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Are There Arbitrage Opportunities in Credit Derivatives Markets? A New Test and an Application to the Case of CDS and ASPs

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Abstract

This paper analyzes possible arbitrage opportunities in credit derivatives markets using self-financing strategies combining Credit Default Swaps and Asset Swaps Packages. We present a new statistical arbitrage test based on the subsampling methodology which has lower Type I error than existing alternatives. Using four different databases covering the period from 2005 to 2009, long-run (cointegration) and statistical arbitrage analysis are performed. Before the subprime crisis, we find long-run arbitrage opportunities in 26% of the cases and statistical arbitrage opportunities in 24% of the cases. During the crisis, arbitrage opportunities decrease to 8% and 19%, respectively. Arbitrage opportunities are more frequent in the case of relatively low rated bonds and bonds with a high coupon rate.

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This paper analyzes potential arbitrage opportunities arising from a cash-and-carry strategy where the arbitrageur trades two self-financing portfolios based in credit derivatives. The first portfolio contains a long position in a Credit Default Swap (CDS) while the second contains a long position in an Asset Swap Package (ASP) funded at Euribor. Note that this second portfolio is equivalent to a synthetic short position in a CDS. For this reason, there should be an equivalence relationship between the payoffs of both portfolios, which are given by the CDS premium and the asset swap spread, respectively. If for a given pair of payments the equivalence does not hold, there exists an arbitrage opportunity. The existence of arbitrage opportunities is studied from two different perspectives. The first perspective analyzes possible long-run (cointegration) arbitrage opportunities while the second one tests the existence of statistical arbitrage opportunities.

The popularity of CDS and ASP has been growing in the recent years. CDS is the most widely traded credit derivative, to the extent that the British Bankers' Association estimates that it accounted for 33% of the market share of credit derivatives in 2006. According to the International Swaps and Derivatives Association (ISDA), the value of CDS outstanding was $62.2 trillion at the end of 2007. After the start of the subprime crisis, the notional amount outstanding decreased up to $38.6 trillion at the end of 2008. ASP is a liquid instrument and it is even easier to trade an ASP than the underlying defaultable bond alone (Schonbucher (2003)).[1]

The existence of long-run arbitrage opportunities is analyzed using the cointegration test proposed by Engle and Granger (1987). Given that both credit derivatives price credit risk, we expect them to be closely linked in the long-run. Blanco, Brennan and Marsh (2005) analyze this equivalence relationship for CDS and bond spreads and find support, in general, for the parity relation as a long-run equilibrium condition. Zhu (2006), in a similar study, finds similar results and also analyzes the determinants of the

[1] Mayordomo, Peña and Romo (2009) report empirical evidence suggesting that ASP spreads lead bond's spreads in the price discovery process.

basis, defined as the difference between the CDS and bond spreads. He finds that both spreads respond differently to credit conditions such as rating events. De Wit (2006) analyzes the basis calculated as the difference between par ASP and CDS spreads and applies a cointegration test to show that the basis is usually stationary. In fact, ASP spreads should be a more accurate measure of credit risk than bond spreads. This idea is supported by De Wit (2006), Felsenheimer (2004), Francis, Kakodkar and Martin (2003) and Mayordomo, Peña and Romo (2009) among others.

Arbitrage strategies in fixed income markets such as swap spread arbitrage, yield curve arbitrage, mortgage arbitrage, volatility arbitrage and capital structure arbitrage are addressed in Duarte, Longstaff and Yu (2007). They find that all the five previous strategies yield positive excess returns which are positively skewed. On the basis of these results, they suggest that there may be more economic substance to fixed income arbitrage than simply "picking up nickels in front of a steamroller". Capital structure arbitrage is usually based on strategies trading equity instruments against CDSs. Yu (2005), Bajlum and Larsen (2007) and Cserna and Imbierowicz (2008) find significant positive capital structure arbitrage returns.

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 exploit persistent anomalies and was firstly introduced by Hogan, Jarrow, Teo and Warachka (2004) (HJTW henceforth) and later improved in Jarrow, Teo, Tse and Warachka (2007) (JTTW henceforth). They test statistical arbitrage on stock markets. 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, although momentum and value strategies offer the most profitable trading opportunities.

HJTW and JTTW tests are based on the behavior of the increment in cumulative trading profits associated with the corresponding strategies. In both studies, innovations are assumed to be weakly dependent and stationary. Therefore, JTTW use a stationary bootstrap methodology to compute the test statistic's empirical distribution. Stationarity is a very convenient assumption but also a restrictive one when modeling financial time series. Just as it is also restrictive to treat the errors in any empirical econometric work as homoskedastic. The first contribution of our paper is to present a new test that allows for nonstationarity in incremental trading profits series and also for non-normal, autocorrelated, heteroskedastic and possibly nonstationary innovations. This new test is based on the subsampling methodology introduced in Politis, Romano and Wolf (1995) and (1997) and extended in Politis, Romano and Wolf (1999) and (2001). This technique is based on asymptotic inference and provides an asymptotically valid test under weak assumptions. Extensive simulation exercises suggest that our test has lower Type I error (false positive) than existing alternatives.

To the best of our knowledge, ours is the first paper that applies the statistical arbitrage methodology to the credit derivatives markets. This is our second contribution.

Our third contribution relates to the appropriate way of testing for arbitrage opportunities. Usually arbitrage analysis is based on the assumption that financial instruments (in our case bonds and ASPs) can be shorted. Nevertheless, shorting a corporate bond or ASP is not always a feasible option (see Schonbucher (2003) or Mengle (2007)). Therefore, we focus our analysis to testing the cases where long positions in CDSs and ASPs are needed. Moreover, we extend the study to test the strategies that are associated with short-sales of bonds or ASPs. We also analyze two different periods which cover the periods before and during the subprime crisis to take into account the effects of the ongoing financial crisis. The results suggest that long-run arbitrage opportunities decreased substantially during the crisis, being the same true but to a lesser extent in the case of statistical arbitrage. This is our fourth contribution.

Using four different databases (GFI, CMA, Reuters, and J.P. Morgan) and a sample of fifty seven cases, which correspond to the same number of bonds, that spans from November 2005 to August 2007, we find fifteen long-run arbitrage opportunities with the cointegration test. Using the methodology of HJTW and JTTW, twenty nine statistical arbitrage opportunities are found. The new test finds fourteen statistical arbitrage opportunities. Employing a sample of forty seven cases which covers the crisis period and spans from August 2007 to June 2009, we find four long-run arbitrage opportunities and nine statistical arbitrage opportunities with the new test. Employing HJTW and JTTW methodology, we find twelve statistical arbitrage opportunities.[2] Moreover, we find that the following factors affect positively and significantly the existence of statistical arbitrage opportunities: bonds with relatively low issuer rating and with a high coupon rate. In general terms, there seems to be one salient factor that determines the existence of statistical arbitrage: credit risk. This is our fifth contribution.

The paper is divided into eight sections. Section I includes the cash-and-carry arbitrage strategies. Section II presents the long-run arbitrage test. In Section III we address the concept of statistical arbitrage and its application. In Section IV we introduce the new test. Section V describes the data. Section VI presents the results for long-run arbitrage and statistical arbitrage analyses. Section VII includes robustness tests and extensions and Section VIII concludes the paper.

[2] It should emphasized that our test is only applied when there is trading activity and liquid enough prices.

I Cash-and-carry arbitrage strategy

A Credit Default Swaps

A CDS is a traded instrument insurance contract which provides protection against credit risk in exchange for periodic premium payments (the CDS spread multiplied by the notional amount) until the occurrence of a credit event[3] or the maturity date of the contract, whichever is first. In the event of default, any accrued premium is paid, and the protection seller makes a payment to the protection buyer for the amount of the notional against the delivery of a reference asset, a previously agreed fixed payoff (irrespective of recovery), or the notional minus post-default market value of a reference asset. A single-name credit default swap (CDS) (also known as a credit swap) is the most popular credit derivative instrument. The British Bankers' Association estimates that it accounted for 33% of the market share of credit derivatives in 2006. According to the ISDA statistics, the CDS market exploded over the past decade to more than $45 trillion in mid-2007[4] and more than $62 trillion at the end of 2007. However, the notional amount outstanding decreased to $38.6 trillion at the end of 2008.[5]

Most CDSs are quoted for a benchmark time-to-maturity of five years but since CDSs are traded Over the Counter (OTC) any maturity is possible. The spread is quoted in annual terms but standard premium payments are settled in quarterly terms with an "actual/360" day count convention. A CDS is unfunded and so, investors do not make an up-front payment (ignoring dealer margins and transaction costs). Thus, the traded CDS premium or the market CDS spread is an at-market annuity premium rate $\bar{s}$ such that the market value of the CDS is zero at origination.

[3]The credit events, similar to other Credit Derivative Definitions, are established by the ISDA and include: bankruptcy, failure to pay, obligation acceleration, repudiation/moratorium or restructuring.

[4]This amount is roughly twice the size of the U.S. stock market (which is valued at about $22 trillion) and far exceeds the $7.1 trillion mortgage market and $4.4 trillion U.S. treasuries market.

[5]In order to provide a further perspective, the value of CDSs outstanding at the end of 2004, 2005 and 2006 was $8.42, $17.1 and $34.4 trillion, respectively.

B Asset Swap Packages

An ASP contains a defaultable coupon bond with coupon $\bar{c}$ and an interest-rate swap (IRS) that swaps the bond's coupon into Euribor plus the asset swap spread rate s^A. The asset swap's fixed leg represents the buyer's periodic fixed rate payments, while its floating leg represents the seller's potential payment.[6] The asset swap spread is chosen such that the value of the whole package is the par value of the defaultable bond and for this reason, it is also known as a par to par swap.[7]

The IRS included in the asset-swap package has zero cost and so the asset swap's cost is the cost associated with the defaultable bond included in the package. Given that the asset swap spread valuation is obtained using the bond's face value (FV), an up-front payment must be added to the bond's price at the investment period t to ensure that the value of the whole package is FV.[8] So, the asset swap spread is computed by setting the present value of all cash flows equal to zero and the up-front payment represents the net present value of the swap.

C Cash-and-carry strategy

A combined long position in a CDS (buy protection) and an ASP is hedged against 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

[6] According to the California Debt and Investment Advisory Commission (CDIAC), floating-rate payment intervals in a 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.

[7] The ASP spread consists of two parts:
(i) The difference between the bond coupon and the par swap rate, which is known as the spread from par swap adjustment.
(ii) The difference between the bond price and its par value, which is known as the spread from notional adjustment.

[8] The up-front payment is paid (received) at origination, compensating the investor for bond price being over (under) par.

cash-and-carry strategies, we construct two equivalent portfolios which should produce the same payments and then analyze the existence of possible arbitrage opportunities.

Portfolio I

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

Portfolio II

- Long position in an ASP whose cost is equal to the bond's par value. The investor pays to the counterparty the bond's coupon at the coupon dates in exchange for receiving every quarter the 3-month Euribor rate ($E_{3m,t}$) plus the asset swap spread (s^A). The quarterly payment dates coincide with the CDS premium payment dates.
- Loan (principal equals to the bond's face value) at 3-month Euribor.[9] Interest payment dates coincide with both CDS premium and asset swap floating leg payment dates.

Portfolio II is equivalent to a synthetic short position in a CDS and so, there should be an equivalence relationship between CDS and asset swap spreads. Otherwise, arbitrage opportunities may appear.

As CDSs are OTC instruments, it is possible to buy a CDS contract whose maturity coincides with the bond's maturity and whose premium payments timing is agreed by the parties.[10] Thus, we take advantage of the range of CDSs maturities to fit a CDS curve using a Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) algorithm that permits us to match asset swap and CDS maturities. This method is also used in Levin, Perli and Zakrajšek (2005).

[9] In order to proceed in this way, we assume that the investor can borrow money at Euribor flat. Other funding rates are analyzed later.

[10] As the bond's maturity date approaches, the use of CDSs with a 5 years constant maturity would lead to an overhedging, given that the maturity dates of CDSs and asset swaps do not coincide. The consequence is that the investor will pay a CDS spread above the one needed to be fully hedged.

At origination the cost of both portfolios is zero, and so the net payoff is also zero. CDS' premium is paid quarterly and the first payment takes place a quarter after origination. At this date and at every subsequent quarter, the investor pays the CDS premium ($\bar{s}$), receives the floating leg payment of the ASP ($E_{3m} + s^A$) and pays the interest associated with the loan (E_{3m}). 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 basis. This payment is repeated every quarter up to maturity or default, whichever comes first.

At the coupon payment dates, the investor receives the coupon ($\bar{c}$) 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. Moreover, from the IRS floating leg, the investor receives 3-month Euribor rate plus the asset swap 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. Again, as in every quarterly payment, the net payoff is equal to the basis.

In case of default, at a given date τ, the investor recovers a portion of the bond face value $R(\tau)$, and through the protection bought in the CDS, the investor receives the difference between the bond face value (FV) and the recovery rate. The loan must be refunded and its accrued interest must also be paid. Moreover, the value of the remaining IRS included in the asset swap, $vs(\tau)$, the CDS accrued premium and the cheapest-to-deliver option, $chdo(\tau)$,[11] might also be taken into account. The payment if a credit event

[11] This option appears because in the event of a default, not only the underlying bond but a given number of bonds can be delivered. These bonds may have different prices after default and it gives the holder of a CDS a cheapest-to-deliver bond option, due to the fact that he could purchase a bond cheaper than the underlying for delivery. We ignore the effect of cheapest-to-deliver options, due to the analytical

occurs at time $\tau\epsilon(t_2, t_3)$, $p(\tau)$, is:

$$p(\tau) = R(\tau) + vs_{t_1}(\tau) - \bar{s}_{t_1}(\frac{\tau - t_2}{360}) + (FV - R(\tau)) - FV - E_{3m,t_2}(\frac{\tau - t_2}{360}) + chdo(\tau) =$$

$$= -\bar{s}_{t_1}(\frac{\tau - t_2}{360}) - E_{3m,t_2}(\frac{\tau - t_2}{360}) + vs_{t_1}(\tau) + chdo(\tau) \tag{1}$$

where $vs_{t_1}(\tau)$ represents the value after the credit event of the IRS bought at t_1. Given that IRSs included in ASPs remain alive after default, they should be serviced or unwounded at market value. $\bar{s}_{t_1}(\frac{\tau - t_2}{360})$ reflects the CDS accrued premium from the last payment date t to the credit event τ. The investor must pay the loan's accrued interest at 3 months effective Euribor, which are calculated from the last payment date to the credit event date: $E_{3m,t_2}(\frac{\tau - t_2}{360})$.

If CDS premium and asset swap spreads are similar, the only payoff difference arises at default. In case of no default, the payments are given by the difference between the credit spreads, $s_t^A - \bar{s}_t$, in quarterly terms. Schonbucher (2003) defines a series of assumptions under which the asset swap spread can be considered a good indicator for a fair CDS spread. Thus, the accuracy of this relationship depends on the degree to which the following assumptions are fulfilled:

(i) The initial value of the underlying bond is at par.

(ii) Interest rate movements and defaults occur independently.

(iii) Short positions in the asset swap market are possible.

Assumptions (i) and (ii) ensure that the value of the IRS does not introduce any bias

limitations on valuing them from the CDS prices.

in the analysis.[12] In particular, from (ii), the expected market value of the IRS at default is zero although the realized value can be different to zero.[13] Assumption (iii) is necessary to reach a two-sided bound on the CDS rate. According to Duffie (1999), the synthetic CDS obtained from the use of an ASP does not exactly replicate CDS payoffs because the IRS involved in it remains alive after default, unless it is an extinguishable IRS which, on the other hand, is a very illiquid instrument. However, under the assumptions (i), (ii) and (iii) and given that we use bonds issued by investment grade firms, one should expect them to be very close.

If $s_t^A - \bar{s}_t > 0$, then a profitable arbitrage opportunity exists. The investor should take long positions in both CDS and ASP and borrow the required quantity of money in order to finance the investment at 3 months Euribor. If $s_t^A - \bar{s}_t < 0$, the inverse strategy will lead to an arbitrage opportunity. Thus, assumption (iii) is needed in order to guarantee that the equivalence relationship holds and therefore, an adequate arbitrage's analysis under the cointegration methodology is based on this assumption. Nevertheless, shorting a corporate bond or an ASP with a required maturity, even years, is unfeasible.[14] This fact implies that deviations in the equivalence relationship might not imply arbitrage opportunities whenever an asset swap short sale is needed. Thus, traders might not be able to exploit price differentials when the CDS premium is higher than the asset swap

[12] Even for bonds whose prices are close to par, one observes differences between CDS premiums and asset swap spreads. There are explanations for this: CDSs contain a cheapest-to-deliver option, the difficulty of short selling a bond and the repo cost associated with it, the existence of a liquidity premia or other ignored costs and differences between asset swap and CDS valuation methods.

[13] Independence hypothesis has been widely used in the literature. For instance, Hull and White (2000) and (2001) extend this hypothesis assuming that default probability, interest rates and recovery rates are independent. High interest rates cause companies to experience financial difficulties and then the probability of default increases. The interval of time between the occurrence of high rates and the company default could even be measured in years.

[14] The short sale of bonds or ASPs could be done via a repurchase agreement (repo) but as Blanco, Brennan and Marsh (2005) explain, it is impossible to borrow a bond via a repo. The reason is that repo market for corporate bonds is illiquid and even if it were possible to short a bond via a repo, the tenor of the agreement would be short. Schonbucher (2003) states that this limitation could be solved by issuing credit-linked notes linked to the corresponding bond and selling them to the investors in the asset swap market. This alternative presents other limitations given that the issuance of credit-linked notes takes time and implies high fixed costs.

spread and this asymmetry may affect significantly the dynamic adjustment of credit spreads. A cointegration test as the one employed in Blanco, Brennan and Marsh (2005) cannot isolate strategies where an ASP short sale is involved because it is based on both types of deviations from the equivalence relation. However, a statistical arbitrage test enables us to relax assumption (iii) given that it permits us to study unilaterally the existence of statistical arbitrage whenever long positions in ASPs are needed. Hence, we exclude from the study any strategy which is associated with short-sales of bonds or ASPs.

Other secondary assumptions which facilitate the analysis are:

(iv) Once the credit event occurs, the termination payment is made immediately after.

(v) Tax effects are ignored.

(vi) Market segmentation does not affect the arbitrageur, who has no restriction on participating in the CDSs market.

In order to detect the existence of possible persistent anomalies, the same self-financing strategy based on the same individual bond should be repeated across time, maintaining all the terms and conditions. Thus, 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. 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.[15] Once the strategy's investments stop, future payments are fully known because both CDS and asset swap spreads are set at the investment date and remain constant. A statistical arbitrage opportunity implies that the amount invested in the risk-free asset

[15] The CDS typical notional amount is €10-20 millions for investment grade credits and €1-5 millions for high yield credits and the standard bond's face value is €1,000. Successive repetitions of this strategy might imply high demand of a given bond 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.

becomes more important over time than the daily investments.

The cumulative trading profits obtained at every period are discounted up to the initial date. Thus, 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 $t-1$.

II Long-Run Arbitrage

The cointegration test proposed by Engle and Granger (1987) has been widely used to study the long-term relationship among non-stationary financial series. The most common example where this test is used is the spot price at t and the forward (futures) contract at time $t-k$, which expires at time t, see Brenner and Kroner (1995). Blanco, Brennan and Marsh (2005), Forte and Peña (2009), Norden and Weber (2004) and Zhu (2006) analyze and, in general, find support for the existence of an equivalence relationship between bond and CDS markets in the long run by means of a cointegration test.[16] The cointegration methodology is also a popular tool among practitioners such as hedge fund managers (see Alexander, Giblin and Weddington, 2001 or Alexander and Dimitriu, 2004).

The arbitrage-based equivalence of CDSs premiums and asset swaps spreads implies that credit risk tends to be priced equally in both credit markets in the long run. By means of the cointegration methodology, we test if a given pair of credit spreads shares a common stochastic trend (Stock and Watson (1988)). As the companies included in our database are free from credit events, the payments are defined as the difference between both credit spreads. Thus, the existence of long-run arbitrage opportunities will be tested through a cointegration analysis based on the cash-and-carry strategy payments from

[16] The package formed by a bond and a CDS on the bond issuer company is default free and as a consequence it is equivalent to a default-free bond. So, the CDS spread should be equal to the spread between the defaultable bond and the default-free bond. These papers use different bonds with different maturities in order to construct a synthetic 5-year bond spread to be compared with the 5-year CDS spread. This synthetic bond is not traded in financial markets and cannot be used for arbitrage strategies.

