ASP pairs included in the portfolio (55 pairs before the crisis and 46 pairs during the crisis). To obtain the profits of each pair we proceed as explained in Sections 4 and 6.1 and consider a stopping rule such than when the total losses exceed €25,000, the investor does not take additional positions on such pair/firm. We are assuming that the arbitrageur is investing in an equally-weighted portfolio of CDS–ASP in which each pair consists of one individual trade. Results for the pre-crisis and crisis periods are reported in Panels A and B of Table 3, respectively. The probability of suffering losses is higher in the crisis period. Thus, the portfolio constructed from firms belonging to the *BBB Rating* category (firms with rating category between BBB+ and BBB−) suffers losses in 8% of the trading days before the crisis but this proportion increases to 23% in the crisis period. Average returns and volatilities are higher in the crisis period. The relative returns are defined as the daily profits for the portfolio relative to the notional amount of each investment (€500,000). Although these relative returns could seem low, it is important to have in mind that the strategy is self-financed. The maximum total profits over the sample period assuming a total of 451 and 480 portfolio trades before and during the crisis with a notional of €500,000 are €110,571 and are obtained from the *BBB Rating* category firms during the crisis. The columns denoted μ, σ, θ, and λ contain the estimated parameters of the cumulative trading profit process according to which we find statistical arbitrage opportunities at 5% significance levels in the portfolio formed by the lowest rated firms before and during the crisis. During the crisis, the profitability of the deviations from the equivalence relationship is larger and we find also statistical arbitrage opportunities in the portfolio formed by all the firms when trading costs and financing costs, to retain self-financing due to drawdowns, are not considered. The absence of arbitrage opportunities for the short-positions strategy suggests that the ASP spread was on average persistently higher than the CDS spread. All apparent mispricings are unlikely to provide statistical arbitrage opportunities once realistic assessments of the borrowing spread or funding cost incurred to borrow funds to buy the ASP; are considered.

To obtain the incremental profits for the second portfolio approach, we compute the equally-weighted average of the bases for all the CDS–ASP pairs in the portfolio. Then, we implement a trading strategy to compute the profits from the average basis following Yu's (2006) strategy. In this strategy, once the arbitrageur has entered the market he needs to know when to liquidate his positions. The liquidation occurs under the following scenarios: (i) the basis reverts to zero, (ii) there is a "drawdown" such that the losses associated to a given investment over the notional amount of each position taken is larger than 1%, or (iii) the basis has not reverted to zero and there are no drawdowns at the end of the holding period (90 days). Once we get the daily portfolio's profits, we discount them, add the discounted profits, and take the first difference to get the increment in the discounted cumulative trading profits. We consider different variations for this trading strategy. The baseline strategies are: (a) investors only take long positions when the ASP spread is above the CDS spread and (b) investors take both long and short positions such that long (short) positions are taken when the ASP spread is above (below) the CDS spread. We also take into account the existence of potential market frictions and so, we redefine the profits for a couple of variations of (a) and (b) in which we consider first trading costs and second trading and financing costs employed to retain self-financing in the strategy due to drawdowns. We also analyze

[23] The cases in which our test does not find statistical arbitrage opportunities exhibit high probabilities of a loss, high volatility, and a significant and negative skewness.

[24] Although we find that our test presents better properties in terms of the lower downside risk than other alternative methods, the aim of the paper is to apply the new test for statistical arbitrage to credit derivatives but not to put into question the findings of HJTW and JTTW. These better properties could be related to the specific characteristics of the dataset employed in our analysis. For this reason, we refrain from making any general statement about the relative merits of our test against existing alternatives but just focus on the specific case under study.

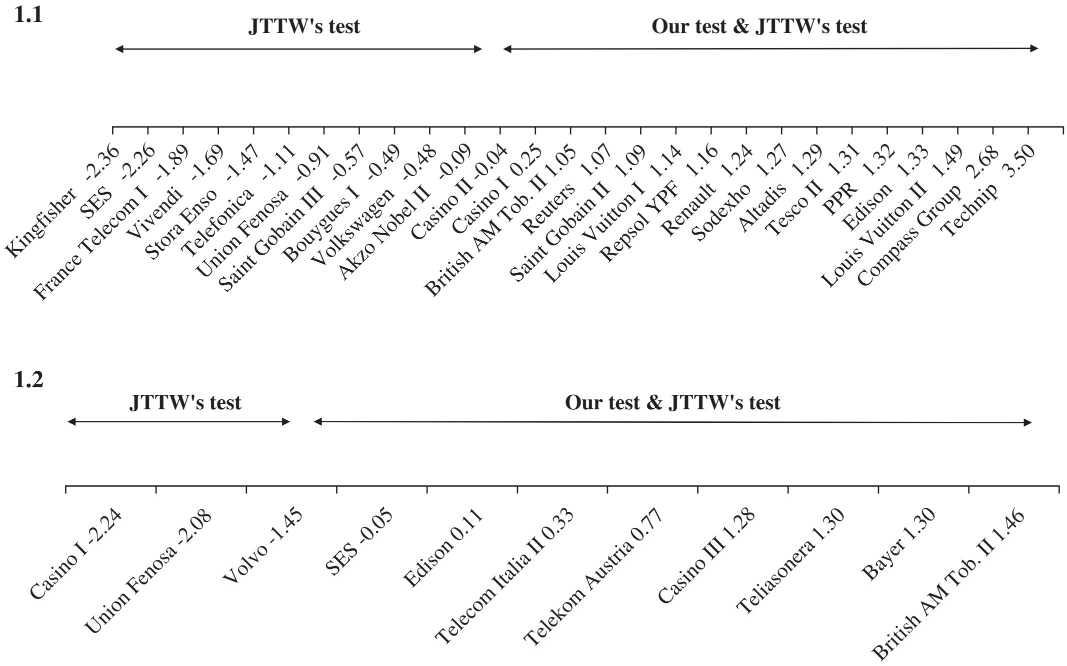

Fig. 1. Fisher's skewness of the payments below the 33rd percentile. This figure shows the Fisher's skewness of the payments when these are below the 33rd percentile. Figure 1.1 shows the Fisher's skewness for the arbitrage opportunities detected by the MPR test and by the JTTW test before the crisis. Figure 1.2 shows the Fisher's skewness for the arbitrage opportunities detected by the MPR test and by the JTTW test during the crisis.

whether the existence of statistical arbitrage opportunities is more frequent for different rating categories and split the portfolios obtained under strategies (a) and (b) into two depending on whether the firms have a rating category between AA− and A− or between BBB+ and BBB−. In both cases we ignore market frictions. Finally, we add another variation according to which (c) investors only take short positions when the ASP spread is below the CDS spread. The portfolio approach is equivalent to creating a synthetic CDS and ASP with spreads equal to the average spreads of the portfolio constituents. The main novelty of this portfolio approach is that it enables drawdowns incurred from one firm-level CDS/ASP pair to be offset from gains on another firm whenever it does not lead to significant drawdowns at the portfolio level. In the previous approach, the trading on a given CDS/ASP pair stops if there is a loss larger than €25,000.

Descriptive statistics on the profitability of the previous strategies are reported in Panels A and B of Table 4. The first columns of these panels detail the total number of investments in the form of either long or short positions. Regarding the returns, we find that their distribution is similar to the one reported in Table 3 with the maximum average return and total profits being the ones obtained when the investors takes both long and short positions, that is, when the investors exploit both positive and negative deviations from the equivalence relationship. The results from this table suggest that the existence of drawdowns is not frequent and in fact, almost no trading is closed because of such reason but because of the end of the holding period (mainly in the pre-crisis period) or the reversion of the basis to zero (mainly in the crisis period). Panel C reports detailed information on the statistical arbitrage test analysis. We observe that the deviations from the equivalence relationship are quite frequent in the trading strategies based on both long and short positions. These arbitrage opportunities persist for both periods even after considering trading costs and financing costs to retain self-financing in the strategy due to drawdowns. For sure, in the presence of those market frictions the average return of the strategy diminishes as shown in Panels A and B. Regarding the trades based only on long positions, we find statistical arbitrage opportunities at the 5% significance level in the portfolio formed by the lowest rated firms before the crisis in the absence of market frictions. However, after considering realistic estimations of funding costs as in Elizalde and Doctor (2009), all the mispricings are unlikely to provide profitable arbitrage opportunities.

6.3. Understanding the CDS–ASP mispricings

6.3.1. CDS–ASP firm level mispricings

To understand the statistical arbitrage opportunities at firm level we test how asset swaps, bonds and CDS characteristics influence the existence of statistical arbitrage. To achieve this, we run a Probit regression with heteroskedasticity robust standard errors for the total 101 cases studied in both subperiods in which the dependent variable is a dummy that equals 1 if there is a statistical arbitrage opportunity, ignoring trading and funding costs, and equals zero otherwise. We use the firm rating as a proxy for firm default risk. We assign 1 to the rating category AA−, and so successively until the value 7 that is assigned to the category BBB−. To proxy the liquidity of the trading strategy we use the percentage of days in which there are no observations for either