Portfolio I (CDS spread) and Portfolio II (ASP spread).

Firstly, we study the series stationarity applying the standard Dickey-Fuller unit root test. Subsequently, the existence of a cointegration relationship is tested based on the following long-run relationship:

$$s_t^A = \alpha + \beta \bar{s}_t \tag{2}$$

Assuming that both series are integrated with order one, $I(1)$, both markets should price credit risk equally in the long run and so, both spreads should be cointegrated with a cointegrating vector $[1, -1, c]$. According to equation (2), it means that β should be equal to 1. Parameter α should be equal to zero in order to assure that no long-run arbitrage exists, but as there could be transaction costs or other market frictions and even misspecifications, we do not impose this condition and α can be different from zero and equal to a given constant c. This is equivalent to saying that the basis should be stationary, in order to support the absence of long-run arbitrage.

III Statistical Arbitrage

A Definition

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) $\lim_{t\to\infty} E^P[v(t)] > 0$

(iii) $\lim_{t\to\infty} P(v(t) < 0) = 0$, and

(iv) $\lim_{t\to\infty} Var[\Delta v(t) \mid \Delta v(t) < 0] = 0$

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 non-negative, their variability is not penalized. In other words, and as JTTW state, this condition avoids penalizing positive profits deviations from their expected values, given that investors benefit from these deviations.

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 is a special case of statistical arbitrage with a zero cost trading strategy that offers the possibility of a gain with no possibility of a loss. Hence, the probability of a loss should be equal to zero at the timepoint t^*, $P(v(t^*) < 0) = 0$. Thus, statistical arbitrage converges to standard arbitrage in the limit (as t tends to infinity).

B Implementation

The methodology for analyzing the existence of a statistical arbitrage opportunity 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. Firstly, we employ a process denoted as the unconstrained mean (UM) model where Δv_i is assumed to evolve over time as:

$$\Delta v_i = \mu i^{\theta} + \sigma i^{\lambda} z_i \tag{3}$$

for $i = 1, 2, ..., n$ 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 equation (3) 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:

$$v(t_n) = \sum_{i=1}^{n} \Delta v_i \overset{d}{\sim} N(\mu \sum_{i=1}^{n} i^{\theta}, \sigma^2 \sum_{i=1}^{n} i^{2\lambda}) \tag{4}$$

while the log likelihood function for the increments in equation (3) is:

$$\log L(\mu, \sigma^2, \lambda, \theta \mid \Delta v) = -\frac{1}{2} \sum_{i=1}^{n} \log(\sigma^2 i^{2\lambda}) - \frac{1}{2\sigma^2} \sum_{i=1}^{n} \frac{1}{i^{2\lambda}} (\Delta v_i - \mu i^{\theta})^2 \tag{5}$$

The parameters are estimated by maximizing the previous log likelihood function from a non-linear optimization method based on a Quasi-Newton-type algorithm.

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

H1: $\mu > 0$,

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

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

The first hypothesis is due to the second property of statistical arbitrage which requires that the expectation of the discounted cumulative trading profits is positive. The second hypothesis is obtained from the fourth property and ensures that the variance of the incremental trading profits, given a potential drop in them, converges to zero. The third hypothesis involves the trend in expected profits and the trend in volatility and its expression comes from the convergence of $P(v(t) < 0)$ to zero. It ensures that any potential decline in expected trading profits do not prevent convergence to arbitrage.

As in JTTW, a more restrictive version of model (3) is also employed in the analysis. It is based on constant expected profits over time and it implies that the parameter θ

is set to zero. This model is defined as the constrained mean (CM) model. Under this assumption, the process for the evolution of the incremental trading profits is:

$$\Delta v_i = \mu + \sigma i^{\lambda} z_i \tag{6}$$

And the required hypotheses to be satisfied for the existence of statistical arbitrage opportunities are:

H1: $\mu > 0$,

H2: $\lambda < 0$.

C Hypothesis Testing

Under the assumption that the trading profits evolve as a UM model, all the following restrictions must be satisfied simultaneously to have a statistical arbitrage opportunity:

$R_1 : \mu > 0$ and

$R_2 : \lambda < 0$ or $\theta - \lambda > 0$, and

$R_3 : \theta - \lambda + \frac{1}{2} > 0$ and

$R_4 : \theta + 1 > 0$.

Nevertheless, if the trading profits evolve as a CM model (6) the restrictions to be satisfied simultaneously become:

$R_1 : \mu > 0$ and

$R_2 : \lambda < 0$.

The existence of statistical arbitrage is thus based on an intersection of sub-hypothesis. On the other hand, the absence of statistical arbitrage is based on a union of four sub-hypotheses which are given by the complementary of the previous four hypotheses. We set the null hypothesis as the absence of statistical arbitrage and then, the restrictions for the UM model become:

$R_1^c : \mu \leq 0$ or

$R_2^c : \lambda \geq 0$ and $\theta - \lambda \leq 0$, or

$R_3^c : \theta - \lambda + \frac{1}{2} \leq 0$ or

$R_4^c : \theta + 1 \leq 0$.

While for the CM model the restrictions are:

$R_1^c : \mu \leq 0$ or

$R_2^c : \lambda \geq 0$.

If one of the previous restrictions is satisfied, we conclude that no statistical arbitrage opportunities exist.

D Statistical Arbitrage Tests

The results obtained by HJTW could be influenced by the limitations of the Bonferroni approach employed in the paper. Their test presents a low statistical power to reject an incorrect null hypothesis in every case. In fact, the statistical power decreases as the number of restrictions increases, leading to an unacceptable level of Type II error. JTTW overcome these limitations by introducing the Min-t test methodology[17] and employing the stationary bootstrap procedure proposed by Politis and Romano (1994), which allows for time dependence and stationary residuals, to estimate the *p-values*. The assumption that the incremental trading profits innovations are normal and uncorrelated seems very restrictive as several studies in empirical finance such as Affleck-Graves and McDonald (1989) and Lo and MacKinlay (1988) reveal. For this reason, JTTW test the case where the innovations z_i follow a stationary weakly dependent process. Thus, both HJTW [18] and JTTW impose a MA(1) process for z_i to test if it could improve the statistical

[17] As the four restrictions R_i must be simultaneously satisfied to reject the null hypothesis of no statistical arbitrage, the minimum of their associated t-statistics serves as a rejection criterion. Thus, Min-t test considers separately the t-statistics associated with the four restrictions R_1, R_2, R_3 and R_4 and finds the minimum.

[18] HJTW proved that the presence of an MA(1) process neither alters the conditions for statistical arbitrage nor increases the number of sub-hypothesis.

efficiency of the remaining parameter estimates and avoid inappropriate standard errors. Nevertheless, JTTW show that allowing for this serial correlation does not change their conclusions significantly.

IV A New Test of Statistical Arbitrage

This paper presents an enhancement with respect to JTTW methodology. The reason is that assuming stationarity seems restrictive when modelling financial time series. Just as it is also restrictive to treat the errors in any empirical econometric work as homoskedastic. We allow incremental trading profits series to be nonstationary and innovations z_i to be non-normal, autocorrelated, heteroskedastic and possibly nonstationary. In this more general situation, the use of the stationary bootstrap is not advisable for estimating the *p-values* for the Min-t statistics.[19] Thus, we employ a new test from the use of the subsampling method introduced in Politis, Romano and Wolf (1995) and (1997) and extended in Politis, Romano and Wolf (1999) and (2001).[20] 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 equation (5).[21]

Let $(x_1, ..., x_n)$ be a sample of n observations that are distributed in a sample space

[19] Stationary bootstrap is generally applicable for stationary weakly dependent time series. Subsampling allows for a more general structure in the innovations. Thus, in Politis, Romano and Wolf (1997), it is shown that in the presence of heteroskedasticity in residuals, subsampling gives better results for "the right choice" than moving blocks 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.

[20] One may expect that both the increment in the discounted cumulative trading profits and the innovations should be stationary. Nevertheless, our sample only spans two years and a unit root test in this case usually has low power (Shiller and Perron (1985)). It should be noted however, that subsampling methodology allows for a more general process both in profits and innovations and even for nonstationarity in some cases.

[21] The use of quasi maximum likelihood estimation enables us to test the existence of potential statistical arbitrage opportunities without imposing a specific process to the residuals based on the log likelihood function derived under normality in equation (5).

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 where the null hypothesis translates into a null hypothesis about a real-valued parameter $\xi_i(P)$. The test statistic is defined as:

$$T_{i,n} = \tau_n t_{i,n}(X_{1,}..., X_n) = \tau_n(\overset{\wedge}{\xi}_{i,n}(X_{1,}..., X_n) - \xi_{i,0}) \qquad for\ i = (1, 2, 3, 4) \tag{7}$$

where τ_n is a normalizing constant and, as in regular cases, we set $\tau_n = n^{\frac{1}{2}}$, $\overset{\wedge}{\xi}_{i,n} = \overset{\wedge}{\xi}_{i,n}(X_1,..., X_n)$ 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 *ith statistic* and $\xi_{i,0}$ is the value of $\xi_{i,n}$ under the null hypothesis. Each of the four statistics are defined from the restrictions R_i^c in Section III.C which lead to four contrasts of hypothesis based on real-valued parameters such that:

$$\begin{cases} H_0 : \xi_i(P) \leqslant \xi_{i,0} \\ H_1 : \xi_i(P) > \xi_{i,0} \end{cases} \qquad for \quad i = (1, 2, 3, 4) \tag{8}$$

where $\xi_{i,0}$ is equal to zero in our analysis. The test is applied to the union of restrictions R_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 *ith* statistic $T_{i,n}$ under P_i can be denoted by:

$$G_{i,n}(x, P_i) = \mathrm{Prob}_{P_i}\{T_{i,n}(X_1,..., X_n) \leq x\} \tag{9}$$

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.

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

$$\hat{G}_{i,n,b}(x) = \frac{1}{n-b+1} \sum_{t=1}^{n-b+1} 1| \left\{ \tau_b t_{i,n,b,t}(X_1, ..., X_n) \leq x \right\} \tag{10}$$

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

$$t_{i,n,b,t}(X_1, ..., X_n) = \overset{\wedge}{\xi}_{i,n,b,t}(X_t, ..., X_{t+b-1}) - \overset{\wedge}{\xi}_{i,n,t} \tag{11}$$

where $\overset{\wedge}{\xi}_{i,n,b,t}$is the estimator of $\xi_{i,n}(P_i) \in \mathbb{R}$ based on the subsample $(X_t, ..., X_{t+b-1})$ and $\overset{\wedge}{\xi}_{i,n,t}$ 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:

(i) The estimator, properly normalized, has a limiting distribution.

(ii) 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 $\hat{G}_{i,n,b}(x)$:

$$g_{i,n,b}(1-\alpha) = \inf\{x : \hat{G}_{i,n,b}(x) \geqslant 1-\alpha\} \tag{12}$$

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, Romano and Wolf (1999), 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 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:

$$T_{i,n}= \tau_n(\overset{\wedge}{\xi}_{i,n}(\Delta v_{1,}..., \Delta v_n) - \xi_{i,0}) \qquad for\ i = (1,2,3,4) \tag{13}$$

and the estimated residuals $\hat{z}_i$:[22]

$$\hat{z}_i = \frac{\Delta v_i - \overset{\wedge}{\mu} i^{\overset{\wedge}{\theta}}}{\overset{\wedge}{\sigma} i^{\overset{\wedge}{\lambda}}} \qquad for\ i = 1, ...n \tag{14}$$

2. We create subsamples of consecutive blocks of data with length b such that the first subsample of residuals is defined by $(\hat{z}_1, ..., \hat{z}_b)$, and so on.

3. We generate $n-b+1$ successive subsamples of trading profits $(\Delta v_i^*, ..., \Delta v_{i+b-1}^*)$ from the corresponding residuals $(\hat{z}_i, ..., \hat{z}_{i+b})$ for $i = 1, ..., n-b$. The trading profits are calculated with the parameters under the null hypothesis such that their values bind the restrictions. Thus, the parameter values are $(\mu, \sigma, \theta, \lambda) = (-10^{-6}, \overset{\wedge}{\sigma}, -1, -0.5)$ for the UM model and $(\mu, \sigma, \lambda) = (0, \overset{\wedge}{\sigma}, 0)$ for the CM model:[23]

[22] We find that the residuals follow ARMA processes and, in some cases, they even present heteroskedasticity. It confirms that it is very restrictive to impose a $MA(1)$ process for z_i.

[23] For the UM model, five restrictions should be simultaneously satisfied to prove the existence of statistical arbitrage. However, these five restrictions involve three parameters and not all the restrictions are necessarily binding. As HJTW suggest, a model within the null family and on the boundary of all the inequality restrictions is not available. We employed other values of μ such as -0.0001 or -10^{-8} in order 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 $\overset{\wedge}{\sigma}$ does not appear in the restrictions and we use the value of the QML estimator for σ in the whole sample.

$$\Delta v_i^* = \mu i^\theta + \hat{\sigma} i^\lambda \hat{z}_i \qquad (15)$$

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 $\widehat{G}_{i,n,b}(x)$ as in equation (10) and compute the critical values $g_i(1-\alpha, P_0)$ as in equation (12) 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, Romano and Wolf (1999) 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.[24]

In the correct range of b, the confidence intervals should be "stable" when considered as a function of the block size. For this reason, we use the method defined by Politis, Romano and Wolf (1999) as the Minimum Volatility Method to select the optimum b :

1. Compute a subsampling quantile $g_{n,b}(1-\alpha)$ for $b = b_{small} = n^{\frac{2}{5}}$ to $b = b_{big} = n^{\frac{4}{5}}$.

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.

After estimating the optimal block size, we confirm, as expected, that there is not a common optimum block size for every sample. In most cases, the optimum block size is

[24] For b too close to n all subsample statistics $\hat{\xi}_{i,n,b,t}$ will be almost equal to $\hat{\xi}_{i,n}$, resulting in the subsampling distribution being too tight and in undercoverage of subsampling confidence intervals. For b too small, the intervals can undercover or overcover depending on the state of nature.

such that the ratio block size/sample size is between 0.2 and 0.45.[25] Longer blocks are needed to capture greater dependence in the innovations.

We now compare the new test with JTTW's looking at their Type I errors. Given that the null hypothesis is no arbitrage opportunities it seems advisable to choose the test with lower "false positive" record (i.e. the most conservative). The absence/existence of statistical arbitrage is based on three hypotheses, each of them associated to different requirements, or equivalently, on four restrictions R_i^c (see Subsection III.C). We study both tests using simulations of the series of the increment in the discounted cumulative trading profits. These profits are simulated by setting parameters μ, θ and λ such that they hold a given restriction R_i^c, associated to the complementary of one of the three hypotheses in Subsection $III.B$, and do not hold the remaining ones. The parameters employed to simulate the profits are close to the limits of the existence/absence of statistical arbitrage in order to discriminate between both tests in the most detailed way as possible.[26] This allows us to have a further perspective of the individual restrictions. We perform 100 different simulations with sample size of 400 observations.[27] As we find that the residuals are neither normal nor follow a $MA(1)$ process, which is the process imposed in JTTW methodology, we compare both test after generating randomly the residuals according to three different processes: $i.i.d.$ normal residuals; the residuals follow an $ARMA(1,1)$

[25] We require that the selected block size, b, can also be obtained from the expression $b = n^x$ with $x \in (0.2, 0.8)$. It guarantees that the required assumption which states that $b \longrightarrow \infty$ as $n \longrightarrow \infty$ and $\frac{b}{n} \longrightarrow 0$ as $n \longrightarrow \infty$ is fulfilled.

[26] The restriction that holds is related with each of the three requirements needed for the existence/absence of statistical arbitrage. We first compare both test using simulations where the first restriction, R_1^c, holds and employing as parameters: $\mu = -0.001$, $\sigma = 1$, $\theta = 0.5$ and $\lambda = -0.5$. The second comparison is based on the ability of the tests to detect the cases where R_2^c holds and we employ as parameters: $\mu = 1$, $\sigma = 1$, $\theta = 0.1$ and $\lambda = 0.05$. Finally, we evaluate the case where both R_3^c and R_4^c hold according to the following parameters: $\mu = 1$, $\sigma = 1$, $\theta = -1.05$ and $\lambda = -0.45$. 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.

[27] This length is close to the average number of observations or investment days in the different cases analyzed in this paper. Moreover, 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.

process with the AR and MA coefficients equal to 0.9 and 0.75, respectively; or the residuals follow an $ARMA(1,1)$ process such that the coefficients of the AR and MA parts are 0.5 and 0.75, respectively.

We find that both tests are equally effective when either restriction R_1^c, which states that the expected cumulative discounted profits are negative, or restrictions R_3^c and R_4^c, which state that the probability of loss does not converge to zero, hold. However, when restriction R_2^c, which states that the variance of the incremental trading profits does not converge to zero, hold, we find that our test cannot reject the absence of statistical arbitrage at any standard confidence level, while JTTW test signals the existence of statistical arbitrage at confidence levels between 1% and 5%, depending on the residuals process, when in fact there is no arbitrage opportunity.

V Data

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

We employ four different CDSs databases in order to have more robust results and to minimize the probability 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.[28] GFI data contain single name CDSs market prices for 1, 2, 3, 4 and 5

[28]Fulop and Lescourret (2007) describes GFI as an hybrid voice-electronic execution platforms for CDSs where dealer may be providers or consumers of liquidity. These authors state that although IDBs systems are not costless due to the existence of the interdealer broker's fee, they allow decreasing search costs and make the matching process between buyers and sellers more efficient. Moreover, and according to GFI, it is the leading broker since it would represent 60% of the interdealer brokerage activity. GFI data are available from Reuters.

years 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.[29] 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 real market prices for the maturity of 5 years, we employ mid-price quotes from a credit curve also reported by GFI.[30] GFI data have also been used by Hull, Predescu, and White (2004), Predescu (2006), Saita (2006), Nashikkar and Subrahmanyam (2007), Fulop and Lescourret (2007) or Nashikkar, Subrahmanyam and Mahanti (2009) among others.

The second source is Reuters. Reuters takes CDS quotes each day from over 30 contributors around the world and offers end of day data for single names CDSs. Before computing a daily composite spread, it applies a rigorous screening procedure to eliminate outliers or doubtful data. According to Longstaff, Mithal and Neis (2005), as the data set includes quotations from a variety of credit derivatives dealers, these quotations should be representative of the entire credit derivatives market. Jankowitsch, Pullirsch, and Veža (2008), among others, employ CDSs data from Reuters.

The third source is CMA DataVision(TM) which is available from Datastream. CMA DataVision is consensus data sourced from 30 buy-side firms, including major global Investment Banks, Hedge Funds and Asset Managers. CMA DataVision provides full co-

[29] Consensus and indicative data are trusted less now that the markets are so volatile. There exist differences of up to 100% between consensus prices from leading providers compared to actual trades on GFI systems. That is because consensus is inherently slow and the prices originate from back office staff who can be swayed by the positions they hold and they do not have a front office view.