Table 3
Statistical arbitrage opportunities at portfolio level. This table contains information on the profitability of the trading strategy that is applied to the profits of a portfolio of firms and the existence of statistical (SA) opportunities. The SA analysis relies on the increment in the discounted cumulative trading profits that under the UM model follow the process: $\Delta v_i = \mu i^{\theta} + i^{\lambda} z_i$. The portfolio's incremental profits are computed from an equally-weighted average of the increment in the discounted cumulative trading profits of all the CDS–ASP pairs forming the portfolio. To obtain the profits of each pair we consider a stop rule such than when the total losses exceed €25,000 the investor does not take additional positions on such pair/firm. Panel A refers to the pre-crisis period (Nov 05–Aug 07) and is constructed from a total of 55 CDS–ASP pairs. Panel B refers to the crisis period (Aug 07–Jun 09) and is constructed from 46 CDS–ASP pairs. The first column denotes the positions taken in the CDS and ASP contracts similar to those in Table 2. The second, third, and fourth columns contain the total number of daily investments in the portfolio and the percentage of days in which the strategy leads to either losses or gains, respectively. The next four columns contain the average, maximum, minimum, and standard deviation of the strategy daily relative profits that are defined as the ratio between the profits over the notional amount of each investment (€500,000). Total Profit refers to the total profits of the portfolio strategy. The columns denoted μ, σ, θ, and λ contain the estimated parameters. The column p-value presents the p-value associated to the rejection of the null hypothesis that states the absence of SA while the last column shows whether there is or not SA on the basis of our test. ***, **, and * denote whether the null hypothesis (no SA) is rejected at 1, 5, and 10%, confidence level, respectively.

Strategy	Total days	Days_Loss	Days_Gain	Av_Ret	Max_Ret	Min_Ret	SD_Ret	Total profit	μ	σ	θ	λ	p-Value	SA
Panel A. Pre-crisis														
Long	451	13%	87%	0.012%	0.033%	−0.018%	0.010%	26,238	0.192	28.199	1.062	−0.040	0.094	Yes*
Long_Liq	451	22%	78%	0.007%	0.023%	−0.021%	0.008%	15,662	0.082	53.739	1.136	−0.182	0.122	No
Long_Liq&Fund	451	24%	76%	0.007%	0.023%	−0.021%	0.008%	15,627	0.082	53.806	1.137	−0.183	0.128	No
Long_ARating	442	25%	75%	0.003%	0.017%	−0.040%	0.006%	6998	0.087	93.162	1.019	−0.304	0.271	No
Long_BRating	451	8%	92%	0.018%	0.047%	−0.011%	0.013%	41,133	0.202	9.064	1.125	0.220	0.006	Yes***
Short	451	24%	76%	0.002%	0.019%	−0.005%	0.003%	5347	66.234	53.148	−0.349	−0.245	0.383	No
Panel B. Crisis														
Long	480	24%	76%	0.029%	0.157%	−0.045%	0.036%	69,658	2.687	23.125	0.735	0.361	0.016	Yes**
Long_Liq	480	31%	69%	0.020%	0.123%	−0.056%	0.032%	47,871	2.614	29.877	0.673	0.300	0.083	Yes*
Long_Liq&Fund	480	31%	69%	0.020%	0.123%	−0.056%	0.032%	47,901	2.611	29.877	0.673	0.300	0.083	Yes*
Long_ARating	480	24%	76%	0.014%	0.070%	−0.038%	0.019%	32,877	1.081	35.363	0.765	0.172	0.521	No
Long_BRating	480	23%	77%	0.046%	0.279%	−0.088%	0.058%	110,571	3.970	17.427	0.748	0.495	0.010	Yes***
Short	480	29%	71%	0.014%	0.080%	−0.024%	0.021%	33,408	0.000	32.715	2.207	0.163	0.359	No

the CDS or the ASP over the total number of days since the beginning of the strategy. The logarithm of the bond amount issued enables us to control for the bond liquidity. The logarithm of the number of bonds issued by a given firm serves as a proxy for the firm's relevance in the fixed-income market or the firm's size. Additionally, we use a crisis dummy to check whether there is an increase in statistical arbitrage during the crisis period. Finally, the interaction of the crisis dummy with the rating is used to analyze whether there is a differential effect of the default risk on the existence of statistical arbitrage opportunities during the crisis. Given that the coefficients in the Probit model are difficult to interpret, we compute the marginal effects that indicate the change in the probability of statistical arbitrage for a marginal change in the independent continuous variable or for a discrete change in the independent dummy variable. Results are shown in Table 5. Column 1 reports the results obtained when the dependent variable refers to the existence of statistical arbitrage opportunities based on long positions in both CDS and ASP. The statistical arbitrage opportunities seem to be more frequent when ASPs contain relatively low-rated bonds. Concretely, a one-notch rating downgrade increases the probability of having a statistical arbitrage opportunity by around 12.1%. The other explanatory variables do not have a significant effect on statistical arbitrage. Column 2 reports the results obtained when the dependent variable refers to the existence of statistical arbitrage based on either long or short potions in CDS and ASP. The only significant effect is the one attributable to the rating. This confirms that there is one salient factor that determines the existence of statistical arbitrage: the issuer's risk. Thus, the higher the bond or issuer risk, the more frequent are the persistent deviations between CDS and ASP spreads.