[30] The GFI FENICS® Credit curves are calculated each hour for over 1900 reference entities. The calculation of the curves gives preference to real trades and quoted mid points where available, and in their absence will calculate a running point level using the John Hull and Alan White methodology to ensure a credit curve always exists for each reference entity. This curve is a good approximation for CDSs at any maturity as several error analyses reveal. The median of the absolute difference in basis points between five years CDS premiums as defined from credit curve and the actual quotes or transaction prices for the period between April 2001 and May 2002, is equal to 1.16, 2.01 and 3.82 basis points for AAA/AA, A and BBB ratings for a total of 2,659, 9,585 and 8,170 companies respectively. Moreover, market CDS spread could be different from what we are assuming to be the true CDS spread by as much as 3.725 bps. on average.

verage of relevant tenors, currencies, and seniorities for single names, indices and tranches and offers quoted CDS prices (bid, ask and mid). Among the papers that employ CMA data we mention Nashikkar and Subrahmanyam (2007) and Nashikkar, Subrahmanyam and Mahanti (2009).[31]

Our fourth database, employed also in Aunon-Nerin, Cossin, Hricko and Huang (2002), Blanco, Brennan and Marsh (2005) and Chen, Cheng and Liu (2008) among others, contains mid-market data provided by J. P. Morgan which is one of the leading players in the CDS market.[32]

Given the four different data sources on CDSs spreads, we cross-check the data using all the sources in order to confirm the validity of any CDS price. Due to liquidity restrictions and in order 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.[33] We find that all data sources are largely in agreement between them. Moreover, at specific dates when the spreads diverge significantly between several sources, the observation is deleted from the sample. The results that we report in the paper are the ones obtained with GFI data.[34]

For each bond there is information on both bid and ask prices, the swap spread, the asset swap spread, the sector of the entity and its geographical location, the currency, the seniority, the rating history (Fitch, S&P and Moody's ratings), the issuance date and

[31] Both papers employ two different data sources, GFI an CMA, to construct their database. They find that there exists consistency between the two sources in the periods where there is an overlap between them. CMA DataVision data are also available via the Bloomberg data service. Among the papers that employ Bloomberg, without detailing if the data proceed from the CMA system or not, are Cserna and Imbierowicz (2008) and Das, Hanouna and Sarin (2009).

[32] According to Aunon-Nerin, Cossin, Hricko and Huang (2002), J.P. Morgan was the most active trader in terms of CDS transactions.

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

[34] The results using the other three databases are consistent with GFI's and are available upon request.

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 may be used whenever they satisfy all the required criteria. The reason is that although CDS spreads quotes are referred to the issuer and not to an individual bond, asset swap spreads are quoted for individual bonds. 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. Moreover, our sample contains fixed-rate senior unsecured Euro denominated bonds whose issued quantity exceeds 150 millions of Euros. Other requirements imposed on bonds to be included in the sample are: i) straight bonds , ii) neither callable nor convertible, iii) with rating history available, iv) with constant coupons and with a fixed frequency, v) without a sinking fund, vi) without options, vii) without an odd frequency of coupon payments, viii) no government bonds and ix) no inflation-indexed bonds. We also cross-check the data on bonds with the equivalent data obtained from Datastream. Due to liquidity restrictions, investments are restricted to periods where there exist 5-year CDS data on either actual trades or bids and offers where capital is committed.

The data spans from November 1st, 2005 to 29th June 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 August 8th, 2007 while the second one spans from August 9th, 2007 to June 29th, 2009.[35] Our sample size is comparable to others in the literature on CDS and bond spreads, both in terms of sample size and number of companies.[36] The final sample consists of 50 non-financial companies

[35] The first subperiod does not show any episode of significant market turbulence. This subperiod starts after the episode of GM and Ford downgrades to "junk category" which reduced market liquidity and ends with the beginning of the subprime crisis which as usually is set at 9th August 2007. The subprime crisis implies an illiquid regime for ASPs, bonds and CDSs markets.

[36] Longstaff, Mithal and Neis (2005) include 68 firms from March, 2001 to October, 2002, Blanco, Brennan and Marsh (2005) use 33 American and European companies from January 2001 to June 2002, Zhu (2006) use 24 investment-grade companies from January 1999 to December 2002 and Forte and Peña (2009) employ data for 20 companies from September 2001 to June 2003.

and 66 bonds. In the first subsample we employ 57 bonds and 45 companies while in the second one we use 47 bonds and 37 companies.[37] Table I presents information about all issuers, asset swaps, bonds and CDSs in the two different periods under study. As shown in Panel B1 and B2 of Table I, there is a great deal of variation in the amount issued and, in the first period, in the sample size. The last column shows that bonds traded, on average, above par in the first period and below par in the second one. Panels C1 and C2 include descriptive statistics for CDS, asset swap and bond spreads for the first and second subperiod, respectively. On average, the CDS spreads seems to be lower and less volatile than the ASP spreads in both subperiods. The last column in this panel also reveals that both CDSs and ASPs are usually highly correlated with few exceptions (Carrefour I, Siemens, Technip and Veolia Environ in Panel C1 and Carrefour II in Panel C2). Note that the average correlation increased substantially in the crisis period. Finally, Panels D1 and D2 present descriptive statistics for the basis for the first and second subperiod, respectively. We observe in Panel D1 that the average basis is negative for 17 of the 57 issues while in Panel D2 it is negative for 20 of the 47 issues. On average, the basis is lower and much more volatile in the second period which suggests that arbitrage strategies become riskier during the crisis. Panels E1 and E2 report the summary statistics of the CDS spreads for the four databases during the first and second subperiod, respectively. We observe that the CDS spreads average values are similar across the different databases.[38] The average of the relative differences between the CDS spreads of the four databases is similar before and after the crisis.

[37] Our initial sample was formed by 301 corporate bond issuers. We found a total of 135 Euro denominated bonds that mature before June 2012 but only 86 of them include reliable information on the CDS spreads and the asset swap spreads. Of these, 2 bonds have been discarded because the issued amount does not exceed 150 million Euros, another 4 bonds were discarded because they were not investment grade bonds during the whole sample period. The time to maturity was lower than twelve months by August 2007 for 4 bonds that were discarded, another 3 bonds were discarded because their asset swap spreads were persistently negative and, finally, 7 bonds were discarded because prices were too far from par. Thus, although we consider all the bonds issued by non-financial European companies to be employed in our study, the final number of bonds is 66 due to the imposed requirements.

[38] Reuters EOD (end of day) data is a relatively new source and is available since 2007.

<Table I about here>

VI Results

A Long-Run Arbitrage Test Empirical Results

Table II shows that most spreads are I(1). Only in four cases during the first subperiod, Carrefour II, Casino II, Compass Group and Siemens, and in other two cases during the crisis period, Carrefour II and Schneider, credit spreads are I(0). Table II indicates that the long-run equivalence relationship holds and the two markets move together in the long run in 33 of the total 53 cases in the first period and in 38 of the total 45 cases in the second subperiod.[39] The potential long-run arbitrage opportunities could be due to the presence of a cheapest-to-deliver option in the CDS price or the constraints in the bonds' short-sales, among other causes. These opportunities should be exploited by means of cash-and-carry arbitrage strategies, where either long or short positions in ASPs are needed. Shorting asset swaps is not an easy thing and for this reason, we distinguish between the strategies that involve shorting asset swaps and the ones that involve long positions in asset swaps. Thus, we consider that a given strategy is based on an asset swap short sale whenever the sum of the discounted trading profits is significantly negative. This occurs in Akzo Nobel I, Bouyges II, Scania, Tesco I and Vodafone in the first subperiod and in Enel, Energias de Portugal I and Thyssenkrupp in the second subperiod. On the other hand, the sum of the discounted trading profits is significantly positive for the rest of the cases which means that there are 15 potential long-run arbitrage opportunities based on long positions in ASPs in the first period and 4 opportunities in the second period. The decrease in long-run arbitrage opportunities is consistent with the increase in correlation across financial markets in crisis periods documented in many papers. Although Table

[39] Blanco, Brennan, and Marsh (2005) and Zhu (2006) find a long-run equivalence relationship between CDS and bond spreads in 26 of 33 cases and in 15 of 24 cases, respectively.

II reports the results obtained from GFI data, the same results are obtained when using any of the other data sources. We next analyze the potential arbitrage opportunities that could be exploited by means of long positions in both asset swaps and CDSs employing the methodology based on the statistical arbitrage test.

<Table II about here>

B Statistical Arbitrage Test Empirical Results

The increments in the discounted cumulative trading profits $\Delta v(t_i)$ are summarized in Table III. Panel A reports the profits obtained in the first subperiod while Panel B reports the profits during the crisis period. We observe that the average value is around 74 Euros in the first subsample and 192 Euros in the second one. These profits present a high deal of variation, 78 and 420 Euros on average in the first and second subsample, respectively. The coefficient of variation for these profits during the crisis doubles the one observed in the first period. Note that the average number of days under study is higher in the second subsample with respect to the first one, 363 against 462 days. The vast majority of the cases where the average basis is negative also have a negative average of $\Delta v(t_i)$.

<Table III about here>

The Panels A and B of Table IV show the results for the analysis of statistical arbitrage under the UM model during the first and second subperiods, respectively. The results obtained for the rest of data sources (Reuters, CMA and JPMorgan) are similar to the ones reported in Table IV. The sign of parameter μ for every company in Panel A is in line with the sign of the mean incremental cumulative trading profits collected in Panel A of Table III with few exceptions (British AM Tob. I and Enel). The unconstrained mean specification is not rejected in most of the cases as the *t-statistic* associated with the parameter θ reveals. Fourteen statistical arbitrage opportunities are found at 5% confidence level during the period before the crisis. Eight of these cases also are long run arbitrage opportunities. However, the existence of statistical arbitrage is strongly rejected for cases such as Akzo Nobel I, Bouygues II, Scania, Stora Enso, Telefonica, Thales, Thyssenkrupp, Tesco I and Vodafone where supposedly there are long run arbitrage opportunities. During the crisis period we find nine statistical arbitrage opportunities and among them, there are the four long run arbitrage opportunities based on long positions in ASPs. As in the first subperiod the existence of statistical arbitrage is strongly rejected for some cases where supposedly there exist long run arbitrage opportunities which should be exploited by shorting ASPs such as Enel, Energias de Portugal I and Thyssenkrupp. The last column in Panels A and B of Table IV show the results using JTTW's test. It finds 29 arbitrage opportunities at 5% confidence level during the first subperiod and 12 opportunities more during the second one.[40] As expected and given the simulation's results, our test seems to be more conservative than JTTW. The differences between both tests are due mainly to the estimators and their corresponding *p-values* associated with restrictions R_1^c and R_2^c which are defined in Section III.C.[41] The UM model usually presents smaller Akaike Information Criteria (AIC) and Schwartz Information Criteria (SC) than the CM model, suggesting that the former is the most appropriate model. For this reason we only

[40] We find that both HJTW and JTTW tests offer similar results.

[41] Our test does not reject the absence of statistical arbitrage in some cases where the mean parameter μ is not significantly different to zero at the 5% level (France Telecom I, Kingfisher, SES and Vivendi in the first subperiod, see Panel A of Table IV, and Casino I and Union Fenosa in the second subperiod, see Panel B of Table IV). With respect to restriction R_2^c, our test does not find that the mean rate of growth is significantly higher than the variance rate of growth for Akzo Nobel II, KPN, Saint Gobain II, Saint Gobain IV, Thyssenkrupp and Volkswagen in the period before crisis and for Volvo in the crisis period. Indeed, in all these cases, the *t-statistic* associated with the difference of the QML parameters $\theta - \lambda$, which is part of the restriction R_2^c in Section III.C, is not significantly higher than zero at a significance level of 5%. Restriction R_2^c ensures that the variance of the incremental trading profits, given a potential drop in them, converges to zero. Note that it corroborates the results obtained when we compare the Type I errors of both tests focused on restriction R_2^c.

report the results obtained for the UM model.[42]

Although shorting a corporate bond or ASP is not always a feasible option, 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 statistical arbitrage opportunities during the period before crisis (Carrefour II, British AM Tob. I and France Telecom III). The number of statistical arbitrage opportunities based on ASP short sales increases to eight during the crisis period (Astrazeneca, BASF, Enel, France Telecom III, Iberdrola I, PPR, Thyssenkrupp and Volkswagen).

The more noticeable difference between both subperiods is the number of statistical arbitrage opportunities found when the strategies are based on ASPs short sales. In periods with low liquidity, ASPs short sales are less feasible that during normal regimes of liquidity. If shorting the ASPs is not feasible, it could prevent investors to exploit potential arbitrage opportunities and then deviations from the equivalence relationship between ASPs and CDSs spreads could persist over time. Comparing Panels A and B of Table III, we observe that the average of the incremental trading profits, $\Delta v(t)$, is noticeably higher during the subprime crisis. This could lead to the appearance of more statistical arbitrage opportunities if that deviation between the ASPs and CDSs spreads persists over time. However, the volatility in credit spreads has also increased considerably during the crisis which makes that the variance of the incremental trading profits also increases and as a consequence, it could even lead to the non-rejection of the restriction R_2^c.

<Table IV about here>

Table V shows the profits, the total investment, the returns, the probability of a loss and a performance ratio of the arbitrage opportunities. As one of the statistical arbitrage

[42] Detailed results for the statistical arbitrage tests with the CM model and for the AICs and SCs corresponding to the UM and CM models for both subperiods are available upon request.

conditions states that investors are only concerned about the variance of a potential decrease in wealth, we avoid penalizing positive profit deviations from their expected values, since investors benefit from these deviations. For this reason, as a performance measure ratio we show a modified version of the symmetric downside-risk Sharpe ratio in Ziemba (2005). This performance ratio is defined as the ratio between the total profits and the corresponding semi-standard deviation of payments.[43] Note that the number of investment days presents a high deal of variation. In fact, we observe that in some cases this number is even below ten. The reason is that in those cases the investment strategy stops because the total expected future losses exceed €25,000.[44] Regarding the returns and the performance ratio obtained during the period before crisis reported in Panel A of Table V, it should be noted that the only attractive opportunities compared to the ones where our test finds statistical arbitrage are KPN, Saint Gobain II, Saint Gobain III, Saint Gobain IV and Vivendi. However, KPN and Saint Gobain II do not fulfill the restriction R_2^c, the probability of loss in Saint Gobain III is around 10%, while in Vivendi and Saint Gobain IV investments take place on only 23% and 21% of the total potential trading days, respectively, and so total profits are low. On the other hand, we find statistical arbitrage opportunities under both HJTW and JTTW methodologies which correspond to cases

[43] The semivariance of payments is calculated as:

$$\sigma_-^2 = \frac{\sum_{i=1}^{n} (payment_i - \overline{payment}^*)_-^2}{n-1}$$

where $payment_i$ represents the payment at time i, $\overline{payment}^*$ refers to the payment in the 30th percentile and n defines the number of observations. The summatory is applied whenever the payment is below $\overline{payment}^*$. The ratio is defined as:

$$S_- = \frac{Total\ \Pr ofits}{\sqrt{2}\sigma_-}.$$

[44] As the stop rule imposed to the strategy leads to a low number of investment days in some of the cases where the existence of statistical arbitrage is rejected, we extend the analysis by excluding this stop rule and find similar results (see Section VII). In that case the number of investment days coincide with the number of observations reported in the Panel B2 of Table I whenever the total investment in a given bond does not exceed 25% of the bond's issued amount. Note also that the cases where the investment strategy stops, due to the high expected future losses, correspond to potential statistical arbitrage opportunities using inverse positions based on short sales of ASPs.

with either a high probability of a loss or a poor performance or both, such as Bouygues I, France Telecom I, Kingfisher, SES, Stora Enso, Union Fenosa or Volkswagen. These are rejected under our test. According to the returns and performance ratio corresponding to the crisis period which are reported in Panel B, we observe that the only attractive opportunities that our test does not detect are France Telecom II and Union Fenosa. However, France Telecom II does not fulfill the restriction R_2^c and in Union Fenosa the mean parameter μ is not significantly higher than 0 and moreover the number of days with losses is around 24% of the total. HJTW and JTTW tests consider as statistical arbitrage opportunities Casino I, Union Fenosa and Volvo. However, in these cases we observe a high probability of a loss and a poor performance compared with the statistical arbitrage opportunities detected by our test which, on the other hand, seem to be the most profitable opportunities according to all the performance measures of Table V.

<Table V about here>

Finally, we test how asset swaps, bonds and CDSs characteristics influence the existence of statistical arbitrage. To achieve this, we run a Probit regression with heteroskedasticity robust standard errors for the total 104 cases studied in both subperiods, using as dependent variable a dummy variable that equals 1 if there is a statistical arbitrage opportunity and 0 otherwise. In order to control and test the effect of the crisis, we create a dummy variable equal to one if a given case corresponds to the second subperiod. As 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 VI. The statistical arbitrage opportunities seem to be more frequent when the asset swaps packages contain relatively low-rated bonds with a high-coupon rate. Moreover, apparent long-run arbitrage opportunities are related with statistical ones. Thus, a long-run arbitrage opportunity is also a statistical arbitrage one with a probability around 34%. Finally, the crisis dummy has a non-significant effect on statistical arbitrage. According to these results, there is one salient factor that determines the existence of statistical arbitrage: credit risk. Thus, the higher the bond or issuer risk, the more frequent are the persistent deviations between CDSs and ASPs spreads. Liquidity may be other salient factor that affects statistical arbitrage. However, as Nashikkar and Subrahmanyam (2007) state, while liquidity is easy to define in theoretical terms, its empirical measurement in an accurate and reliable manner is quite difficult, except in markets that are relatively very liquid. Credit markets are not the most liquid ones and moreover, we find that the potential liquidity proxies are correlated with the issuer rating and bond coupon. We have employed several liquidity measures in the Probit regression but they are not significant with high p-values which suggests a potential relation between credit quality and liquidity and so, the liquidity effect could be implicit in the issuer rating or the coupon bond.[45]

<Table VI about here>

VII Robustness Tests and Extensions

In this section, we perform some robustness tests and extensions.[46] First, we analyze the effect on results of a periodic liquidation of positions every quarter. Then, we test how the results are affected by the introduction of some market frictions. We also repeat the analysis by allowing the standard deviation parameter to evolve as a GARCH process. Finally, we study whether a change in the limit of acceptable losses, which had been set at 25,000 Euros, has any influence on the previous results. We comment the results under

[45] We have employed as liquidity proxies: the number of 5-year CDS missing trading prices during the corresponding period, the logarithm of the bond issued amount, the number of issued bonds by the underlying company, the bond time-to-maturity (in years) and the bond age (in years). The CDS liquidity measure presents more missing trading prices during the crisis.

[46] Detailed results of the robustness tests and extensions are available on request.

the model that best fits the data according to AIC and SC.

A Closing Positions

The investor positions were not closed in the previous analysis since future losses are perfectly known at the current 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, at the end of every quarter, any investment made during that quarter under the assumption that both CDSs and asset swaps positions can be closed at the same time.[47] Positions are closed whenever the basis $(s_t^A - \bar{s}_t)$ is negative to avoid closing positions at dates when an important and certain loss would take place. If the basis is positive at a given date, the positions will be closed on the first subsequent date when the basis is negative. 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. The number of arbitrage opportunities decreases to seven during the period before crisis (Bouygues I, Louis Vuitton II, Renault, Saint Gobain IV, Sodexho, Stora Enso, Technip and Tesco II) and increases to ten during the crisis period (British AM. Tob. II, Casino III, Edison, Kingfisher, KPN, Repsol, SES, Telekom Austria, Teliasonera and Union Fenosa).

[47] Note that it is easier to get into credit derivatives contracts than it is to get out of them. This is partly due to the fact that the maturity is set at a given horizon for CDSs and one can take the other side of the nearest maturity contract and build a book of offsetting positions, or try and sell the current contract.

B Market Frictions Analysis

The strategy is developed assuming the absence of borrowing spreads and transaction costs. This assumption could be acceptable during the period before crisis but it seems less feasible during the crisis. Thus, we also measure the impact of market frictions such as transactions costs and higher borrowing costs. In those cases, the basis is usually lower. For the first subperiod analyzed in this paper, if the sum of transaction costs and borrowing spreads is greater than 2 b.p. the statistical arbitrage opportunities disappear in British AM Tob. II, Louis Vuitton I, Repsol YPF, Reuters and Technip. When they are greater than 3 b.p., the same is true for Altadis, Casino I and II and Compass Group. Ditto for 4 b.p. in Edison and Renault and in PRR and Tesco II for 5 b.p.. Finally, the statistical arbitrage opportunity found in Sodexho remains until costs exceed 7 b.p.. In order to have a better perspective of these 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. In the crisis period, we find that if the sum of the transaction costs and borrowing spreads is greater than 1 b.p., the statistical arbitrage opportunities disappear in SES, Telecom Italia II and Telekom Austria. When they are greater than 2 b.p., the same is true for Casino III and Edison. Ditto for 3 b.p. in Bayer, British AM. Tob. II and Teliasonera and in KPN for 6 b.p..