6.3.2. CDS–ASP portfolio level mispricings

On the basis of the results obtained from the portfolio approach we can address other interesting questions such as whether the statistical arbitrage profits can be explained by three relevant systematic risk factors: funding costs, counterparty risk, and global risk. We use the difference between the 90-day US AA-rated commercial paper interest rates for financial companies and the 90-day US T-bill to proxy for funding costs of the participants in the CDS and ASP markets. As a proxy for counterparty risk, we use the first principal component obtained from the CDS spreads of the main 14 banks that act as dealers in the CDS market. The first principal component series should reflect the common default probability and, hence, it is akin to an aggregate measure of counterparty risk. In fact, the first PC for the series of CDS spreads of this set of dealers explains 87.5% of the total variance of the observed variables. Finally, global risk is proxied by means of the VIX Index. These additional variables are obtained from Datastream.

Due to the high correlation between the three systematic factors and to avoid any problem of multicollinearity, we orthogonalize the three factors. For such aim, we first regress the counterparty risk on the funding costs proxy and use the residual as the new proxy for counterparty risk. Then, we regress the global risk proxy on the funding costs and the new proxy for counterparty risk and use the residual as the new proxy for global risk. Once we have constructed the orthogonal proxies for the three systematic factors, we regress the strategy profits obtained from the two portfolio approaches without market frictions on the three aforementioned regressors. Colum 1 of Table 6 contains the results obtained when the dependent variable is the profits

Table 4

Statistical arbitrage opportunities at portfolio level based on Yu's (2006) methodology. This table contains information on (i) the profitability of the trading strategy that is applied to the profits of a portfolio of firms and (ii) the existence of statistical arbitrage (SA) opportunities. The SA analysis relies on the increment in the discounted cumulative trading profits that under the UM model follow the process $\Delta v_i = \mu i^{\theta} + i^{\lambda} z_i$. To obtain the portfolio's incremental profits we first compute the equally-weighted average of the bases for all the CDS–ASP pairs forming the portfolio and then we discount and add them to take the first difference. Panel A refers to the pre-crisis period (Nov 05–Aug 07) and is constructed from a total of 55 CDS–ASP pairs. Panel B refers to the crisis period (Aug 07–Jun 09) and is constructed from 46 CDS–ASP pairs. The first column denotes the positions taken in the CDS and ASP contracts (Long&Short, Long or Short), the market frictions faced by the investor in terms of trading costs (Liq) or both trading and financing costs when additional leverage is need to retain self-financing (FLiq), and the rating category of the underlying firms (A Rating or BBB Rating). A Rating denotes that the firms have rating category between AA− and – while BBB Rating firms have rating category between BBB+ and BBB−. The second column contains the total number of daily investments while the third and fourth detail whether such investments are in the form of long or short positions. The fifth and sixth columns present the percentage of days in which the strategy leads to either losses or gains, respectively. Close_End is the percentage of trades that are closed the last day of the holding period (3-months) because the basis did not revert to zero and there were no drawdowns during the holding period. Close_Loss is the percentage of trades that are closed because of a "drawdown" such that the losses associated to ta given investment over the notional amount of each position taken is larger than 1%. Close_Conv is the percentage of trades ending in convergence such that the basis reverts to zero. The next four columns contain the average, maximum, minimum, and standard deviation of the strategy daily relative profits that are defined as the ratio between the profits over the notional amount of each investment (€500,000). Total profit refers to the total profits of the portfolio strategy. Panel C reports the details about the statistical arbitrage estimated parameters (μ, σ, θ, and λ), the p-value associated to the rejection of the null hypothesis that states the absence of SA, and the indicator of whether there is or not SA joint with the confidence level at which the null hypothesis (no SA) is rejected for the pre-crisis and crisis periods. ***, **, and * denote whether the null hypothesis is rejected at 1, 5, and 10%, respectively.