C 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 some execution platforms for CDSs the minimum trade size if 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 two additional statistical arbitrage opportunities: Bouygues I and Louis Vuitton II. In the crisis period we find an additional statistical arbitrage opportunity: Union Fenosa.

D Non-Constant Variance Parameter

Although the standard deviation parameter of the profits process, σ, was assumed to be constant, it could evolve as a GARCH process. We have repeated the analysis by letting the standard deviation parameter evolve as a GARCH. Results do not change significantly.

E Limit of Losses Analysis

The barrier of 25,000 Euros 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 Euros and with no barrier under both UM and CM models. Results confirm that a barrier of 10,000 Euros seems too low given that it could lead to stopping the strategy prematurely. However, a barrier of 50,000 Euros leads to the same results as using a limit of 25,000 Euros for both subperiods. Finally, if the strategy does not stop independently of the investor's losses, we only find one additional statistical arbitrage opportunity for Tesco I under the CM model in the first subperiod and none under the UM model. As the preferred model for Tesco I is UM, we conclude that the last alternative does not lead to additional statistical arbitrage opportunities and moreover its use would involve a high risk.

VIII Conclusions

The ongoing financial crisis and its possible consequences for the regulation of financial markets makes the study of the possible persistent mispricing in credit derivatives markets a topic of salient relevance.

We make five contributions to this important topic. First, we present a new test of statistical arbitrage allowing for more general structure in the innovations and with lower Type I error than existing alternatives. Second, we apply the new test to a specific segment of the credit derivatives markets: CDS and ASP. We also apply cointegration techniques to the same problem. Our third contribution relates to the appropriate way of testing for arbitrage opportunities. We focus our analysis to test the cases where long positions in CDSs and ASPs are needed. Fourth, we employ four different databases to document that during the period before the subprime crisis, in 26% of the cases there are long-run arbitrage opportunities and in 24% there are statistical arbitrage opportunities. On the other hand, during the crisis we find 8% of cases of long-run arbitrage and 19% of statistical arbitrage. In this second period, we find a lower average basis, a higher correlation between credit spreads and a higher volatility in the basis and the credit spreads. Finally, we show that statistical arbitrage opportunities seem to be more frequent when the asset swaps packages contain relatively low-rated bonds with a high-coupon rate.

Our results may be interpreted as tentative evidence in favor of the hypothesis that some persistent mispricings can be found in this segment of the credit derivatives markets. Looking forward, we expect more definite evidence on other arbitrage strategies as well as in other market segments. The new test and the procedure (long positions only) of this paper can also be applied to other financial markets and instruments.

References

Affleck-Graves, John, and Bill McDonald, 1989, Nonnormalities and tests of asset pricing theories, *Journal of Finance* 44, 889-908.

Alexander, Carol, and Anca Dimitriu, 2004, A Comparison of Cointegration and Tracking Error Models for Mutual Funds and Hedge Funds, ISMA Centre Discussion Papers in Finance 2004-04, University of Reading.

Alexander, Carol, Ian Giblin, and Wayne Weddington III, 2002, Cointegration and Asset Allocation: A New Active Hedge Fund Strategy, *Research in International Business and Finance* 16, 65-90.

Aunon-Nerin, Daniel., Didier Cossin, Tomas Hricko, and Zhijiang Huang, 2002, Exploring for theDeterminants of Credit Risk in Credit Default Swap Transaction Data: Is Fixed-Income Markets'Information Sufficient to Evaluate Credit Risk? Working paper, HEC-University of Lausanne andFAME.

Bajlum, Claus, and Tind Larsen, 2007, Capital Structure Arbitrage: Model Choice and Volatility Calibration, Working Paper Series No. 230, Centre for Analytical Finance University of Aarhus.

Blanco, Roberto, Simon Brennan, Ian W. Marsh, 2005, An Empircal Analysis of the Dynamic Relationship Between Investment Grade Bonds and Credit Default Swaps, *Journal of Finance* 60, 2255-2281.

British Bankers' Association, 2006, BBA Credit Derivatives Report 2006.

Brenner, Robin J., and Kenneth F. Kroner, 1995, Arbitrage, Cointegration, and Testing the Unbiasedness Hypothesis in Financial Markets, *Journal of Financial and Quantitative Analysis* 30, 23-42.

California Debt and Investment Advisory Commission, Understanding Interest Rate Swap Match & Pricing, CDIAC No. 06-11, January 2007.

Chen, Ren-Raw, Xiaolin Cheng, and Bo Liu, 2008, Estimation and evaluation of the term structure of credit default swaps: An empirical study, *Insurance: Mathematics and Economics,* 43, 339-349.

Cserna, Balázs, and Björn Imbierowicz, 2008, How Efficient are Credit Default Swap Markets? An Empirical Study of Capital Structure Arbitrage based on Structural Pricing Models, Working Paper, Goethe University Franckfurt.

Das, Sanjiv R., Paul Hanouna, and Atulya Sarin, 2009, Accounting-based versus market -based cross-sectional models of CDS spreads, *Journal of Banking and Finance* 33, 719-730.

De Wit, Jan, 2006, Exploring the CDS-Bond Basis, Research series 200611-16, National Bank of Belgium.

Duarte, Jefferson, Francis A. Longstaff, and Fan Yu, 2007, Risk and Return in Fixed Income Arbitrage: Nickels in Front of a Steamroller, *The Review of Financial Studies* 20, 769-811.

Duffie, Darrell, 1999, Credit Swap Valuation, *Financial Analysts Journal* 55, 73-87.

Engle, Robert F., and Clive W. J. Granger, 1987, Co-Integration and Error Correction: Representation, Estimation, and Testing, *Econometrica* 55, 251-276.

Felsenheimer, Jochen, 2004, CDS: Mechanism, Pricing and Application, HVB Global Markets Research, 2 June 2004.

Forte, Santiago, and Juan Ignacio Peña, 2009, Credit Spreads: Theory and Evidence About The Information Content of Stocks, Bonds and CDSs, Forthcoming Journal of Banking and Finance.

Francis, Chris, Atish Kakodkar, and Barnaby Martin, 2003, *Credit Derivative Handbook 2003. A Guide to Products, Valuation, Strategies and Risks,* Merrill Lynch Global Securities Research and Economics Group, April.

Fulop, Andras and Laurence Lescourret, 2007, An analysis of intra-daily patterns on the CDS market, Working Paper.

Hogan, Steve, Robert A. Jarrow, Melvyn Teo, and Mitch Warachka, 2004, Testing Market Efficiency using Statistical Arbitrage with Applications to Momentum and Value Strategies, *Journal of Financial Economics* 73, 525-565.

Hull, John, Mirela Predescu and Alan White, 2004, The Relationship between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements, *Journal of Banking and Finance* 28, 2789-2811.

Hull, John, and Alan White, 2000, Valuing Credit Default Swaps I: No Counterparty Default Risk, *Journal of Derivatives* 8, 29-40.

Hull, John, and Alan White, 2001, Valuing Credit Default Swaps II: Modeling Default Correlations, *Journal of Derivatives*, 8, 12-22.

Jankowitsch, Rainer, Rainer Pullirsch, and Tanja Veža, 2008, The delivery option in credit default swaps, *Journal of Banking and Finance* 32, 1269-1285.

Jarrow, Robert A., Melvyn Teo, Yiu Kuen Tse, and Mitch Warachka, 2007, Statistical Arbitrage and Market Efficiency: Enhanced Theory, Robust Tests and Further Applications, Working Paper Series, Singapore Management University.

Levin, Andrew, Roberto Perli, and Egon Zakrajšek, 2005, The Determinants of Market Frictions in the Corporate Market, Computing in Economics and Finance 2005 379, Society for Computational Economics.

Lo, Andrew W., and Craig A. Mackinlay, 1988, Stock Market do not Follow Random Walks: Evidence from a Simple Specification Test, *Review of Financial Studies* 1, 41-66.

Longstaff, Francis A, Sanjay Mithal, and Eric Neis, 2005, Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market, *Journal of Finance* 60, 2213-2253.

Mayordomo, Sergio, Juan Ignacio Peña, and Juan Romo, 2009, Does Liquidity Affect the Price Discovery Process in Credit Derivatives Markets?, Universidad Carlos III de Madrid Working Paper.

Mengle, David, 2007, Credit derivatives: an overview, Economic Review, Federal Reserve Bank of Atlanta, issue Q4, 1 - 24.

Nashikkar, Amrut J., Marti G. Subrahmanyam and Sriketan Mahanti, 2009, Limited Arbitrage and Liquidity in the Market for Credit Risk, NYU Working Paper No. FIN-08-011.

Nashikkar, Amrut J., and Marti G. Subrahmanyam, 2007, Latent Liquidity and Corporate Bond yield Spreads, NYU Working Paper No. FIN-07-013.

Norden, Lars, and Martin Weber, 2004, Informational Efficiency of Credit Default Swap and Stock Markets: The Impact of Credit Ratings Announcements, *Journal of Banking and Finance* 28, 2813-2843.

Politis, Dimitris N., and Joseph P. Romano, 1994, The Stationary Bootstrap, *Journal of the American Statistical Association* 89, 1303-1313.

Politis, Dimitris N., Joseph P. Romano, and Michael Wolf, 1995, Subsampling for Nonstationary Time Series, Technical Report no. 483, Department of Statistics, Stanford University.

Politis, Dimitris N., Joseph P. Romano, and Michael Wolf, 1997, Subsampling for Heteroskedastic Time Series, *Journal of Econometrics* 81, 281-317.

Politis, Dimitris N., Joseph P. Romano, and Michael Wolf, 1999, *Subsampling* (Springer Series in Statistics. New York: Springer).

Politis, Dimitris N., Joseph P. Romano, and Michael Wolf, 1999, Subsampling Intervals in Autoregressive Models with Linear Time Trend, *Econometrica* 69, 1283-1314.

Predescu, Mirela, 2006, The Performance of Structural Models of Default for Firms with Liquid CDS Spreads, Working Paper.

Saita, Leandro, 2006, The Puzzling Price of Corporate Default Risk, Working paper, Standford Graduate School of Business.

Schonbucher, Philipp J., 2003, *Credit Derivatives Pricing Models: Models, Pricing, Implementation* (Wiley Finance, New York).

Shiller, Robert J., and Pierre Perron, 1985, Testing the Random Walk Hypothesis: Power versus Frequency of Observation, *Economic Letters* 18, 381-386.

Stock, James H., and Mark W. Watson, 1988, Testing for common trends, *Journal of the American Statistical Association* 83, 1097-1107.

Yu, Fan, 2006, How Profitable is Capital Structure Arbitrage?, *Financial Analysts Journal* 62, 47-62.

Zhu, Haibin, 2006, An Empirical Comparison of Credit Spreads between the Bond Market and the Credit Default Swap Market, *Journal of Financial Services Research* 29, 211-235.

Ziemba, William, 2005, The Symmetric Downside-Risk Sharpe Ratio, *The Journal of Portfolio Management* 32, 108–122.

Table I: Descriptive Statistics

Panel A describes the rating and sector of the CDS and bond issuer. We report the rating at the end of the first subperiod, which spans from November 2005 to August 2007, and at the end of the second subperiod, which covers the subprime crisis and spans from August 2007 to June 2009. Panel B provides descriptive statistics for bonds during the first subperiod (Panel B1) and during the second one (Panel B2). Panel C includes descriptive statistics for ASP, bond and CDS spreads and splits into two panels, Panel C1 and Panel C2, corresponding to the first and second subperiod, respectively. Panel D reports descriptive statistics for the basis, which is defined as the difference between ASP and CDS spreads, during the first subperiod (Panel D1) and the second one (Panel D2). Panels E1 and E2 report the descriptive statistics of the CDS spreads for the four different databases in the first and second subperiod, respectively.

Panel A

Issuer	Rating	Sector
Akzo Nobel	A- / BBB+	Chemicals
Altadis	BBB / -	Beverages & Tobacco
Astrazeneca	- / AA-	Pharmaceuticals & Biotechnology
Auchan	- / A	Retail - Department Stores
BASF	- / A+	Chemicals
Bayer	- / A-	Chemicals
Belgacom	- / A+	Fixed-Line Telecommunication Svs.
BMW	A+ / A	Automobile
Bouygues	BBB+ / BBB+	Construction
British AM Tob.	BBB+ / BBB+	Beverages & Tobacco
Carrefour	A / A	Food & Drug Retailers
Casino G. P.	BBB- / BBB-	Food & Drug Retailers
Compass Group	BBB+ / -	Support Services
Edison	BBB+ / BBB+	Public Utilities
Enel	A- / A-	Public Utilities
Energias de Portugal	A- / A-	Electricity
E.ON	A+ / -	Utilities
France Telecom	A- / A-	Fixed-Line Telecommunication Svs.
Iberdrola	A / A-	Petrol and Power
Kingfisher	BBB- / BBB-	General Retailers
Koninklijke KPN	BBB+ / BBB+	Telecommunication Services
Louis Vuitton	BBB+ / BBB+	Other Textiles and Leather Goods
Philips	- / A-	Electronic & Electrical Equipment
PPR	BBB- / BBB-	Retailers - Multi Department
Reed Elsevier	A- / -	Media & Entertainment
Renault	BBB+ / -	Automobiles
Repsol YPF	BBB+ / BBB+	Petrol and Power
Reuters	A- / -	Publishing
Saint Gobain	BBB+ / BBB+	Building and Construction Materials
Scania	A- / -	Machinery and Engineering
Schneider	- / A-	Electrical Equipment
SES	BBB / BBB	Telecommunications
Siemens	AA- / A+	Industrial
Sodexho	BBB+ / -	Business Support Services
Stora Enso	BBB- / -	Forest Product & Paper
Technip	BBB / BBB	Oil - Services
Telecom Italia	BBB+ / BBB	Public Utilities
Telefonica	BBB+ / A-	Technology and Telecommunications
Telekom Austria	BBB+ / BBB+	Machinery, Transport and Technology
Teliasonera	- / A-	Telecommunications
Tesco	A / A-	Food & Drug Retailers
Thales	A- / A-	Defence
Thyssenkrupp	BBB+ / BBB-	Industrial
Union Fenosa	A- / A-	Petrol and Power
Veolia Environ.	BBB+ / -	Water
Vinci	BBB+ / -	Other Construction
Vivendi	BBB / -	Subscription Entertainment Networks
Vodafone	A- / -	Wireless Telecomunications Svs.
Volkswagen	A- / BBB+	Automobile
Volvo	A- / BBB+	Machinery & Engineering

Panel B1

Issuer	Amount issued (millions of euros)	Observations	Coupon (%)	Price Mean	Price Max	Price Min
Akzo Nobel I	750	220	4.250	100.03	101.36	98.31
Akzo Nobel II	1,000	286	5.625	103.94	106.95	101.96
Altadis	600	330	4.250	100.32	102.59	99.30
BMW	750	295	3.875	98.63	100.02	96.50
Bouygues I	750	197	4.625	101.40	104.00	98.76
Bouyges II	1,000	221	5.875	104.64	107.97	101.79
British AM Tob. I	1,700	338	4.875	101.86	104.58	100.00
British AM Tob. II	1,000	232	4.375	99.61	101.07	97.53
Carrefour I	1,100	221	4.375	100.22	101.96	97.91
Carrefour II	1,000	314	6.125	107.15	111.98	103.26
Casino G. P. I	400	148	4.750	99.98	101.36	97.80
Casino G. P. II	500	195	5.250	102.18	103.97	100.01
Compass Group	300	121	6.000	104.08	106.40	101.97
Edison	700	339	5.125	103.43	106.91	100.51
Enel	750	91	4.125	99.22	100.95	96.99
Energias de Portugal I	1,000	184	6.400	107.40	111.13	103.77
Energias de Portugal II	747.352	162	5.875	106.80	108.90	103.07
E.ON	4,250	200	5.750	104.44	108.20	101.61
France Telecom I	750	119	4.625	99.77	101.48	97.82
France Telecom II	1,000	100	4.375	98.48	100.26	96.89
France Telecom III	1,000	294	3.000	95.82	98.74	94.34
Iberdrola I	750	234	4.375	98.35	103.68	100.71
Iberdrola II	600	195	4.500	101.36	103.60	99.64
Kingfisher	500	270	4.500	100.11	102.13	98.00
Koninklijke KPN	1,425	221	4.500	99.18	100.54	97.21
Louis Vuitton I	600	251	4.625	100.85	102.44	98.75
Louis Vuitton II	750	352	5.000	102.69	105.87	100.28
PPR	800	289	5.250	102.71	104.58	99.79
Reed Elsevier	500	208	5.000	102.68	105.61	100.89
Renault	1,000	249	6.125	104.53	106.59	102.29
Repsol YPF	1,175	298	6.000	105.68	110.12	102.50
Reuters	500	229	4.625	101.23	105.38	98.91
Saint Gobain I	1,000	316	4.750	101.46	104.10	99.80
Saint Gobain II	1,100	261	4.250	99.03	100.60	97.00
Saint Gobain III	1,000	337	5.000	102.55	106.34	100.09
Saint Gobain IV	150	273	6.250	101.00	103.00	99.74
Scania	600	219	3.625	97.36	99.97	95.65
SES	500	52	3.875	100.78	101.96	99.55
Siemens	2,000	72	5.750	105.55	108.13	102.85
Sodexho	1,000	350	5.875	104.09	107.10	101.64
Stora Enso	500	316	3.250	96.31	94.71	98.36
Technip	650	112	4.625	100.97	102.30	98.52
Telecom Italia I	750	300	4.500	99.88	102.78	97.75
Telecom Italia II	2,000	269	7.250	110.40	113.22	106.55
Telefonica	2,250	317	3.750	97.41	99.34	95.65
Telekom Austria	500	137	3.375	97.40	99.05	96.27
Tesco I	750	347	4.750	102.18	105.92	99.66
Tesco II	500	303	3.875	98.67	100.15	96.60
Thales	500	111	4.375	100.17	101.76	97.91
Thyssenkrupp	750	235	5.000	101.73	103.06	99.46
Union Fenosa	500	317	5.000	103.00	106.84	100.16
Veolia Environ.	2,000	239	5.875	103.20	106.50	100.92
Vinci	1,025	158	5.875	104.73	108.47	101.87
Vivendi	630	97	3.625	97.85	100.50	96.50
Vodafone	1,900	311	5.125	100.22	102.35	98.90
Volkswagen	1,000	255	4.125	98.93	100.32	97.05
Volvo	300	324	5.375	103.79	107.64	101.17
Average	938.64	236	4.862	101.53	103.99	99.45

Panel B2

Issuer	Amount issued (millions of euros)	Observations	Coupon (%)	Price Mean	Max	Min
Akzo Nobel I	750	396	4.250	99.26	102.70	96.25
Astrazeneca	750	157	4.625	100.68	103.74	97.68
Auchan	600	169	3.000	96.69	98.49	95.35
BASF	1,400	290	3.375	97.44	102.39	93.73
Bayer	2,000	347	6.000	104.55	108.38	99.72
Belgacom	775	38	4.125	98.06	102.23	95.65
BMW	750	393	3.875	98.00	101.65	88.64
Bouygues I	750	260	4.625	99.79	104.05	97.05
British AM Tob. II	1,000	300	4.375	98.92	103.37	95.19
Carrefour I	1,100	324	4.375	100.24	104.98	96.94
Carrefour II	1,000	324	6.125	103.45	105.10	101.10
Casino G. P. I	400	304	4.750	98.34	103.37	94.37
Casino G. P. II	500	304	5.250	100.59	102.89	98.46
Casino G. P. III	700	304	6.000	100.74	104.67	94.33
Edison	700	338	5.125	101.31	104.21	92.69
Enel	750	206	4.125	100.23	103.75	96.75
Energias de Portugal I	1,000	258	6.400	102.17	104.26	100.09
Energias de Portugal II	747	251	5.875	103.41	106.10	99.60
France Telecom I	750	298	4.625	100.75	104.96	96.54
France Telecom II	1,000	298	4.375	99.49	104.57	94.50
France Telecom III	1,000	298	3.000	97.73	101.70	94.69
Iberdrola I	750	291	4.375	100.06	103.05	97.40
Kingfisher	500	146	4.500	95.27	98.91	89.01
Koninklijke KPN	1,425	398	4.500	98.70	103.60	93.60
Louis Vuitton I	600	368	4.625	100.25	104.92	97.28
Louis Vuitton II	750	369	5.000	100.93	103.24	98.63
Philips	750	237	6.125	104.46	106.45	101.34
PPR	800	339	5.250	98.71	102.80	91.83
Repsol YPF	1,175	358	6.000	102.02	103.91	99.12
Saint Gobain II	1,100	384	4.250	97.11	101.96	91.18
Saint Gobain III	1,000	384	5.000	100.15	102.12	97.79
Schneider	900	110	3.125	96.11	100.92	94.29
SES	500	119	3.875	96.77	101.50	93.36
Siemens	2,000	228	5.750	103.86	106.75	100.23
Technip	650	194	4.625	98.97	102.95	95.83
Telecom Italia I	750	299	4.500	98.35	102.31	89.08
Telecom Italia II	2,000	299	7.250	104.28	108.05	96.45
Telefonica	2,250	272	3.750	97.89	102.50	94.03
Telekom Austria	500	255	3.375	98.36	100.86	96.52
Teliasonera	500	383	3.625	95.65	101.73	91.46
Tesco I	750	276	4.750	100.85	103.69	98.76
Tesco II	500	286	3.875	98.74	103.27	95.88
Thales	500	298	4.375	99.95	103.66	93.97
Thyssenkrupp	750	358	5.000	100.52	105.13	92.51
Union Fenosa	500	288	5.000	100.92	103.20	98.28
Volkswagen	1,000	400	4.125	98.01	101.63	91.65
Volvo	300	327	5.375	99.86	102.62	94.79
Average	885.58	287.72	4.69	99.76	103.39	95.61