Strategy	Total Inv	Total Long	Total Short	Days_Loss	Days_Gain	Close_End	Close_Loss	Close_Conv	Av_Ret	Max_Ret	Min_Ret	SD_Ret	Total profit
Panel A. Pre-crisis profitability													
Long	297	297		42%	58%	65%	0%	35%	0.002%	0.018%	−0.014%	0.005%	5,075
Long&Short	437	297	140	7%	93%	51%	0%	49%	0.010%	0.037%	−0.009%	0.008%	21,841
Long_Liq	254	254		50%	50%	73%	0%	27%	0.001%	0.017%	−0.011%	0.004%	2794
Long&ShortLiq	437	254	183	12%	88%	51%	0%	49%	0.010%	0.040%	−0.011%	0.009%	22,511
Long_Liq&Fund	254	254		50%	50%	73%	0%	27%	0.001%	0.017%	−0.011%	0.004%	2,791
Long&Short_Liq&Fund	437	254	183	12%	88%	51%	0%	49%	0.010%	0.040%	−0.011%	0.009%	22,511
Long_ARating	209	209		41%	59%	36%	0%	64%	0.003%	0.017%	−0.007%	0.004%	5,331
Long&ShortARating	427	209	218	3%	97%	26%	0%	74%	0.019%	0.062%	−0.002%	0.014%	41,482
Long_BRating	347	347		28%	72%	62%	0%	38%	0.004%	0.029%	−0.015%	0.006%	10,028
Long&Short_BRating	431	347	84	10%	90%	54%	0%	46%	0.008%	0.045%	−0.013%	0.007%	17,019
Short	140		140	44%	56%	14%	0%	86%	0.002%	0.023%	−0.001%	0.004%	4,492
Panel B. Crisis profitability													
Long	240	240		32%	68%	36%	0%	64%	0.015%	0.152%	−0.038%	0.027%	34,870
Long&Short	472	240	232	12%	88%	49%	0%	51%	0.069%	0.308%	−0.049%	0.071%	165,664
Long_Liq	198	198		34%	66%	39%	0%	61%	0.013%	0.116%	−0.022%	0.024%	29,256
Long&ShortLiq	472	198	274	10%	90%	49%	0%	51%	0.067%	0.300%	−0.069%	0.069%	160,108
Long_Liq&Fund	198	198		35%	65%	39%	0%	61%	0.013%	0.116%	−0.022%	0.024%	29,256
Long&ShortLiq&Fund	472	198	274	10%	90%	49%	0%	51%	0.067%	0.300%	−0.069%	0.069%	160,108
Long_ARating	220	229		24%	76%	25%	0%	75%	0.015%	0.126%	−0.053%	0.024%	35,156
Long&Short_ARating	471	220	251	3%	97%	31%	0%	69%	0.085%	0.325%	−0.050%	0.069%	203,249
Long_BRating	254	254		26%	74%	1%	0%	99%	0.029%	0.255%	−0.024%	0.041%	67,637
Long&Short_BRating	470	254	216	3%	97%	3%	1%	96%	0.098%	0.383%	−0.040%	0.074%	236,317
Short	232		232	36%	64%	63%	0%	38%	0.014%	0.131%	−0.053%	0.027%	34,661

Panel C. Statistical arbitrage analysis	Pre-crisis						Crisis					
Strategy	μ	σ	θ	λ	p-Value	SA	μ	σ	θ	λ	p-Value	SA
Long	0.002	1.227	1.597	0.530	0.161	No	0.463	6.587	0.925	0.543	0.229	No
Long&Short	2.110	24.028	0.586	0.073	0.036	Yes**	0.221	23.305	1.328	0.431	0.040	Yes**
Long_Liq	0.000	0.300	2.282	0.766	0.289	No	2.424	8.629	0.601	0.483	0.188	No
Long&ShortLiq	3.906	24.041	0.480	0.107	0.047	Yes**	0.505	23.533	1.177	0.435	0.050	Yes**
Long_Liq&Fund	0.000	0.300	2.284	0.766	0.289	No	2.423	8.628	0.601	0.483	0.130	No
Long&Short_Liq&Fund	3.906	24.041	0.480	0.107	0.047	Yes**	0.505	23.533	1.177	0.435	0.050	Yes**
Long_ARating	0.005	0.038	1.435	1.148	0.192	No	46.128	61.453	0.089	0.127	0.172	No
Long&Short_ARating	29.437	68.600	0.223	0.000	0.028	Yes**	3.205	17.375	0.894	0.477	0.047	Yes**
Long_BRating	0.361	3.055	0.767	0.419	0.043	Yes**	24.449	20.167	0.336	0.423	0.453	No
Long&Short_BRating	0.104	7.346	1.081	0.256	0.038	Yes**	3.945	23.059	0.884	0.429	0.038	Yes**
Short	77.492	56.099	−0.422	−0.213	0.622	No	2.965	29.065	0.592	0.276	0.063	Yes*

obtained from long positions in both CDS and ASP according to the methodology employed in Section 6.1. Column 2 of Table 6 contains the results obtained when the dependent variable corresponds to the profits obtained from a trading strategy based on Yu (2006), employing both long and short positions (see Section 6.2). Results in both columns are similar and show that that there is a significant relation between statistical arbitrage daily profits and the three systematic factors. In particular, the higher the funding costs, the counterparty risk, or the global risk; the more difficult it is to hold the equivalence relationship and the larger are the deviations from the equivalence relationship.

Table 5
Determinants of statistical arbitrage opportunities at firm level. This table documents the potential determinants of statistical arbitrage (SA) opportunities at firm level. The results are estimated using a Probit model with heteroskedasticity robust standard errors. The sample consists of 101 cases/bonds: 55 in the pre-crisis period and 46 in the crisis period. The dependent variable is a dummy that is equal to 1 if there is a SA opportunity and 0 otherwise. The potential determinants of SA are: (i) Rating, with values between 1 (AA−) and 7 (BBB−); (ii) strategy liquidity, which is proxied by means of the percentage of days in which there are no observations for either the CDS or the ASP; (iii) bond amount issued, which is used to proxy the bond liquidity; (iv) number of bonds issued by a given firm, which serves as a proxy for the firm's relevance in the fixed-income market or the firm's size; (v) crisis dummy, which is used to check whether there is an increase in statistical arbitrage during the crisis period; and (vi) interaction of the crisis dummy with the rating, which is used to analyze whether there is a differential effect of the default risk on the existence of SA opportunities during the crisis. The constant term is also employed in the estimation. The dependent variable employed in Column 1 is the existence of SA based on long positions in CDS and ASP while the one used in Column 2 is the existence of SA obtained from either long or short positions in CDS and ASP. Each column reports the marginal effects of each variable. ***, ** and * denote whether the coefficient is significantly different from zero at 1%, 5% and 10% significance levels, respectively.