Panel C1

	CDS Premium (basis points)				Asset Swap Spread (b.p.)				Bond Spread (b.p.)				CDS vs AS
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD	Corr
Akzo Nobel I	23.55	17.14	30.72	2.31	17.66	3.80	35.60	8.25	19.29	4.50	37.40	8.43	0.48
Akzo Nobel II	14.11	9.85	27.89	3.47	17.17	4.90	28.80	5.57	18.26	5.60	30.80	5.49	0.72
Altadis	16.83	8.59	35.00	6.36	20.91	9.90	37.50	5.84	23.49	12.30	39.50	5.66	0.33
BMW	12.10	6.61	23.86	4.77	10.49	2.10	18.70	3.69	12.03	4.30	20.60	3.80	0.72
Bouygues I	21.10	12.00	35.00	5.81	25.52	11.50	39.30	6.56	26.93	12.80	41.30	6.55	0.70
Bouygues II	20.24	11.94	33.60	6.35	15.80	4.00	28.10	5.33	16.91	6.10	29.70	5.08	0.79
British AM Tob. I	24.81	6.05	54.00	13.18	20.20	3.00	45.90	9.31	22.01	3.20	47.80	9.05	0.88
British AM Tob. II	24.89	13.12	40.00	6.96	32.99	16.19	54.10	8.86	35.03	20.00	57.00	9.01	0.90
Carrefour I	16.19	9.43	38.63	4.58	18.75	8.17	31.20	5.13	20.35	9.70	31.90	5.17	0.20
Carrefour II	12.87	6.80	28.05	3.51	7.45	1.20	22.80	3.90	8.30	1.20	23.20	3.87	0.61
Casino I	48.03	31.05	76.51	8.67	55.06	33.70	77.20	9.87	57.60	36.90	79.80	9.83	0.68
Casino II	45.02	22.31	122.71	24.22	49.67	17.30	126.10	25.99	51.29	19.30	128.20	25.78	0.95
Compass Group	22.99	10.80	83.29	15.59	31.36	4.53	94.00	18.18	32.42	6.20	93.40	17.70	0.94
Edison	16.90	6.52	30.40	5.30	23.93	10.20	32.80	5.71	24.97	10.80	34.10	5.53	0.76
Enel	15.51	8.98	38.05	5.73	13.50	2.40	29.84	6.61	14.93	4.00	30.30	6.95	0.71
Energias de Portugal I	12.30	6.37	23.65	4.92	12.11	1.80	19.60	3.18	19.93	2.20	19.90	3.02	0.47
Energias de Portugal II	14.80	8.46	28.00	4.93	16.72	3.24	24.20	3.49	17.41	5.00	24.00	3.07	0.54
E.ON	10.87	5.02	15.46	2.63	9.47	2.10	18.60	3.63	10.58	2.50	19.40	3.67	0.50
France Telecom I	21.25	14.56	39.39	4.31	25.22	18.80	44.01	4.75	27.45	21.00	48.50	5.34	0.73
France Telecom II	21.39	15.00	40.57	4.64	25.36	19.30	38.99	4.20	27.53	20.90	43.40	4.68	0.88
France Telecom III	25.15	10.68	50.03	10.18	17.46	4.10	30.00	6.82	19.68	6.50	32.70	7.28	0.81
Iberdrola I	16.63	6.82	27.97	5.00	16.78	3.30	28.70	5.39	19.48	5.40	30.10	5.23	0.65
Iberdrola II	11.70	6.00	18.40	3.09	10.77	2.50	17.00	2.47	12.30	7.50	19.90	2.49	0.36
Kingfisher	44.81	31.99	80.96	8.85	49.22	29.10	71.80	9.07	51.53	31.90	74.20	8.89	0.81
Koninklijke KPN	47.20	31.74	73.82	10.68	52.78	29.50	79.80	12.81	55.61	33.30	83.70	12.95	0.96
Louis Vuitton I	19.26	9.09	29.19	5.45	23.04	10.30	38.70	7.77	24.61	11.70	41.40	7.85	0.87
Louis Vuitton II	16.40	5.86	27.07	6.22	21.62	4.06	31.20	7.14	22.98	5.40	33.50	7.04	0.93
PPR	39.60	25.73	72.88	6.89	47.98	30.10	60.90	6.79	49.47	32.80	63.70	6.65	0.74
Reed Elsevier	13.83	8.67	28.18	4.03	12.57	4.80	21.10	3.25	14.84	8.00	23.50	2.87	0.48
Renault	16.85	5.05	30.80	6.69	22.29	5.00	43.90	9.10	23.15	6.07	45.40	9.02	0.93
Repsol YPF	21.08	9.69	36.24	7.15	26.49	10.40	37.90	7.73	27.17	13.02	38.50	7.26	0.80
Reuters	17.75	9.13	31.78	5.64	23.42	6.68	34.20	6.55	24.92	8.70	35.30	6.49	0.81
Saint Gobain I	18.10	10.13	31.77	4.64	17.36	6.30	28.30	5.19	18.84	7.30	29.80	5.29	0.65
Saint Gobain II	26.86	15.93	47.58	6.86	31.75	16.90	49.60	8.42	33.96	19.90	52.70	8.57	0.89
Saint Gobain III	22.78	11.65	38.06	7.23	26.75	9.60	39.00	8.15	28.07	11.80	40.40	7.93	0.81
Saint Gobain IV	16.20	11.04	27.47	3.57	21.58	5.55	31.77	4.82	22.19	5.00	31.40	6.26	0.52
Scania	24.69	10.31	41.00	8.58	23.53	8.60	38.20	7.46	25.79	10.20	41.30	7.66	0.53
SES	20.92	14.28	26.18	3.16	21.42	11.02	28.30	4.82	23.95	16.20	30.90	4.14	0.65
Siemens	12.08	9.35	17.00	1.58	9.60	4.94	13.50	1.81	10.61	6.60	14.40	1.63	-0.04
Sodexho	9.98	4.45	25.89	4.56	18.90	3.39	34.40	5.56	20.21	6.30	34.60	5.11	0.81
Stora Enso	38.10	21.18	88.19	13.38	40.27	21.30	62.30	12.15	43.66	24.60	64.80	12.66	0.91
Technip	24.55	15.79	34.93	3.61	33.84	20.60	41.40	4.17	35.57	21.90	45.10	4.29	0.17
Telecom Italia I	44.46	23.01	71.60	10.27	46.49	20.90	84.80	11.94	48.87	24.00	87.00	12.02	0.92
Telecom Italia II	45.95	24.40	75.40	10.85	45.34	22.00	64.30	10.64	44.46	23.70	62.80	9.65	0.87
Telefonica	33.40	16.46	59.20	8.87	36.77	17.70	57.90	9.32	39.55	20.20	60.10	9.59	0.93
Telekom Austria	24.04	9.55	64.27	12.71	25.57	11.32	51.60	9.61	28.00	11.70	55.20	9.95	0.94
Tesco I	9.45	4.06	21.63	4.81	12.09	1.70	24.60	5.06	13.35	2.50	25.90	5.03	0.52
Tesco II	10.38	5.00	22.95	4.36	14.46	2.30	29.30	5.99	16.10	3.30	30.60	6.17	0.77
Thales	13.98	9.31	19.08	3.19	18.63	6.74	27.40	5.39	20.21	8.60	28.70	5.35	0.74
Thyssenkrupp	35.04	17.12	68.64	12.85	36.92	9.80	75.90	18.28	38.63	12.10	78.70	18.30	0.96
Union Fenosa	20.74	7.29	38.08	7.63	25.07	7.86	36.10	6.47	26.28	9.00	35.50	6.29	0.89
Veolia Environ.	10.70	5.03	21.04	4.00	11.50	5.40	17.40	2.80	13.47	5.40	19.30	2.91	-0.05
Vinci	23.96	12.26	38.82	7.08	23.16	10.62	35.00	6.05	24.14	10.10	34.50	5.82	0.72
Vivendi	34.30	17.70	55.20	8.30	38.95	18.40	51.40	9.18	41.97	23.40	56.40	9.33	0.90
Vodafone	15.31	10.93	24.78	3.28	12.25	4.00	25.90	7.10	14.04	0.20	29.70	7.23	0.78
Volkswagen	21.21	10.82	37.60	6.33	23.61	6.97	37.60	8.11	25.52	7.50	40.40	8.30	0.77
Volvo	20.86	9.80	35.07	6.77	21.92	4.54	40.90	8.08	23.03	6.00	43.40	7.93	0.74
Average	22.53	12.24	41.82	6.78	24.76	10.11	41.57	7.36	26.54	11.86	43.43	7.35	0.70

Panel C2

Issuer	CDS Premium (basis points)				Asset Swap Spread (b.p.)				Bond Spread (b.p.)				CDS vs AS
	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD	Corr
Akzo Nobel I	65.19	13.58	172.60	42.68	72.45	3.17	254.30	69.83	73.77	0.30	304.70	72.63	0.91
Astrazeneca	51.12	16.53	170.83	32.64	40.94	16.31	169.50	25.25	40.61	15.10	154.70	23.51	0.77
Auchan	27.82	8.62	68.00	12.04	37.37	1.09	145.40	34.79	34.19	1.02	132.00	28.01	0.73
BASF	64.26	14.37	159.37	41.23	36.69	2.30	119.20	31.94	35.32	2.00	125.30	31.74	0.78
Bayer	64.72	20.42	137.87	27.24	87.10	27.43	202.70	40.64	84.96	26.50	286.20	40.75	0.85
Belgacom	40.88	18.18	89.92	17.06	46.44	14.00	103.90	15.58	47.95	11.80	102.10	16.03	0.57
BMW	144.24	12.83	537.50	143.93	99.04	1.10	479.00	102.82	101.42	1.30	515.40	106.08	0.86
Bouygues I	102.76	23.00	270.32	67.01	101.66	16.73	262.10	65.28	99.20	16.70	263.50	64.47	0.91
British AM Tob. II	67.14	19.16	173.66	32.03	107.03	27.40	293.10	60.43	109.13	25.30	298.20	61.14	0.72
Carrefour I	49.82	13.89	153.67	28.23	52.93	1.00	174.60	42.99	50.76	2.00	174.20	41.51	0.83
Carrefour II	47.49	11.14	159.47	31.39	30.89	2.81	116.30	19.42	31.18	2.40	137.40	24.21	0.28
Casino I	142.33	38.24	390.00	75.60	172.53	58.08	389.70	95.31	177.10	59.50	418.30	99.07	0.90
Casino II	130.09	26.59	390.00	81.10	111.67	19.89	284.90	61.22	115.18	17.90	292.90	69.88	0.53
Casino III	146.96	45.32	390.00	73.33	208.31	64.89	456.20	110.23	211.57	64.60	489.80	114.06	0.88
Edison	65.48	16.87	198.00	52.92	82.27	6.30	215.50	62.45	81.05	4.80	218.80	59.79	0.87
Enel	178.55	23.43	743.31	166.70	53.71	0.20	146.00	39.91	53.71	0.80	150.10	40.08	0.80
Energias de Portugal I	73.52	17.11	205.52	50.81	53.74	1.50	165.00	37.86	52.70	0.40	167.34	38.64	0.67
Energias de Portugal II	82.34	21.48	190.27	45.93	100.71	4.94	244.90	65.18	98.78	4.90	247.70	65.40	0.81
France Telecom I	64.58	21.74	121.87	26.03	74.94	23.70	193.10	38.64	72.99	3.30	187.00	37.58	0.67
France Telecom II	64.98	21.96	121.65	25.90	87.54	35.12	209.80	39.49	88.27	32.10	211.60	38.92	0.78
France Telecom III	59.48	17.98	122.00	26.99	50.08	5.80	195.00	32.83	49.27	6.00	189.50	30.67	0.66
Iberdrola I	92.62	13.12	295.50	57.70	75.65	0.91	211.00	56.40	74.15	1.50	218.30	55.43	0.90
Kingfisher	191.71	46.30	435.00	101.87	218.77	41.00	376.50	109.45	232.37	43.30	407.50	119.06	0.84
Koninklijke KPN	72.20	25.16	159.51	28.04	113.57	38.53	321.60	54.66	118.22	36.80	348.10	58.81	0.71
Louis Vuitton I	71.15	15.74	246.00	50.72	70.56	11.09	200.90	47.50	69.89	12.00	201.30	47.31	0.90
Louis Vuitton II	65.95	11.55	246.00	54.05	62.37	1.13	234.20	49.06	61.37	1.20	211.70	48.38	0.88
Philips	59.31	13.80	162.66	34.89	65.24	5.07	197.00	58.26	63.13	6.00	194.60	56.32	0.87
PPR	252.50	49.20	759.03	199.38	200.16	35.18	553.70	144.48	205.98	36.10	590.60	151.84	0.97
Repsol YPF	115.13	21.18	441.16	111.58	107.20	18.21	368.40	87.01	106.35	13.40	391.90	88.56	0.91
Saint Gobain II	177.26	25.63	555.63	134.35	158.10	38.24	458.10	111.38	162.70	41.10	496.70	115.75	0.92
Saint Gobain III	156.89	19.87	522.04	132.37	110.95	22.78	323.10	72.01	117.41	23.10	366.30	85.89	0.85
Schneider	68.66	17.59	199.78	42.03	70.63	12.64	252.60	34.20	73.11	11.70	232.50	34.13	0.85
SES	77.35	24.58	181.86	41.73	122.23	30.11	352.30	83.71	127.17	30.80	369.60	87.52	0.88
Siemens	76.03	13.98	238.85	56.55	62.58	3.00	175.60	47.26	61.59	3.00	171.40	46.51	0.77
Technip	98.66	16.83	302.73	80.09	109.91	24.42	303.50	83.61	114.41	18.50	314.90	89.36	0.76
Telecom Italia I	183.38	30.18	546.17	138.43	158.12	38.94	434.70	95.31	171.65	36.10	654.50	118.10	0.84
Telecom Italia II	184.89	30.95	540.33	136.07	216.49	38.01	536.70	148.10	215.13	36.50	552.30	149.77	0.97
Telefonica	97.99	25.54	247.69	54.96	102.31	31.61	276.10	56.25	103.94	32.80	278.00	56.46	0.90
Telekom Austria	59.18	13.71	142.58	30.07	93.66	12.43	326.80	62.25	99.57	9.40	321.90	64.89	0.68
Teliasonera	62.75	18.82	127.51	25.89	82.56	0.00	259.30	62.00	86.10	0.00	270.40	64.48	0.86
Tesco I	59.59	8.94	182.00	52.12	63.17	1.93	246.30	61.63	62.76	1.73	239.70	60.91	0.79
Tesco II	64.20	11.19	182.19	49.32	67.64	2.43	189.70	53.60	66.84	2.10	197.40	53.13	0.91
Thales	78.50	12.70	300.99	60.90	74.07	0.70	211.10	67.53	77.81	0.64	557.20	78.43	0.58
Thyssenkrupp	192.95	25.52	580.00	166.28	106.84	0.30	313.30	96.80	114.43	0.10	327.00	101.68	0.87
Union Fenosa	88.40	13.73	382.50	82.13	89.31	6.30	215.80	65.98	86.99	5.60	213.30	63.84	0.79
Volkswagen	132.69	18.92	360.02	91.15	119.99	17.44	352.20	94.58	123.23	17.70	363.40	96.96	0.89
Volvo	219.66	16.24	733.80	234.40	252.10	0.20	777.80	271.29	263.15	1.00	857.90	290.67	0.96
Average	100.71	20.50	298.67	71.23	99.62	16.30	282.73	69.50	101.46	15.34	306.71	72.09	0.80

Panel D1

Issuer	Basis (b.p.)			
	Mean	Min	Max	SD
Akzo Nobel I	-5.89	-20.04	10.21	7.43
Akzo Nobel II	3.06	-7.51	11.51	3.92
Altadis	3.57	-14.29	16.19	7.09
BMW	-1.61	-15.77	8.49	3.31
Bouygues I	4.41	-7.42	13.43	4.87
Bouygues II	-4.43	-22.81	3.00	3.88
British AM Tob. I	-4.61	-26.30	10.90	6.65
British AM Tob. II	8.10	-7.18	15.10	4.04
Carrefour I	2.56	-26.95	15.53	6.15
Carrefour II	-5.42	-21.84	4.10	3.28
Casino I	7.04	-27.10	17.56	7.46
Casino II	4.66	-27.15	16.25	7.98
Compass Group	8.37	-14.26	20.86	6.44
Edison	7.03	-15.85	15.74	3.84
Enel	-2.01	-19.47	5.89	4.81
Energias de Portugal I	-0.18	-10.00	7.59	4.44
Energias de Portugal II	1.91	-14.88	9.05	4.22
E.ON	-1.41	-9.36	9.08	3.24
France Telecom I	3.97	-6.25	14.46	3.36
France Telecom II	3.97	-6.32	7.99	2.17
France Telecom III	-7.68	-30.40	0.53	6.19
Iberdrola I	0.15	-11.47	12.10	4.40
Iberdrola II	-0.93	-8.61	6.31	3.18
Kingfisher	0.41	-43.52	10.18	5.55
Koninklijke KPN	5.59	-6.34	13.92	4.07
Louis Vuitton I	3.78	-16.28	13.70	4.03
Louis Vuitton II	3.22	-6.21	10.34	2.60
PPR	8.38	-23.05	16.78	4.92
Reed Elsevier	-1.26	-11.96	5.94	3.77
Renault	5.43	-7.00	21.04	3.75
Repsol YPF	5.41	-11.79	17.12	4.77
Reuters	5.67	-8.30	15.08	3.85
Saint Gobain I	-0.74	-21.91	9.16	4.17
Saint Gobain II	4.89	-16.54	14.34	3.96
Saint Gobain III	3.97	-16.68	14.70	4.79
Saint Gobain IV	5.37	-11.33	14.23	4.26
Scania	-1.17	-19.60	14.03	7.88
SES	0.42	-9.91	5.59	3.70
Siemens	-2.48	-10.89	2.56	2.45
Sodexho	8.92	-5.86	15.52	3.27
Stora Enso	2.17	-33.44	11.16	5.54
Technip	9.30	-12.92	19.33	5.03
Telecom Italia I	2.03	-13.60	17.54	4.69
Telecom Italia II	-0.61	-11.77	18.98	5.54
Telefonica	3.37	-15.80	12.72	3.51
Telekom Austria	1.53	-17.34	8.82	5.03
Tesco I	2.64	-10.02	12.06	4.86
Tesco II	4.08	-12.61	13.15	3.81
Thales	4.64	-9.70	13.73	3.74
Thyssenkrupp	1.87	-19.24	15.79	6.88
Union Fenosa	4.32	-7.49	10.88	3.53
Veolia Environ	0.86	-9.87	9.87	4.97
Vinci	-0.80	-16.18	9.03	4.98
Vivendi	4.66	-6.54	18.36	4.06
Vodafone	-3.05	-15.04	7.93	4.97
Volkswagen	2.40	-27.12	11.22	5.14
Volvo	1.06	-17.49	13.48	5.48
Average	2.12	-15.34	12.11	4.66