	Long	Long&Short
Rating	0.121**	0.134**
Strategy liquidity	−0.269	−0.312
Log of bond amount issued	−0.025	0.040
Log of number of bonds	−0.065	−0.034
Crisis	−0.304	−0.345
Crisis × Rating	0.069	0.115
Pseudo R-squared	0.16	0.07
Observations	101	101

7. Robustness tests and extensions

7.1. Accuracy with autocorrelation and jumps

In this section we analyze whether the model is robust to deviations from the normality assumption or the occurrence of jumps. The absence or existence of statistical arbitrage is based on four hypotheses H_1^c, H_2^c, H_3^c and H_4^c (see Section 2). We study the adequacy of the model from simulations of the series of the increment in the discounted cumulative trading profits. The profits are simulated by setting parameters μ, θ, and λ such that they hold one given hypothesis H_i^c and do not hold the remaining ones (H_3^c and H_4^c are considered jointly). That is, the parameters employed to simulate the profits guarantee that there are no statistical arbitrage opportunities but are close to the limits of the existence or absence of statistical arbitrage for each of the four hypotheses.[25] It allows us to have a further perspective of the individual restrictions. We perform one hundred different simulations with a sample size of 400 observations. This length is close to the average number of observations or investment days in the different cases analyzed in this paper.[26] We analyze the validity of the test after generating randomly the residuals according to four different processes and three alternative jump specifications.

We first generate randomly the residuals according to four different processes: i.i.d. normal residuals; the residuals follow a MA(1) process with the MA coefficient equal to 0.75; the residuals follow an ARMA(1; 1) process with the AR and MA coefficients equal to 0.1 and 0.75, respectively; or the residuals follow an ARMA(1; 1) process such that the coefficients of the AR and MA parts are 0.9 and 0.75, respectively. Given that we are imposing the absence of statistical arbitrage opportunities the methodology will be reliable in case it rejects the existence of statistical arbitrage in a large percentage of cases. The percentage of cases in which our test rejects the existence of statistical arbitrage at 5% significance level is equal to 100% for the three restrictions considered.

Second, we assume that the residuals follow a normal distribution with jumps defined from three specifications with different probabilities of occurrence and magnitudes normally distributed with the same mean μ and different standard deviations: (i) probability of jump 0.5% and standard deviation of the normal distribution 2σ; (ii) probability of jump 1% and standard deviation 2σ; (iii) probability of jump 0.5% and standard deviation 3σ. As in the previous analysis, our test rejects the existence of statistical arbitrage at 5% significance level in 100% of the simulations for the three jump processes and the three sets of parameters. These results are in line with HJTW's in the sense that the statistical test correctly accepts the null hypothesis of no statistical arbitrage with great accuracy, even when there are deviations (non-normality, jumps) from the baseline process.

[25] The restriction that holds is related with each of the three requirements needed for the existence/absence of statistical arbitrage. We first compare both tests using simulations where the first restriction, H_1^c, holds and employing as parameters: $\mu = -0.005$, $\sigma = 1$, $\theta = 0.5$ and $\lambda = -0.5$. The second comparison is based on the ability of the tests to detect the cases in which H_2^c holds and we employ as parameters: $\mu = 1$, $\sigma = 1$, $\theta = 0.1$ and $\lambda = 0.05$. Finally, we evaluate the case in which both H_3^c and H_4^c hold according to the following parameters: $\mu = 1$, $\sigma = 1$, $\theta = -1.025$ and $\lambda = -0.475$. Note that the last case involves two restrictions; the reason is that both of them are associated with the requirement which states that the probability of loss converges to zero.

[26] As a test of convergence, we simulate a series of profits with a sample length equal to 5,000, and find that the estimated coefficients are exactly the same to the ones employed to do the simulation.

Table 6
Relation between portfolio strategies' profits and systematic factors. This table documents the relation between the portfolio strategies' profits obtained using the baseline (Column 1) and Yu's (Column 2) methodologies. For the computation of the profits we consider the whole sample period. As explanatory variables we use proxies for three systematic risk factors: funding costs, counterparty risk, and global risk. Each column reports the coefficients for the three previous factors and the constant term. ***, ** and * denote whether the coefficient is significantly different from zero at 1%, 5% and 10% significance levels, respectively.