Panel D2

	Basis (b.p.)			
Issuer	Mean	Min	Max	SD
Akzo Nobel I	7.26	-53.23	117.83	35.69
Astrazeneca	-10.19	-86.63	93.67	20.74
Auchan	9.55	-26.74	101.42	27.25
BASF	-27.57	-123.71	21.75	25.80
Bayer	22.37	-43.90	112.97	22.69
Belgacom	5.56	-25.12	30.95	15.18
BMW	-45.20	-356.80	273.54	76.37
Bouygues I	-1.10	-58.90	101.42	28.11
British AM Tob. II	47.36	-16.35	202.58	44.59
Carrefour I	3.11	-50.27	120.18	25.26
Carrefour II	-16.60	-145.87	73.84	31.96
Casino G. P. I	30.20	-55.30	170.01	42.99
Casino G. P. II	-18.42	-315.10	112.15	71.18
Casino G. P. III	61.35	-31.73	218.98	57.14
Edison	16.79	-30.09	134.90	30.66
Enel	-124.83	-656.01	20.97	136.64
Energias de Portugal I	-9.78	-71.42	95.40	28.60
Energias de Portugal II	28.37	-72.24	155.44	42.72
France Telecom I	10.36	-64.55	94.61	28.52
France Telecom II	22.56	-38.73	110.98	25.33
France Telecom III	-9.41	-79.81	103.03	25.32
Iberdrola I	-16.97	-110.50	57.54	25.66
Kingfisher	27.06	-130.16	153.20	59.81
Koninklijke KPN	41.37	-25.61	212.95	40.11
Louis Vuitton I	-0.59	-86.30	82.79	22.17
Louis Vuitton II	-3.58	-91.90	135.19	26.22
Philips	5.93	-51.09	109.81	32.95
PPR	-52.34	-340.83	60.54	70.35
Repsol YPF	-7.93	-173.30	110.67	47.86
Saint Gobain II	0.84	-122.94	161.76	44.82
Saint Gobain III	-31.94	-267.54	101.73	55.43
Schneider	1.97	-49.42	86.03	21.94
SES	44.88	-43.05	192.58	51.28
Siemens	-13.46	-188.60	40.29	35.99
Technip	11.24	-167.69	127.37	56.59
Telecom Italia I	-25.26	-356.17	84.10	78.72
Telecom Italia II	31.59	-34.29	168.70	34.92
Telefonica	4.31	-81.50	106.08	25.40
Telekom Austria	34.48	-31.41	239.45	47.33
Teliasonera	32.49	-20.96	181.59	36.83
Tesco I	3.59	-64.70	155.67	37.88
Tesco II	3.43	-43.35	100.88	22.78
Thales	-4.43	-296.49	73.78	59.07
Thyssenkrupp	-72.11	-326.40	80.24	89.82
Union Fenosa	12.91	-169.00	132.75	45.34
Volkswagen	-12.70	-151.92	180.09	43.70
Volvo	32.44	-154.80	378.40	82.12
Average	1.04	-127.29	127.25	43.36

Panel E1

Issuer	GFI CDS Premium (b.p.)				CMA CDS Premium (b.p.)				JPMorgan CDS Premium (b.p.)			
	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD
Akzo Nobel I	23.55	17.14	30.72	2.31	23.39	15.40	41.80	3.68	22.98	14.55	49.90	4.10
Akzo Nobel II	14.11	9.85	27.89	3.47	12.57	6.31	25.30	3.95	12.93	5.46	31.33	4.45
Altadis	16.83	8.59	35.00	6.36	14.17	5.20	34.42	4.22	-	-	-	-
BMW	12.10	6.61	23.86	4.77	11.98	6.28	26.11	4.80	11.66	5.11	26.82	4.92
Bouygues I	21.10	12.00	35.00	5.81	20.18	11.18	35.45	5.99	19.58	10.68	35.46	5.90
Bouygues II	20.24	11.94	33.60	6.35	20.01	11.45	33.15	6.02	19.22	10.38	35.14	6.01
British AM Tob. I	24.81	6.05	54.00	13.18	24.21	6.34	53.36	13.01	23.48	5.79	54.61	13.35
British AM Tob. II	24.89	13.12	40.00	6.96	24.38	14.51	38.73	6.18	23.96	12.12	36.72	6.48
Carrefour I	16.19	9.43	38.63	4.58	15.83	9.54	33.35	4.39	15.27	9.67	35.10	4.30
Carrefour II	12.87	6.80	28.05	3.51	12.67	6.80	23.20	3.54	12.84	6.82	30.78	3.97
Casino I	48.03	31.05	76.51	8.67	48.76	30.39	80.98	8.90	46.30	28.14	69.67	7.96
Casino II	45.02	22.31	122.71	24.22	44.97	20.26	122.98	24.35	42.33	16.81	124.43	25.45
Compass Group	22.99	10.80	83.29	15.59	24.05	11.19	80.48	14.62	22.33	9.88	80.93	14.86
Edison	16.90	6.52	30.40	5.30	15.94	6.36	28.38	5.04	15.91	5.64	28.87	5.32
Enel	15.51	8.98	38.05	5.73	15.32	9.39	36.99	5.36	14.64	8.40	33.27	5.42
Energias de Portugal I	12.30	6.37	23.65	4.92	11.37	4.43	20.87	4.36	11.59	4.96	22.70	4.97
Energias de Portugal II	14.80	8.46	28.00	4.93	14.26	7.40	27.50	4.83	14.57	8.69	26.22	4.08
E.ON	10.87	5.02	15.46	2.63	9.75	3.37	15.96	2.76	9.91	2.96	16.18	3.28
France Telecom I	21.25	14.56	39.39	4.31	21.90	15.73	43.61	4.48	20.85	14.60	40.45	4.17
France Telecom II	21.39	15.00	40.57	4.64	22.00	15.99	44.53	4.96	20.94	15.07	41.36	4.58
France Telecom III	25.15	10.68	50.03	10.18	25.12	11.05	49.58	9.84	24.51	10.29	49.29	10.18
Iberdrola I	16.63	6.82	27.97	5.00	16.06	8.17	27.87	4.74	16.56	7.84	27.81	4.92
Iberdrola II	11.70	6.00	18.40	3.09	10.57	6.05	18.89	3.00	10.58	4.48	20.39	3.61
Kingfisher	44.81	31.99	80.96	8.85	43.39	31.21	83.74	8.31	43.33	30.52	81.16	8.95
Koninklijke KPN	47.20	31.74	73.82	10.68	47.20	30.81	73.55	10.66	45.70	26.69	72.48	11.04
Louis Vuitton I	19.26	9.09	29.19	5.45	18.93	11.49	31.60	4.50	17.12	7.97	27.68	5.03
Louis Vuitton II	16.40	5.86	27.07	6.22	16.27	8.10	32.02	5.78	15.11	5.69	31.44	6.60
PPR	39.60	25.73	72.88	6.89	39.39	24.11	69.37	6.52	38.58	21.95	63.33	6.65
Reed Elsevier	13.83	8.67	28.18	4.03	8.92	5.61	24.61	3.09	7.59	3.52	29.28	3.28
Renault	16.85	5.05	30.80	6.69	17.20	6.85	29.85	5.34	15.68	6.05	29.27	5.54
Repsol YPF	21.08	9.69	36.24	7.15	20.81	10.14	40.99	7.03	21.25	9.52	43.77	8.16
Reuters	17.75	9.13	31.78	5.64	17.55	9.15	29.33	4.79	17.00	8.87	29.39	4.88
Saint Gobain I	18.10	10.13	31.77	4.64	15.87	8.34	28.59	5.21	14.90	4.29	32.66	5.90
Saint Gobain II	26.86	15.93	47.58	6.86	26.21	15.66	48.31	6.77	25.13	13.28	52.85	7.43
Saint Gobain III	22.78	11.65	38.06	7.23	21.62	11.09	34.22	6.83	20.51	8.15	40.03	7.68
Saint Gobain IV	16.20	11.04	27.47	3.57	14.62	10.34	25.46	3.43	14.23	10.14	28.19	3.27
Scania	24.69	10.31	41.00	8.58	23.90	11.11	40.50	7.78	22.46	9.94	38.53	7.71
SES	20.92	14.28	26.18	3.16	21.88	15.07	27.45	3.19	20.33	15.55	27.07	3.14
Siemens	12.08	9.35	17.00	1.58	11.26	8.50	16.07	1.82	10.98	7.49	16.46	1.97
Sodexho	9.98	4.45	25.89	4.56	10.05	4.51	23.83	3.86	-	-	-	-
Stora Enso	38.10	21.18	88.19	13.38	36.55	20.79	73.32	11.71	34.90	16.47	99.83	14.20
Technip	24.55	15.79	34.93	3.61	22.82	13.98	28.30	2.53	22.00	10.89	26.68	2.91
Telecom Italia I	44.46	23.01	71.60	10.27	44.17	23.29	70.06	10.02	44.06	22.81	70.80	10.03
Telecom Italia II	45.95	24.40	75.40	10.85	45.88	24.90	74.26	10.65	45.69	23.93	74.02	10.55
Telefonica	33.40	16.46	59.20	8.87	32.45	15.82	57.05	9.06	31.73	15.44	56.67	9.15
Telekom Austria	24.04	9.55	64.27	12.71	23.91	9.19	60.32	11.48	23.20	8.99	62.40	12.21
Tesco I	9.45	4.06	21.63	4.81	9.74	3.80	22.28	4.69	10.47	4.94	20.87	4.42
Tesco II	10.38	5.00	22.95	4.36	11.07	5.42	22.50	4.38	11.42	6.09	22.35	4.01
Thales	13.98	9.31	19.08	3.19	14.22	9.77	23.05	3.10	14.31	10.19	22.47	2.98
Thyssenkrupp	35.04	17.12	68.64	12.85	33.76	16.59	64.20	12.35	32.72	14.96	61.79	12.54
Union Fenosa	20.74	7.29	38.08	7.63	21.15	8.30	35.56	6.99	21.69	9.22	34.86	7.11
Veolia Environ.	10.70	5.03	21.04	4.00	8.74	3.67	20.35	3.35	8.78	3.12	21.94	3.55
Vinci	23.96	12.26	38.82	7.08	20.48	10.08	32.71	6.12	19.81	7.54	37.90	7.84
Vivendi	34.30	17.70	55.20	8.30	32.49	17.06	47.89	7.25	32.25	17.76	50.12	7.85
Vodafone	15.31	10.93	24.78	3.28	14.02	8.62	22.85	3.69	12.70	7.50	78.08	5.07
Volkswagen	21.21	10.82	37.60	6.33	21.47	11.37	37.23	6.27	20.96	10.77	41.23	6.47
Volvo	20.86	9.80	35.07	6.77	20.50	8.69	33.77	6.45	18.84	7.80	34.08	6.67
Average	22.86	12.45	42.23	6.83	22.25	12.12	41.28	6.54	21.61	11.03	43.22	6.86

Panel E2

	GFI CDS Premium (b.p.)				CMA CDS Premium (b.p.)				Reuters CDS Premium (b.p.)				JPMorgan CDS Premium (b.p.)			
Issuer	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD	Mean	Min	Max	SD
Akzo Nobel I	65.19	13.58	172.60	42.68	68.28	13.97	179.18	46.97	68.86	13.58	189.58	48.77	66.15	12.70	200.50	43.36
Astrazeneca	51.12	16.53	170.83	32.64	43.85	14.94	151.87	35.36	47.78	16.53	162.13	38.51	-	-	-	-
Auchan	27.82	8.62	68.00	12.04	26.39	9.33	59.06	10.66	30.45	8.62	83.37	16.05	32.89	10.56	100.16	17.00
BASF	64.26	14.37	159.37	41.23	69.65	14.22	183.67	49.02	66.28	14.37	155.00	44.42	67.70	13.47	180.66	46.22
Bayer	64.72	20.42	137.87	27.24	67.40	20.19	151.83	31.81	65.77	20.42	145.00	30.04	67.58	18.65	177.00	34.73
Belgacom	40.88	18.18	89.92	17.06	40.88	18.18	89.92	17.06	38.84	18.18	93.43	16.79	-	-	-	-
BMW	144.24	12.83	537.50	143.93	147.89	14.47	537.88	144.01	148.77	0.01	607.12	148.52	147.68	11.87	558.53	145.91
Bouygues I	102.76	23.00	270.32	67.01	100.60	20.42	271.44	69.67	104.58	23.00	270.44	74.15	105.66	23.25	330.46	78.81
British AM Tob. II	67.14	19.16	173.66	32.03	67.65	19.96	175.64	33.76	67.84	19.16	197.07	37.61	69.46	18.40	195.15	36.91
Carrefour I	49.82	13.89	153.67	28.23	47.19	13.20	111.50	22.28	50.26	13.89	142.59	28.58	55.16	8.78	154.90	32.58
Carrefour II	47.49	11.14	159.47	31.39	41.78	9.30	99.42	24.55	46.64	11.14	150.45	32.30	52.18	7.52	166.25	34.73
Casino I	142.33	38.24	390.00	75.60	135.51	40.03	316.49	65.06	143.83	19.12	419.32	87.12	150.97	34.70	425.99	91.91
Casino II	130.09	26.59	390.00	81.10	112.60	26.61	267.23	60.19	135.61	26.59	450.48	98.85	137.72	21.87	438.15	102.39
Casino III	146.96	45.32	390.00	73.33	143.81	46.53	338.00	65.83	148.11	45.32	405.34	80.40	153.80	41.71	424.19	87.68
Edison	65.48	16.87	198.00	52.92	60.62	16.78	168.94	45.33	60.43	17.58	230.22	44.52	63.61	14.93	190.48	48.41
Enel	178.55	23.43	743.31	166.70	182.04	26.04	627.55	164.44	191.97	23.43	687.16	177.35	189.28	18.47	678.26	177.13
Energias de Portugal I	73.52	17.11	205.52	50.81	71.86	13.79	206.06	52.63	82.55	17.11	198.06	55.94	81.86	9.97	212.77	60.11
Energias de Portugal II	82.34	21.48	190.27	45.93	79.96	20.77	195.22	45.77	83.88	21.48	185.04	47.08	90.13	14.53	191.58	53.91
France Telecom I	64.58	21.74	121.87	26.03	67.44	20.45	126.01	27.44	66.41	21.74	124.21	27.23	68.28	18.48	129.98	29.45
France Telecom II	64.98	21.96	121.65	25.90	67.87	20.82	125.68	27.38	66.82	21.96	124.98	27.15	68.63	18.82	129.60	29.33
France Telecom III	59.48	17.98	122.00	26.99	59.21	14.99	123.47	27.92	58.61	17.98	124.98	27.74	60.56	14.42	131.52	29.89
Iberdrola I	92.62	13.12	295.50	57.70	94.08	15.55	222.38	58.51	95.11	13.12	279.93	64.98	99.38	14.87	288.35	68.69
Kingfisher	191.71	46.30	435.00	101.87	193.77	48.05	417.92	104.68	196.90	46.30	504.99	110.12	198.97	42.65	451.60	112.29
Koninklijke KPN	72.20	25.16	159.51	28.04	73.19	27.06	150.60	28.68	72.43	25.16	150.34	29.54	74.99	24.66	153.50	32.63
Louis Vuitton I	71.15	15.74	246.00	50.72	66.59	15.97	192.27	44.48	68.54	15.74	241.28	51.84	68.94	13.52	215.16	50.47
Louis Vuitton II	65.95	11.55	246.00	54.05	56.99	11.08	172.17	43.20	63.18	11.55	256.77	56.03	62.13	10.45	215.36	53.00
Philips	59.31	13.80	162.66	34.89	60.41	15.05	178.02	36.68	60.01	13.80	177.75	38.07	62.20	16.88	544.72	50.23
PPR	252.50	49.20	759.03	199.38	235.09	42.71	626.48	178.01	260.37	0.31	777.31	214.88	253.72	20.45	766.72	209.60
Repsol YPF	115.13	21.18	441.16	111.58	111.62	21.93	418.33	103.32	129.17	21.18	538.76	135.36	129.48	17.89	540.68	136.95
Saint Gobain II	177.26	25.63	555.63	134.35	177.34	26.74	598.69	135.17	178.87	25.63	542.81	139.96	184.10	24.75	716.99	150.31
Saint Gobain III	156.89	19.87	522.04	132.37	157.73	19.99	558.35	136.76	162.85	19.87	551.90	145.83	166.59	16.22	678.78	149.80
Schneider	68.66	17.59	199.78	42.03	59.11	16.01	190.79	36.62	59.73	17.59	224.02	48.43	66.01	18.25	205.27	45.13
SES	77.35	24.58	181.86	41.73	67.10	25.24	209.14	49.28	75.85	24.58	171.71	38.95	73.58	22.70	186.25	46.81
Siemens	76.03	13.98	238.85	56.55	76.03	15.31	221.31	52.55	75.30	13.98	237.34	53.11	76.17	14.24	243.46	54.22
Technip	98.66	16.83	302.73	80.09	104.16	18.73	337.98	85.92	104.66	16.83	331.48	82.84	118.05	9.19	359.02	89.82
Telecom Italia I	183.38	30.18	546.17	138.43	181.85	31.08	509.91	134.23	185.45	30.18	506.29	140.39	183.89	30.76	533.91	140.90
Telecom Italia II	184.89	30.95	540.33	136.07	183.87	32.87	502.01	131.94	187.16	30.95	503.61	137.81	186.49	33.07	532.19	138.95
Telefonica	97.99	25.54	247.69	54.96	93.37	28.53	203.95	46.64	94.97	25.54	228.13	49.22	98.27	25.26	258.90	53.15
Telekom Austria	59.18	13.71	142.58	30.07	67.44	14.34	194.68	41.74	63.00	13.71	160.78	34.63	69.16	14.41	206.46	44.21
Teliasonera	62.75	18.82	127.51	25.89	67.02	19.01	130.62	27.39	65.70	18.82	126.65	26.67	68.52	18.76	186.44	30.58
Tesco I	59.59	8.94	182.00	52.12	52.16	8.43	152.47	42.97	59.16	8.94	198.54	51.65	57.72	6.61	175.34	46.65
Tesco II	64.20	11.19	182.19	49.32	60.26	11.31	162.82	43.96	66.21	11.19	198.35	51.82	62.94	11.47	175.18	44.84
Thales	78.50	12.70	300.99	60.90	75.73	13.66	314.25	63.64	77.27	12.70	313.26	61.36	77.59	14.90	299.55	61.62
Thyssenkrupp	192.95	25.52	580.00	166.28	198.62	25.45	599.56	174.80	204.98	17.06	652.42	182.89	206.40	23.67	589.30	180.49
Union Fenosa	88.40	13.73	382.50	82.13	90.06	17.20	396.35	84.08	92.34	13.73	388.82	84.11	92.00	14.71	349.09	79.00
Volkswagen	132.69	18.92	360.02	91.15	143.18	18.38	418.14	104.23	142.96	5.87	415.92	104.38	140.31	15.61	429.68	103.28
Volvo	219.66	16.24	733.80	234.40	230.55	16.02	790.37	237.53	226.83	16.24	774.29	228.44	217.25	10.26	724.63	227.37
Average	103.14	20.64	306.15	73.29	102.11	20.84	291.86	72.04	105.70	18.38	318.75	77.71	107.20	18.21	334.28	79.59

Table II: Unit Root Test for Credit Spreads

Table II reports the results of the unit root test for the credit spreads and the basis. The first three columns contain the order of integration of the CDS premium, ASP spread and the basis for the period before the crisis. The last three column contain the order of integration of the CDS premium, ASP spread and the basis for the crisis period.