	Baseline method	Yu's method
Financing costs	41.936***	27.695***
Counterparty risk	22.118***	31.787***
Global risk	2.299***	2.208***
Intercept	105.110***	109.410***
R-squared	0.34	0.40
Observations	930	930

7.2. Convergence of arbitrage opportunities towards the statistical arbitrage properties

In this section we implement a test to show that during the 50 days before the last trading, the cumulative discounted profits fulfill all the criteria required for being a statistical arbitrage opportunity. Concretely, we test whether (i) the average cumulative discounted trading profit for those 50 days is higher than zero, (ii) the probability of loss is zero, and (iii) the variance of the incremental trading profits, given a decrease in wealth, is zero. To analyze the degree to which the statistical arbitrage opportunities fulfill the three previous requirements we use the statistical arbitrage opportunities at the individual firm level obtained from long positions in both CDS and ASP contracts and ignoring market frictions. We find that the cumulative discounted profits are always positive and there are no losses for any of the 16 and 8 CDS–ASP pairs before and during the crisis, respectively, in which we found statistical arbitrage. Additionally, the volatility of the incremental trading profits relative to the notional amount of each CDS trade (€500,000) is negligible for all the previous pairs. Similar properties are obtained for the two approaches employed to construct the portfolio's profits. We conclude that there is a convergence towards the statistical arbitrage requirements.

7.3. Alternative definitions of the trading strategy at the individual firm level

In this subsection, we perform some robustness tests and extensions of the statistical arbitrage analysis under the UM model at the individual firm level and ignoring market frictions.

7.3.1. Closing positions

The investor positions were not closed in the previous analysis since future losses are perfectly known at each moment if no default occurs. CDSs transfer credit risk from one party to another and it is possible that the investors only want exposure to risk for a limited period of time. These investors could liquidate their positions at a given price if there is an adequate level of liquidity in this OTC market. Thus, we analyze the same strategy but closing, every 90 days, any investment made during that period under the assumption that both CDS and ASP positions can be closed at the same time.[27] Positions are closed whenever the long basis is negative $\left(s_t^A < \bar{s}_t\right)$ to avoid closing positions at dates when an important and certain loss would take place. If the long basis is positive $\left(s_t^A > \bar{s}_t\right)$ at a given date, the positions will be closed on the first subsequent date when it is positive. However, if investors close a high number of positions at a given date, it would lead to a large payment a quarter after that date which is derived from the closed positions. It affects the mean and variance growth rates. Ignoring funding and trading costs, the number of persistent positive long bases before the crisis increases to 18 (the 16 opportunities found in the baseline analysis plus Bouygues I and Stora Enso). Nevertheless, we find the same eight mispricings during the crisis.

7.3.2. Trading days and CDS prices analysis

The investment strategy is implemented whenever there is an adequate grade of liquidity according to the information on transaction prices. However, we repeat the analysis ignoring this restriction and assume that the investments are implemented every day. For this aim, we employ quotes from CMA, Reuters, J.P. Morgan, and the Fenics curve from GFI. In the first subperiod, we find five additional mispricings. The additional mispricings are common to CMA, J.P. Morgan, and Fenics (GFI) databases: Bouygues I, Saint Gobain III, Stora Enso, Telefonica, and Vivendi. In the crisis period and ignoring funding and trading costs, we find two persistent positive long bases less, for the four databases: Edison and Telecom Italia II.

7.3.3. Trade size analysis

We employ CDSs with a notional equal to €500,000 and assume that the strategy stops if the total investment in a given bond exceeds 25% of the bond's issued amount or if the total expected future losses exceed €25,000. The reason for using this notional is to guarantee a substantial number of investments to test the existence of persistent anomalies in credit markets. However, as in

[27] Note that it is easier to get into credit derivatives contracts than it is to get out of them. The CDSs' maturity is set at a given horizon and the investor can take the other side of the nearest maturity contract and build a book of offsetting positions, or try to sell the current contract.

some execution platforms for CDSs the minimum trade size is of €1 million, we repeat the analysis employing CDSs of this notional value and increasing the barrier of losses to €50,000. In the first subperiod we find one additional persistent mispricing: Bouygues I. In the crisis period and ignoring funding and trading costs, we find an additional mispricing: Union Fenosa.

7.3.4. Limit of losses analysis

The barrier of €25,000 for the total expected losses which determine the point at which the strategy stops could seem to be an arbitrary limit. For this reason, we repeated the test with barriers of €10,000 and €50,000 and with no barrier under both UM and CM models. Results confirm that a barrier of €10,000 seems too low given that it could lead to stopping the strategy prematurely. However, a barrier of €50,000 and the absence of a barrier lead to the same results as using a limit of €25,000 for both subperiods. However, the absence of a barrier would involve a high risk for a given investor who tries to exploit such mispricing.

8. Conclusions

The 2007–2009 financial crisis and its possible consequences for the regulation of financial markets make the study of the possible persistent mispricing in financial asset markets a topic of salient relevance. In this paper, we make the following contributions to this important topic.