	November 2005 - August 2007			August 2007 - June 2009		
Issuer	CDS	ASP	Basis	CDS	ASP	Basis
Akzo Nobel I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Akzo Nobel II	I(1)	I(1)	I(0)	-	-	-
Altadis	I(1)	I(1)	I(1)	-	-	-
Astrazeneca	-	-	-	I(1)	I(1)	I(0)
Auchan	-	-	-	I(1)	I(1)	I(0)
BASF	-	-	-	I(1)	I(1)	I(0)
Bayer	-	-	-	I(1)	I(1)	I(0)
Belgacom	-	-	-	I(1)	I(1)	I(0)
BMW	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Bouygues I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Bouygues II	I(1)	I(1)	I(1)	-	-	-
British AM Tob. I	I(1)	I(1)	I(0)	-	-	-
British AM Tob. II	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Carrefour I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Carrefour II	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Casino I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Casino II	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)
Casino III	-	-	-	I(1)	I(1)	I(0)
Compass Group	I(0)	I(0)	I(0)	-	-	-
Edison	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Enel	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Energias de Portugal I	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Energias de Portugal II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
E.ON	I(1)	I(1)	I(0)	-	-	-
France Telecom I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
France Telecom II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
France Telecom III	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Iberdrola I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Iberdrola II	I(1)	I(1)	I(0)	-	-	-
Kingfisher	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Koninklijke KPN	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Louis Vuitton I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Louis Vuitton II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Philips	-	-	-	I(1)	I(1)	I(0)
PPR	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Reed Elsevier	I(1)	I(1)	I(0)	-	-	-
Renault	I(1)	I(1)	I(1)	-	-	-
Repsol YPF	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Reuters	I(1)	I(1)	I(1)	-	-	-
Saint Gobain I	I(1)	I(1)	I(0)	-	-	-
Saint Gobain II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Saint Gobain III	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Saint Gobain IV	I(1)	I(1)	I(0)	-	-	-
Scania	I(1)	I(1)	I(1)	-	-	-
Schneider	-	-	-	I(0)	I(0)	I(0)
SES	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Siemens	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)
Sodexho	I(1)	I(1)	I(1)	-	-	-
Stora Enso	I(1)	I(1)	I(1)	-	-	-
Technip	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Telecom Italia I	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Telecom Italia II	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Telefonica	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Telekom Austria	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Teliasonera	-	-	-	I(1)	I(1)	I(1)
Tesco I	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Tesco II	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Thales	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
Thyssenkrupp	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Union Fenosa	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Veolia Environ	I(1)	I(1)	I(0)	-	-	-
Vinci	I(1)	I(1)	I(0)	-	-	-
Vivendi	I(1)	I(1)	I(0)	-	-	-
Vodafone	I(1)	I(1)	I(1)	-	-	-
Volkswagen	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)
Volvo	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)

Table III: Descriptive Statistics for Incremental Cumulative Trading Profits

This table provides descriptive statistics for the increment in the discounted cumulative trading profits, which are obtained from the cash-and-carry arbitrage strategy and are denoted as $\Delta v(t)$. Panel A reports the descriptive statistics corresponding to the period before crisis while Panel B reports the descriptive statistics corresponding to the crisis. * indicates long-run arbitrage opportunities according to Table II.

Panel A

Issuer	Sample Size	Min (€)	Max (€)	Median (€)	Mean (€)	S.D. (€)	Skewness	Kurtosis
Akzo Nobel I*	252	-263.31	127.31	-15.14	-28.12	89.85	-0.36	2.48
Akzo Nobel II	405	-117.31	314.56	124.47	124.77	87.34	-0.09	2.36
Altadis*	402	-36.73	541.64	220.79	225.94	126.69	0.13	2.47
BMW	343	-118.89	6.38	0.00	-18.63	33.93	-1.43	3.49
Bouygues I*	377	-85.84	378.81	108.99	111.47	100.66	0.20	2.33
Bouygues II*	414	-119.82	5.94	-0.18	-27.97	41.79	-0.98	2.20
British AM Tob. I	418	-224.29	136.07	-1.95	-25.35	75.36	-0.74	4.01
British AM Tob. II	299	49.11	637.32	236.93	258.20	125.55	0.74	2.92
Carrefour I	299	-210.59	342.67	123.07	127.35	70.13	-0.10	5.27
Carrefour II	443	-158.68	10.16	0.02	-20.31	42.58	-1.79	4.67
Casino I*	273	-236.88	531.98	148.18	147.37	124.15	0.22	2.54
Casino II	397	-167.80	554.81	121.12	131.37	127.81	0.70	2.98
Compass Group	405	-36.25	554.61	113.24	129.38	136.74	0.95	3.28
Edison*	404	-33.58	671.12	297.26	273.62	161.16	-0.03	1.91
Enel	316	-233.54	122.46	-0.01	-3.99	48.76	-0.93	6.00
Energias de Portugal I	363	-110.53	3.70	-0.04	-25.28	36.30	-0.84	2.00
Energias de Portugal II	349	-127.60	68.35	-0.01	-16.09	44.16	-1.11	3.45
E.ON	410	-116.90	42.08	-0.90	-20.13	35.30	-0.98	3.02
France Telecom I*	146	-33.50	212.43	46.13	52.98	53.61	0.74	3.16
France Telecom II	122	-77.94	158.41	51.03	55.29	42.01	0.33	3.34
France Telecom III	440	-332.43	8.65	0.05	-14.86	67.25	-4.23	18.98
Iberdrola I	400	-84.76	8.87	-0.05	-19.38	30.28	-0.96	2.05
Iberdrola II	348	-107.16	4.15	-1.28	-30.11	33.61	-0.52	1.78
Kingfisher	400	-147.86	222.92	44.36	42.28	60.03	-0.21	3.94
Koninklijke KPN	273	-0.41	398.51	181.80	178.27	84.24	0.11	2.38
Louis Vuitton I	287	-64.87	345.12	138.34	146.09	70.97	0.12	3.12
Louis Vuitton II	414	-35.14	352.81	119.32	121.76	84.66	0.32	2.43
PPR	353	-120.38	679.26	291.10	285.61	170.16	-0.04	2.09
Reed Elsevier	387	-158.42	12.96	-12.63	-35.87	44.16	-0.84	2.38
Renault*	344	-26.46	483.63	188.59	187.04	94.12	0.06	2.80
Repsol YPF	410	-64.16	573.18	151.33	174.82	140.43	0.47	2.27
Reuters*	415	-79.56	523.83	109.21	127.21	111.02	0.70	2.85
Saint Gobain I	398	-326.44	132.47	0.05	2.09	60.54	-0.83	5.38
Saint Gobain II	310	-25.82	402.05	192.10	186.13	81.36	0.15	2.45
Saint Gobain III	452	-132.28	479.56	177.52	160.39	124.46	-0.03	1.95
Saint Gobain IV	356	-27.17	176.08	53.42	55.83	49.54	0.50	2.35
Scania*	380	-209.71	7.99	0.04	-16.79	49.86	-2.73	8.86
SES*	367	-118.50	93.99	0.00	8.54	24.59	0.19	6.97
Siemens	274	-122.21	24.30	0.00	-10.11	23.42	-2.81	11.59
Sodexho*	403	-0.43	776.56	369.08	357.99	192.90	-0.01	1.96
Stora Enso*	449	-147.99	318.71	107.43	104.74	90.16	-0.03	1.97
Technip*	311	-6.32	512.24	137.88	143.40	131.97	0.76	2.89
Telecom Italia I	397	-168.95	67.73	-4.11	-14.96	41.02	-1.31	6.40
Telecom Italia II	338	-327.23	248.78	-8.94	-17.73	90.59	-0.54	3.84
Telefonica*	394	-161.50	351.80	119.98	116.38	96.16	0.11	2.46
Telekom Austria	407	-216.61	10.43	0.04	-23.45	55.39	-2.20	6.49
Tesco I*	411	-124.89	9.89	0.00	-22.96	40.64	-1.27	2.86
Tesco II*	358	-0.04	388.22	187.28	177.83	89.68	-0.26	2.07
Thales*	260	-64.51	308.67	72.56	75.33	68.35	0.92	3.83
Thyssenkrupp*	355	-177.82	371.69	117.90	114.70	103.87	0.12	2.35
Union Fenosa	409	-144.62	365.64	107.83	119.61	104.52	0.13	2.04
Veolia Environ	424	-123.08	6.13	-36.26	-36.83	38.85	-0.36	1.62
Vinci	431	-248.46	87.01	-0.02	-18.57	53.56	-1.77	7.32
Vivendi	414	-63.05	299.16	25.82	54.13	71.76	1.20	3.89
Vodafone*	384	-169.58	121.65	-9.99	-24.64	61.25	-0.39	2.45
Volkswagen	310	-232.47	295.36	108.34	109.53	74.00	-0.45	3.95
Volvo	412	-121.11	136.63	-19.39	-24.37	38.92	-0.44	3.46
Average	363	-125.32	263.64	78.63	73.53	78.11	-0.38	3.73

Panel B

Issuer	Sample Size	Min (€)	Max (€)	Median (€)	Mean (€)	S.D. (€)	Skewness	Kurtosis
Akzo Nobel I	480	-312.96	38.05	0.01	-21.73	66.99	-2.87	7.00
Astrazeneca	415	-506.96	187.62	19.78	-33.32	161.45	-0.96	0.10
Auchan	472	-635.74	1373.19	11.49	115.85	381.50	1.54	2.24
BASF	480	-223.42	20.64	-0.01	-17.54	51.05	-2.83	6.88
Bayer	480	-269.88	2987.31	459.25	627.79	582.89	1.16	1.11
Belgacom	480	-308.50	390.79	0.21	36.99	120.29	0.58	2.01
BMW	480	-331.21	25.63	-0.16	-24.83	67.34	-2.75	7.01
Bouygues I	480	-1367.03	1392.84	62.97	57.50	383.58	0.04	2.19
British AM Tob. II*	480	-121.11	5192.88	777.32	1211.50	1176.86	1.19	0.62
Carrefour I	480	-233.06	22.32	-0.36	-24.08	55.41	-2.19	3.62
Carrefour II	463	-203.87	28.80	-1.04	-33.02	62.00	-1.44	0.30
Casino G. P. I	480	-694.12	2827.54	99.17	296.95	603.76	1.76	3.57
Casino G. P. II	442	-1493.23	834.44	-0.25	-93.64	401.82	-0.81	0.94
Casino G. P. III	480	-295.07	4439.21	575.94	921.33	995.94	1.36	1.22
Edison	480	-753.78	3190.80	291.44	536.99	693.19	1.40	1.54
Enel*	480	-404.82	22.50	-0.05	-24.41	83.35	-3.33	9.83
Energias de Portugal I*	312	-327.60	243.70	-0.12	-34.30	93.76	-1.14	2.37
Energias de Portugal II	480	-282.72	27.18	-0.09	-25.69	72.00	-2.56	4.94
France Telecom I	480	-938.23	508.55	0.42	-89.40	316.69	-0.52	-0.64
France Telecom II	480	-622.14	2641.78	357.34	514.26	540.29	1.27	1.39
France Telecom III	480	-239.45	25.13	-0.82	-30.18	62.72	-1.95	2.49
Iberdrola I	480	-252.78	39.22	-0.32	-27.42	64.19	-2.19	3.51
Kingfisher	324	-1425.17	3383.41	77.86	329.24	797.85	0.89	1.49
Koninklijke KPN	480	-181.45	6018.88	905.42	1313.90	1224.85	1.37	1.33
Louis Vuitton I	480	-1616.56	1107.59	90.56	-36.30	546.18	-0.82	0.43
Louis Vuitton II	445	-1025.47	593.97	29.03	-56.82	362.17	-0.60	-0.32
Philips	480	-572.69	200.56	0.03	-11.42	130.34	-1.89	5.82
PPR	480	-1089.23	344.26	35.50	-10.88	264.10	-1.83	3.68
Repsol YPF	451	-3134.09	2119.35	151.50	97.05	861.39	-1.20	2.68
Saint Gobain II	480	-2070.10	2296.55	141.71	75.26	634.94	0.08	1.27
Saint Gobain III	435	-1617.87	783.78	36.35	-98.24	485.71	-0.88	0.07
Schneider	480	-617.60	1017.40	27.88	50.62	254.37	-0.28	0.36
SES*	480	-522.90	4192.00	264.83	479.69	702.76	2.25	5.92
Siemens	480	-243.25	22.16	-0.07	-23.48	64.81	-2.40	3.92
Technip	480	-1727.33	3282.13	324.61	346.18	649.37	-0.42	1.81
Telecom Italia I	480	-4577.43	1531.38	121.73	-265.17	1253.56	-1.61	1.88
Telecom Italia II	480	-811.16	4560.67	591.18	783.26	812.20	1.37	2.22
Telefonica	480	-1127.02	2126.51	195.86	227.94	391.27	0.84	3.03
Telekom Austria*	372	-589.60	3955.00	272.20	503.60	743.14	2.50	6.50
Teliasonera*	480	-60.45	5151.41	900.01	1257.90	1127.19	1.28	0.97
Tesco I	433	-1568.02	2058.54	25.06	153.66	542.60	1.60	3.20
Tesco II	480	-732.93	1390.59	43.92	119.07	377.67	1.17	1.67
Thales	480	-185.89	21.57	-0.42	-22.50	45.84	-1.85	2.15
Thyssenkrupp*	480	-429.46	57.17	-0.25	-26.40	67.95	-3.56	15.27
Union Fenosa	480	-247.97	60.78	-0.58	-28.10	61.62	-1.70	1.94
Volkswagen	480	-205.68	44.81	-0.62	-25.05	49.73	-1.91	3.04
Volvo	371	-648.70	556.50	76.04	58.94	256.32	-0.31	-0.17
Average	462	-805.23	1560.36	148.12	192.16	420.11	-0.49	2.86

Table IV: Statistical Arbitrage Test for Unconstrained Mean (UM) model

Under the UM model, the process for the increment in the discounted cumulative trading profits is defined as $\Delta v_i = \mu i^{\theta} + i^{\lambda} z_i$. Panel A reports the statistical test results obtained for the period before crisis (November 2005 - August 2007) while Panel B reports the results obtained during the crisis (August 2007 - June 2009). The first four columns of each panel include the estimated parameters. The next four columns report the *t-statistic* of the corresponding parameter. The nineth column of each panel shows whether statistical arbitrage (SA) opportunities exist or not.† The tenth column of each panel presents the *p-value* associated to the absence of SA. The last column reports the existence or absence of SA under JTTW test. In boldface are the statistical arbitrage opportunities detected by our test.

Panel A

Issuer	Parameters				t-stat					SA	
	μ	σ	θ	λ	μ	σ	θ	λ	SA	p-value	SA (JTTW)
Akzo Nobel I	-2×10^{-3}	67.55	2.05	0.02	-0.59	5.05	6.53	0.50	No	0.59	No
Akzo Nobel II	14.18	11.46	0.42	0.38	5.05	4.64	11.01	8.98	No	0.35	Yes***
Altadis	**12.48**	**13.82**	**0.56**	**0.38**	**6.24**	**5.06**	**18.45**	**9.83**	**Yes****	**0.04**	**Yes*****
BMW	-59.66	37.89	-0.25	-0.03	-2.76	4.98	-3.00	-0.63	No	1.00	No
Bouygues I	1.52	32.67	0.83	0.18	2.59	5.57	11.84	4.97	Yes*	0.06	Yes***
Bouygues II	-82.59	40.11	-0.22	0.01	-3.63	4.81	-3.66	0.14	No	1.00	No
British AM Tob. I	98.68	90.79	-1.62	-0.03	1.16	4.86	-1.89	-0.67	No	1.00	No
British AM Tob. II	**54.86**	**40.32**	**0.32**	**0.19**	**4.90**	**5.38**	**7.75**	**4.97**	**Yes****	**0.04**	**Yes*****
Carrefour I	39.84	6.03	0.25	0.48	13.48	6.01	14.26	13.91	No	0.92	No
Carrefour II	-71.84	53.33	-0.26	-0.05	-2.66	5.40	-3.18	-1.32	No	1.00	No
Casino I	**7.71**	**27.83**	**0.61**	**0.28**	**2.79**	**4.74**	**8.58**	**6.36**	**Yes****	**0.02**	**Yes*****
Casino II	**3.32**	**28.60**	**0.70**	**0.26**	**2.22**	**7.01**	**8.57**	**9.44**	**Yes*****	**0.00**	**Yes*****
Compass Group	**3.37**	**52.32**	**0.70**	**0.17**	**1.88**	**7.16**	**7.25**	**6.15**	**Yes****	**0.04**	**Yes*****
Edison	**2.71**	**12.80**	**0.87**	**0.34**	**6.56**	**6.52**	**31.78**	**11.30**	**Yes*****	**0.00**	**Yes*****
Enel	0.00	14.79	4.42	0.23	0.00	3.62	53.93	8.23	No	0.86	No
Energias de Portugal I	-74.31	36.63	-0.23	-0.01	-3.59	4.86	-3.61	-0.12	No	1.00	No
Energias de Portugal II	-68.21	47.46	-0.31	-0.02	-2.49	5.34	-3.23	-0.45	No	1.00	No
E.ON	-37.51	40.50	-0.13	-0.03	-2.33	5.62	-1.44	-0.82	No	1.00	No
France Telecom I	0.27	11.86	1.22	0.28	1.45	5.48	8.24	6.44	No	0.10	Yes***
France Telecom II	11.14	5.03	0.40	0.49	4.89	3.71	7.47	7.14	No	0.50	No
France Telecom III	-330.98	73.33	-0.81	-0.03	-4.25	5.26	-4.86	-0.67	No	1.00	No
Iberdrola I	-58.25	33.35	-0.23	-0.02	-3.63	5.15	-3.79	-0.59	No	1.00	No
Iberdrola II	-57.61	27.08	-0.15	0.04	-4.51	4.43	-3.16	0.76	No	1.00	No
Kingfisher	1.57	27.82	0.63	0.14	1.35	5.38	4.70	3.88	Yes*	0.08	Yes***
Koninklijke KPN	31.58	15.03	0.36	0.31	8.11	5.79	14.13	8.59	No	0.23	Yes***
Louis Vuitton I	**57.60**	**50.72**	**0.20**	**0.06**	**4.70**	**4.99**	**4.52**	**1.37**	**Yes****	**0.04**	**Yes*****
Louis Vuitton II	1.18	26.05	0.87	0.15	3.17	6.33	15.57	4.98	Yes*	0.08	Yes***
PPR	**3.94**	**20.21**	**0.83**	**0.29**	**5.51**	**5.50**	**24.84**	**8.07**	**Yes*****	**0.00**	**Yes*****
Reed Elsevier	-48.31	54.90	-0.06	-0.05	-3.20	5.28	-0.97	-1.19	No	1.00	No
Renault	**11.75**	**19.38**	**0.55**	**0.24**	**6.37**	**5.19**	**18.38**	**6.14**	**Yes****	**0.02**	**Yes*****
Repsol YPF	**0.71**	**13.99**	**1.03**	**0.36**	**3.15**	**7.49**	**18.27**	**14.02**	**Yes****	**0.02**	**Yes*****
Reuters	**0.52**	**8.99**	**1.03**	**0.41**	**2.56**	**7.21**	**14.79**	**15.39**	**Yes****	**0.04**	**Yes*****
Saint Gobain I	4.36	8.76	-1.46	0.36	0.52	6.30	-0.92	11.75	No	1.00	No
Saint Gobain II	46.42	20.30	0.28	0.23	7.81	6.01	10.89	7.03	Yes*	0.09	Yes**
Saint Gobain III	0.49	15.38	1.07	0.30	3.41	5.51	20.87	8.72	No	0.13	Yes***
Saint Gobain IV	18.79	24.61	0.22	0.14	3.68	5.12	4.11	3.49	Yes*	0.08	Yes***
Scania	-68.78	75.84	-0.29	-0.09	-1.86	5.46	-2.50	-2.44	No	1.00	No
SES	0.22	4.49	0.71	0.32	0.88	6.87	3.37	11.28	No	0.10	Yes***
Siemens	-0.43	5.99	0.65	0.28	-0.82	4.81	2.69	6.34	No	0.95	No
Sodexho	**6.52**	**41.16**	**0.76**	**0.15**	**6.64**	**6.53**	**28.16**	**5.16**	**Yes****	**0.03**	**Yes*****
Stora Enso	0.29	9.84	1.08	0.35	2.68	5.36	16.63	9.88	No	0.17	Yes***
Technip	**16.92**	**39.30**	**0.43**	**0.23**	**2.78**	**5.09**	**6.13**	**5.75**	**Yes****	**0.02**	**Yes*****
Telecom Italia I	-4.47	14.91	0.24	0.20	-1.37	4.45	1.67	4.45	No	1.00	No
Telecom Italia II	-3×10^{-4}	32.82	2.17	0.19	-0.41	5.46	4.97	5.15	No	0.58	No
Telefonica	0.36	10.71	1.09	0.35	2.91	5.54	17.72	9.76	No	0.17	Yes***
Telekom Austria	-43.98	70.42	-0.13	-0.05	-1.63	5.86	-1.02	-1.47	No	1.00	No
Tesco I	-78.92	40.38	-0.26	-1×10^{-3}	-3.37	5.29	-3.81	-0.03	No	1.00	No
Tesco II	**6.96**	**22.14**	**0.63**	**0.16**	**6.85**	**6.74**	**23.46**	**5.39**	**Yes*****	**0.00**	**Yes*****
Thales	48.80	26.02	0.09	0.20	4.06	4.67	1.67	4.39	No	0.63	No
Thyssenkrupp	18.67	17.40	0.36	0.35	4.18	4.45	7.61	7.69	No	0.53	No
Union Fenosa	0.55	19.32	1.01	0.26	2.74	6.79	15.69	9.12	No	0.24	Yes***
Veolia Environ.	-39.40	44.15	-0.01	-0.03	-3.60	5.59	-0.25	-0.74	No	1.00	No
Vinci	-0.42	8.50	0.71	0.35	-0.92	5.03	3.60	9.00	No	0.94	No
Vivendi	0.94	9.68	0.77	0.36	1.58	6.58	6.66	12.37	No	0.11	Yes***
Vodafone	-2×10^{-7}	2.18	3.44	0.60	-0.49	3.92	9.70	11.81	No	0.47	No
Volkswagen	17.07	17.09	0.38	0.27	4.66	6.74	8.81	9.00	No	0.11	Yes***
Volvo	-6.68	40.84	0.25	-0.01	-1.94	5.89	2.68	-0.38	No	1.00	No