First, we apply the statistical arbitrage methodology to study the existence of deviations between the prices of CDS and ASP, at the individual firm level and at the portfolio level. At the individual firm level, we find evidence of a number of persistent deviations between ASP and CDS before and during the financial crisis of 2007–2009. When we aggregate the firms' CDS and ASP in a portfolio we still find persistent deviations. The empirical evidence suggests that the higher the bond's (or bond portfolio's) credit risk, the higher the probability of persistent deviations between CDS and ASP spreads. In aggregate terms the deviations from the parity relation can be explained from systematic factors such as funding costs, counterparty risk, and global risk. Once realistic assessments of the funding costs are included, all these mispricings are unlikely to provide profitable arbitrage opportunities.

The second contribution is a subsampling-based enhanced version of the previous statistical arbitrage tests that allow for non-normal, autocorrelated, and heteroskedastic innovations of the incremental trading profits. The new test finds potential arbitrage opportunities with lower downside risk than existing alternatives in the particular sample used in this study.

Our third contribution is methodological. We present a procedure which is more appropriate for misprice testing than the cointegration analysis, because it focuses on the existence of statistical arbitrage whenever only long positions in CDSs and ASPs are needed. This method is more appropriate because taking short positions in bonds included in an ASP in not likely to be feasible in most cases.

Looking forward, we expect more definite evidence on other arbitrage strategies as well as in other credit derivatives. The new test and the procedure (long positions only) of this paper can also be applied to other financial markets.

References

Bai, J., Collin-Dufresne, P., 2011. The determinants of the CDS-bond basis during the financial crisis of 2007–2009. Working Paper.

Blanco, R., Brennan, S., Marsh, I.W., 2005. An empirical analysis of the dynamic relationship between investment grade bonds and credit default swaps. J. Financ. 60, 2255–2281.

California Debt and Investment Advisory Commission, 2007. Understanding interest rate swap match & pricing. CDIAC No. 06–11 (January).

Choudhry, M., 2006. The credit default swap basis. Bloomberg Financial.

Duarte, J., Longstaff, F.A., Yu, F., 2007. Risk and return in fixed income arbitrage: nickels in front of a steamroller. Rev. Financ. Stud. 20, 769–811.

Elizalde, A., Doctor, S., 2009. The bond–CDS funding basis. J. P. Morgan European Credit Derivatives Research.

Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica 55, 251–276.

Hogan, S., Jarrow, R.A., Teo, M., Warachka, M., 2004. Testing market efficiency using statistical arbitrage with applications to momentum and value strategies. J. Financ. Econ. 73, 525–565.

Jarrow, R.A., Li, H., Ye, X., 2009. Exploring statistical arbitrage opportunities in the term structure of CDS spreads. Working Paper.

Jarrow, R.A., Teo, M., Tse, Y.K., Warachka, M., 2012. An improved test for statistical arbitrage. J. Financ. Mark. 15, 47–80.

Levin, A., Perli, R., Zakrajšek, E., 2005. The determinants of market frictions in the corporate market. Computing in Economics and Finance 2005. Society for Computational Economics, 379.

Longstaff, F.A., Mithal, S., Neis, E., 2005. Corporate yield spreads: default risk or liquidity? New evidence from the credit default swap market. J. Financ. 60, 2213–2253.

Mayordomo, S., Peña, J.I., Romo, J., 2011. The effect of liquidity on the price discovery process in credit derivatives markets in times of financial distress. Eur. J. Finance 17, 851–881.

Mengle, D., 2007. Credit derivatives: an overview. Econ. Rev. Fed. Reserve Bank Atlanta 1–24 (issue Q4).

Politis, D.N., Romano, J.P., 1994. The stationary bootstrap. J. Am. Stat. Assoc. 89, 1303–1313.

Politis, D.N., Romano, J.P., Wolf, M., 1995. Subsampling for nonstationary time series. Technical Report no. 483, Department of Statistics, Stanford University.

Politis, D.N., Romano, J.P., Wolf, M., 1997. Subsampling for heteroskedastic time series. J. Econ. 81, 281–317.

Politis, D.N., Romano, J.P., Wolf, M., 1999a. Subsampling. Springer Series in Statistics. Springer, New York.

Politis, D.N., Romano, J.P., Wolf, M., 1999b. Subsampling intervals in autoregressive models with linear time trend. Econometrica 69, 1283–1314.

Schonbucher, P.J., 2003. Credit Derivatives Pricing Models: Models, Pricing, Implementation. Wiley Finance, New York.

Trapp, M., 2009. Trading the bond–CDS basis — the role of credit risk and liquidity. Centre for Financial Research-Working Paper No. 09–16.

Yu, F., 2006. How profitable is capital structure arbitrage? Finan. Anal. J. 62, 47–62.

Zhu, H., 2006. An empirical comparison of credit spreads between the bond market and the credit default swap market. J. Financ. Serv. Res. 29, 211–235.