Panel B

Issuer	Parameters				t-stat				SA	SA	SA (JTTW)
	μ	σ	θ	λ	μ	σ	θ	λ	SA	p-value	
Akzo Nobel I	-238.73	67.18	-0.53	-0.01	-3.89	5.38	-6.08	-0.15	No	1.00	No
Astrazeneca	-0.25	82.09	0.93	0.13	-0.44	5.26	2.32	3.48	No	0.67	No
Auchan	-157.36	14.62	-1.17	0.58	-10.74	8.06	-3.69	25.18	No	1.00	No
BASF	-76.46	65.90	-0.30	-0.05	-1.99	6.12	-2.71	-1.68	No	1.00	No
Bayer	**4.12**	**17.32**	**0.92**	**0.58**	**2.55**	**5.18**	**13.09**	**15.83**	**Yes****	**0.04**	**Yes*****
Belgacom	4.65	11.35	0.40	0.44	1.72	3.94	3.58	9.06	No	0.53	No
BMW	-198.15	71.26	-0.44	-0.01	-3.35	5.47	-5.33	-0.43	No	1.00	No
Bouygues I	10.91	21.76	0.36	0.51	1.88	7.04	3.53	19.21	No	0.65	No
British AM Tob. II	**0.69**	**11.45**	**1.35**	**0.74**	**2.59**	**8.38**	**20.07**	**33.28**	**Yes****	**0.03**	**Yes*****
Carrefour I	-70.70	69.77	-0.21	-0.05	-2.09	5.97	-2.17	-1.46	No	1.00	No
Carrefour II	-91.26	69.85	-0.20	-0.02	-2.48	5.60	-2.41	-0.73	No	1.00	No
Casino I	0.15	10.45	1.45	0.75	0.92	7.30	7.74	29.21	No	0.16	Yes**
Casino II	0.00	4.06	2.65	0.41	-0.34	5.93	5.42	12.82	No	0.67	No
Casino III	**1.08**	**21.69**	**1.22**	**0.64**	**2.05**	**7.23**	**14.37**	**24.51**	**Yes****	**0.05**	**Yes*****
Edison	**1.36**	**32.40**	**1.09**	**0.52**	**1.83**	**8.14**	**11.38**	**22.79**	**Yes****	**0.05**	**Yes*****
Enel	-82.74	116.84	-0.24	-0.07	-1.42	6.40	-1.67	-2.28	No	1.00	No
Energias de Portugal I	-66.19	98.89	-0.12	-0.01	-1.75	5.64	-1.08	-0.35	No	1.00	No
Energias de Portugal II	-82.64	96.30	-0.23	-0.06	-1.72	6.28	-2.03	-1.93	No	1.00	No
France Telecom I	72.24	43.58	-0.38	0.37	2.36	5.35	-2.51	10.51	No	1.00	No
France Telecom II	23.22	15.56	0.57	0.61	4.01	5.63	11.74	18.07	No	0.55	No
France Telecom III	-104.98	74.34	-0.25	-0.04	-2.50	5.73	-2.92	-1.06	No	1.00	No
Iberdrola I	-89.98	78.76	-0.24	-0.04	-2.14	5.80	-2.42	-1.27	No	1.00	No
Kingfisher	0.00	15.45	2.30	0.74	0.25	5.86	3.14	21.39	No	0.46	No
Koninklijke KPN	**2.03**	**18.07**	**1.17**	**0.66**	**2.35**	**7.53**	**15.71**	**26.52**	**Yes****	**0.04**	**Yes*****
Louis Vuitton I	-11.53	16.33	-0.94	0.63	-0.76	5.99	-1.05	19.99	No	1.00	No
Louis Vuitton II	-176.41	23.14	-0.79	0.51	-8.16	5.18	-4.74	13.82	No	1.00	No
Philips	-80.45	82.09	-0.43	0.09	-1.39	5.25	-2.15	2.42	No	1.00	No
PPR	-135.61	79.49	-0.57	0.22	-2.20	6.17	-2.64	7.30	No	1.00	No
Repsol YPF	3.90	11.75	0.68	0.75	1.73	8.53	6.28	34.31	No	0.44	No
Saint Gobain II	29.38	16.66	0.32	0.65	3.73	6.11	5.31	21.15	No	0.93	No
Saint Gobain III	0.00	52.84	2.12	0.40	-0.31	5.68	3.95	12.07	No	1.00	No
Schneider	11.01	18.70	0.32	0.48	1.82	4.50	2.87	11.39	No	0.64	No
SES	**0.26**	**2.86**	**1.36**	**0.94**	**2.18**	**6.67**	**13.82**	**33.24**	**Yes****	**0.05**	**Yes*****
Siemens	-166.11	71.49	-0.41	-0.02	-2.97	5.55	-4.70	-0.66	No	1.00	No
Technip	3.82	3.54	0.85	0.93	3.76	5.34	16.54	26.17	No	0.80	No
Telecom Italia I	72.40	9.96	0.07	0.85	8.74	8.02	1.07	36.51	No	1.00	No
Telecom Italia II	**16.25**	**21.86**	**0.71**	**0.56**	**3.39**	**6.55**	**13.01**	**21.43**	**Yes****	**0.05**	**Yes*****
Telefonica	24.20	13.19	0.42	0.60	4.56	7.18	9.36	22.94	No	0.76	No
Telekom Austria	**0.21**	**2.23**	**1.47**	**1.04**	**2.11**	**7.49**	**17.59**	**41.54**	**Yes****	**0.05**	**Yes*****
Teliasonera	**7.01**	**9.26**	**0.92**	**0.70**	**6.60**	**24.42**	**69.97**	**7.44**	**Yes****	**0.04**	**Yes*****
Tesco I	-128.68	5.52	-0.24	0.81	-25.52	6.76	-6.23	29.18	No	1.00	No
Tesco II	-108.21	15.23	-0.48	0.58	-8.25	6.99	-5.20	21.55	No	1.00	No
Thales	-32.44	49.43	-0.07	-0.01	-2.06	5.81	-0.76	-0.46	No	1.00	No
Thyssenkrupp	-69.91	86.34	-0.19	-0.05	-1.83	5.92	-1.73	-1.49	No	1.00	No
Union Fenosa	0.40	33.52	1.29	0.53	1.35	7.03	10.09	19.71	No	0.12	Yes***
Volkswagen	-83.03	56.11	-0.24	-0.03	-2.80	5.85	-3.16	-0.79	No	1.00	No
Volvo	10.22	62.75	0.30	0.27	1.18	5.96	2.16	8.57	No	0.25	Yes**

Table V: Profits and Performance Measures

Table V reports the profits and performance measures corresponding to the different cases under study. This table splits into two panels. Panel A refers to the period before the crisis (November 2005 - August 2007) while Panel B corresponds to the crisis period (August 2007 - June 2009). The first column of each panel reports the total profits in Euros. The second column of each panel shows the number of investment days while the third one shows the total investment in ASPs or CDSs, which is calculated as the number of investment days multiplied by the nominal of each purchase (500,000 euros). The fourth column includes the returns in basis points obtained as the ratio between the first and the third columns. The fifth column reports the probability of a loss, which is defined as the ratio between the number of days with losses and the total number of investment days. The last column includes a modification of the symmetric downside-risk Sharpe ratio in Ziemba (2005), which is obtained as the ratio between the total profits and the corresponding semivariance of the payments. In boldface are the statistical arbitrage opportunities deteced by our test.

Panel A

Issuer	Total Profits	Number of investment days	Total investment in AS/CDSs	Returns per AS/CDS invest. (b.p.)	Days with losses (%)	Modified Ziemba Ratio
Akzo Nobel I	-7,089	152	76,000,000	-0.93	0.49	-117.71
Akzo Nobel II	50,534	344	172,000,000	2.94	0.06	871.42
Altadis	**90,829**	**300**	**150,000,000**	**6.06**	**0.00**	**1274.58**
BMW	-6,391	15	7,500,000	-8.52	1.00	-114.33
Bouygues I	42,025	197	98,500,000	4.27	0.11	880.47
Bouygues II	-11,578	21	10,500,000	-11.03	1.00	-234.42
British AM Tob. I	-10,595	42	21,000,000	-5.05	0.76	-140.05
British AM Tob. II	**77,202**	**232**	**116,000,000**	**6.66**	**0.00**	**2632.81**
Carrefour I	38,077	221	110,500,000	3.45	0.04	809.54
Carrefour II	-8,996	13	6,500,000	-13.84	1.00	-131.55
Casino I	**40,231**	**148**	**74,000,000**	**5.44**	**0.05**	**1173.74**
Casino II	**52,153**	**196**	**98,000,000**	**5.32**	**0.08**	**1293.27**
Compass Group	**52,398**	**121**	**60,500,000**	**8.66**	**0.01**	**24460.91**
Edison	**110,543**	**339**	**169,500,000**	**6.52**	**0.00**	**1610.33**
Enel	-1,263	91	45,500,000	-0.28	0.58	-21.70
Energias de Portugal I	-9,176	21	10,500,000	-8.74	1.00	-474.67
Energias de Portugal II	-5,615	37	18,500,000	-3.04	0.62	-106.64
E.ON	-8,255	43	21,500,000	-3.84	0.70	-251.67
France Telecom I	7,735	119	59,500,000	1.30	0.09	597.31
France Telecom II	6,745	100	50,000,000	1.35	0.01	268.70
France Telecom III	-6,537	3	1,500,000	-43.58	1.00	-65.60
Iberdrola I	-7,752	19	9,500,000	-8.16	1.00	-439.92
Iberdrola II	-9,596	28	14,000,000	-6.85	1.00	-615.27
Kingfisher	16,911	270	135,000,000	1.25	0.19	396.31
Koninklijke KPN	48,667	221	110,500,000	4.40	0.00	1186.67
Louis Vuitton I	**41,928**	**251**	**125,500,000**	**3.34**	**0.01**	**975.46**
Louis Vuitton II	50,408	345	172,500,000	2.92	0.03	1127.47
PPR	**100,819**	**289**	**144,500,000**	**6.98**	**0.02**	**1117.27**
Reed Elsevier	-13,883	36	18,000,000	-7.71	0.97	-414.19
Renault	**64,342**	**249**	**124,500,000**	**5.17**	**0.01**	**1058.43**
Repsol YPF	**71,678**	**298**	**149,000,000**	**4.81**	**0.04**	**1665.42**
Reuters	**52,793**	**229**	**114,500,000**	**4.61**	**0.02**	**1684.79**
Saint Gobain I	833	312	156,000,000	0.05	0.51	15.86
Saint Gobain II	57,699	261	130,500,000	4.42	0.00	1818.04
Saint Gobain III	72,495	348	174,000,000	4.17	0.09	1402.95
Saint Gobain IV	19,875	75	37,500,000	5.30	0.03	2101.89
Scania	-6,382	7	3,500,000	-18.23	1.00	-84.03
SES	3,134	52	26,000,000	1.21	0.35	179.61
Siemens	-2,771	36	18,000,000	-1.54	0.83	-83.01
Sodexho	**144,270**	**350**	**175,000,000**	**8.24**	**0.00**	**1386.46**
Stora Enso	47,029	250	125,000,000	3.76	0.13	1136.87
Technip	**44,597**	**112**	**56,000,000**	**7.96**	**0.00**	**1339.04**
Telecom Italia I	-5,940	63	31,500,000	-1.89	0.70	-138.85
Telecom Italia II	-5,993	197	98,500,000	-0.61	0.56	-77.62
Telefonica	45,854	317	158,500,000	2.89	0.09	1015.34
Telekom Austria	-9,545	11	5,500,000	-17.35	1.00	-109.26
Tesco I	-9,439	150	75,000,000	-1.26	1.00	-139.61
Tesco II	**63,664**	**250**	**125,000,000**	**5.09**	**0.00**	**1070.41**
Thales	19,586	110	55,000,000	3.56	0.05	738.67
Thyssenkrupp	40,719	235	117,500,000	3.47	0.10	820.77
Union Fenosa	48,922	250	125,000,000	3.91	0.13	1036.56
Veolia Environ.	-15,617	34	17,000,000	-9.19	1.00	-727.89
Vinci	-8,006	53	26,500,000	-3.02	0.66	-110.11
Vivendi	22,408	97	48,500,000	4.62	0.08	2131.29
Vodafone	-9,462	233	116,500,000	-0.81	0.52	-198.53
Volkswagen	33,954	256	128,000,000	2.65	0.05	681.39
Volvo	-10,040	71	35,500,000	-2.83	0.69	-320.31

Panel B

Issuer	Total Profits	Number of investment days	Total investment in AS/CDSs	Returns per AS/CDS invest. (b.p.)	Days with losses (%)	Modified Ziemba Ratio
Akzo Nobel I	-10,431	6	3,000,000	-34.77	1.000	-101.75
Astrazeneca	-13,828	81	40,500,000	-3.41	0.407	-99.34
Auchan	54,683	169	84,500,000	6.47	0.373	305.36
BASF	-8,417	7	3,500,000	-24.05	1.000	-107.18
Bayer	**301,341**	**347**	**173,500,000**	**17.37**	**0.032**	**2000.15**
Belgacom	17,754	38	19,000,000	9.34	0.289	212.54
BMW	-11,920	8	4,000,000	-29.80	1.000	-114.36
Bouygues I	27,598	260	130,000,000	2.12	0.377	86.12
British AM Tob. II	**581,521**	**300**	**150,000,000**	**38.77**	**0.017**	**2386.71**
Carrefour I	-11,560	11	5,500,000	-21.02	1.000	-130.99
Carrefour II	-15,850	13	6,500,000	-24.38	1.000	-156.35
Casino G. P. I	177,187	200	100,000,000	17.72	0.230	1065.67
Casino G. P. II	-18,947	190	95,000,000	-1.99	0.453	-122.91
Casino G. P. III	**442,238**	**231**	**115,500,000**	**38.29**	**0.056**	**2584.89**
Edison	**257,755**	**338**	**169,000,000**	**15.25**	**0.080**	**1780.05**
Enel	-11,719	5	2,500,000	-46.87	1.000	-92.62
Energias de Portugal I	-16,025	20	10,000,000	-16.02	0.750	-126.52
Energias de Portugal II	-12,331	7	3,500,000	-35.23	1.000	-111.00
France Telecom I	-17,910	154	77,000,000	-2.33	0.442	-211.82
France Telecom II	246,844	298	149,000,000	16.57	0.108	1626.87
France Telecom III	-14,488	13	6,500,000	-22.29	1.000	-143.50
Iberdrola I	-13,160	10	5,000,000	-26.32	1.000	-129.91
Kingfisher	106,675	146	73,000,000	14.61	0.267	233.51
Koninklijke KPN	**630,671**	**398**	**199,000,000**	**31.69**	**0.005**	**3246.02**
Louis Vuitton I	-17,424	282	141,000,000	-1.24	0.379	-33.23
Louis Vuitton II	-17,272	243	121,500,000	-1.42	0.449	-103.31
Philips	-5,484	44	22,000,000	-2.49	0.455	-33.04
PPR	-5,221	116	58,000,000	-0.90	0.379	-15.63
Repsol YPF	46,583	358	179,000,000	2.60	0.310	49.07
Saint Gobain II	36,126	384	192,000,000	1.88	0.393	71.12
Saint Gobain III	-17,957	202	101,000,000	-1.78	0.361	-107.86
Schneider	24,296	110	55,000,000	4.42	0.364	101.75
SES	**230,252**	**119**	**59,500,000**	**38.70**	**0.091**	**2721.04**
Siemens	-11,270	7	3,500,000	-32.20	1.000	-112.62
Technip	166,168	194	97,000,000	17.13	0.144	328.26
Telecom Italia I	-19,283	205	102,500,000	-1.88	0.341	-75.31
Telecom Italia II	**375,964**	**299**	**149,500,000**	**25.15**	**0.057**	**1549.79**
Telefonica	109,413	272	136,000,000	8.05	0.235	438.23
Telekom Austria	**366,608**	**250**	**125,000,000**	**29.33**	**0.056**	**3242.14**
Teliasonera	**479,520**	**250**	**125,000,000**	**38.36**	**0.007**	**2186.69**
Tesco I	73,755	276	138,000,000	5.34	0.453	308.19
Tesco II	57,154	250	125,000,000	4.57	0.408	294.27
Thales	-10,800	15	7,500,000	-14.40	0.933	-145.61
Thyssenkrupp	-12,673	12	6,000,000	-21.12	1.000	-118.63
Union Fenosa	240,685	250	125,000,000	19.25	0.236	965.01
Volkswagen	-12,026	15	7,500,000	-16.03	1.000	-149.18
Volvo	23,846	150	75,000,000	3.18	0.373	116.86

Table VI: Determinants of Statistical Arbitrage Opportunities

This table presents the effects of the potential determinants of statistical arbitrage opportunities. The results are estimated by a Probit model with heteroskedasticity robust standard errors. The sample is formed by 104 cases/bonds from two different periods, 57 cases correspond to the period before crisis and 47 of them to the crisis period. The dependent variable is a dummy variable that equals 1 if there is a statistical arbitrage opportunity and 0 otherwise. The potential determinants of statistical arbitrage considered are: *Rating* is a discrete variable with values between 1 and 7, such that 1 corresponds to rating BBB- and 7 to rating AA-, the rest of the values correspond to the intermediate ratings; *Bond coupon* ; *Existence of long-run arbitrage opportunities* that refers to a dummy variable equals to one if there exists a long run arbitrage opportunity; *Crisis* which is a dummy variable with value equals to one when the observation corresponds to the crisis period. The first column reports the estimated coefficients. The second column presents the heteroskedasticity-robust standard errors. The third column reports the coefficient *p-value* and last column reports the marginal effect.

	Coefficient	Robust Std. Err.	P-value	Marginal Effect
Rating	-0.377	0.124	0.002	-0.093
Bond coupon	0.313	0.176	0.075	0.078
Existence of long-run arbitrage opportunities	1.114	0.353	0.002	0.339
Crisis	0.003	0.334	0.992	0.001
Constant	-1.467	1.029	0.154	
R-squared	0.214			
Number of observations	104			
Wald chi2(4 df)	22.110			
Prob > chi2	0.000			