Rethinking Capital Structure Arbitrage: A Price Discovery Perspective

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**Abstract**

The capital structure arbitrage strategy exploits the discrepancies between the credit default swap and equity markets. It assumes that both markets instantaneously react to new information, so it fails to take into account the lead-lag relationships between the prices in the two markets and their form of cointegration. Here we introduce three new alternative strategies that exploit the information provided by the time-varying price discovery of the equity and credit markets and the cointegration of the two markets. We implement the strategies for both US and European obligors and find that these outperform traditional arbitrage trading during the financial crisis. Furthermore, the returns of the new strategies have lower correlation with market returns than the standard capital structure arbitrage.

*JEL classification*: G01; G11; G12; G14; G20; D8; D53

*Keywords*: credit spreads; price discovery; credit derivatives; convergence trading; financial crisis; limit of arbitrage

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1. **Introduction**

Exploiting the mispricings between the credit default swap (CDS) and equity markets is the main objective of the so-called “capital structure arbitrage” (CSA) strategy. At the turn of the century, this strategy was thought of as one of the most promising and popular arbitrage strategies within the fixed income market.[[1]](#endnote-1) Over the last decade, the CDS market has experienced an impressive growth reaching its peak at the end of 2007 with a notional amount of USD 62 trillion. Since then, the market hit by the “Great Recession” went through a downward trend which has reduced the size of the market to USD 25 trillion by August 2012 ([www.dtcc.com](http://www.dtcc.com)). Driven by this explosion and then decline in the CDS market, fixed income arbitrage outstanding total assets increased to almost USD 59 billion in mid-2008, before reducing to about USD 23.5 billion by the end of the same year (Lipper/Tass, 2009).

Typically, when implementing this strategy, a trader would look for a significant divergence between the CDS spread and the equity implied spread. The latter is obtained from the implementation of a structural credit risk model which extracts equity-based information. Hence, a trader would sell (buy) a CDS contract if the CDS spread is significantly higher (lower) than the implied spread and sell (buy) a given number of shares as an equity hedge to offset the CDS position. Historically, fixed income arbitrage has consistently generated losses during periods of crisis in the financial markets, and these losses have caused the closure of many hedge funds and trading divisions of large investment banks (Lowenstein, 2000). Examining the profitability of the CSA strategy, Yu (2006) found that hedging strategies used to offset CDS positions with equities can be indeed ineffective.[[2]](#endnote-2) Alexander and Kaeck (2008) argued that a reason for this ineffectiveness may be the model’s inability to capture different market regimes.[[3]](#endnote-3)

One possible alternative is to look at the change in the information content of different prices. If the CDS and equity-implied spreads have a long-run relationship, and one market consistently leads the other one, then profits could be made by trading the market which adjusts towards the long-run equilibrium and is slower at impounding new information into prices. For instance, Alexander and Dimitriu (2005) implemented a dynamic equity indexing strategy based on cointegration that enhanced the benchmark performance during high volatile regimes.

In the last decade, a growing number of studies have focussed on lead-lag relations and price discovery in credit, bond and equity markets (Zhu, 2004; Blanco et al., 2005; Acharya and Johnson, 2007; Norden and Weber, 2009; Longstaff et al., 2003; Forte and Peña, 2009). Their findings are mixed, but all show evidence of time variation in the price discovery of credit-related information. In particular, Hodgson et al. (2003) and Avino et al. (2013) have shown how the price discovery process in bear and bull markets varies substantially.

Given that hedging could be ineffective for the CSA strategy (Yu, 2006) and that there is evidence of a lead-lag relationship between equity and CDS markets, we explore the possibility to trade in one market only, namely the market that is being led. We propose three new trading strategies and compare their performance with CSA over the period 2005-2009, contributing to the understanding of the role of the equity hedge for CDS positions. The strategies are inspired by three possible flaws of the CSA strategy, namely: (1) ineffective hedging; (2) its lack of sensitivity to the informational efficiency of different markets; and (3) it does not take into account the exact form of cointegration between the two markets.

The new strategies are based on the price discovery process of the CDS and equity markets. The methodology we use in this paper derives from the literature on common factor models, pioneered by Hasbrouck (1995), who introduced the information share (IS) measure of price discovery.

One of the contributions of our analysis is that we use time-varying price discovery measures, built on volatility forecasts, to construct new trading strategies. We also add to the literature by (1) introducing strategies which are based on the cointegration of CDS and equity-implied spreads, (2) giving new empirical evidence on the controversial hedging role of equity for CDS positions after accounting for lead-lag relations and (3) dealing with the issue of asynchronous trading existing between the CDS and equity markets.

Our first step is to compute the equity implied spreads from CreditGrades[[4]](#endnote-4), a Merton-like structural credit risk model (Merton, 1974) for the companies in our sample.[[5]](#endnote-5) This is followed by fitting a multivariate GARCH model to the innovations obtained by estimating a VECM model to the CDS spreads and the equity implied spreads. Both the VECM and GARCH models are used to compute the time-varying IS measure for the equity and CDS markets for all the obligors, and we propose new trading strategies based on these.

Our main findings show that, during the 2005-2009 period, hedging CDS positions with equities is only effective in the period preceding the outbreak of the subprime crisis. The new unhedged strategies we introduce outperform the hedged strategies during the subprime crisis period generating positive Sharpe ratios (the best performing strategy produces a Sharpe ratio of 1.24). In the pre-crisis period, our hedged strategy based on the use of price discovery trading triggers delivers a very similar performance to the CSA but with a much lower trading frequency (almost 40% less trading). Unhedged strategies based on price discovery triggers generate a very poor performance in the pre-crisis period. More importantly, a portfolio combining the four strategies we analyse generates returns which are much less correlated with market risk factors than the standard CSA strategy. The structure of the paper is as follows: the next section discusses price discovery in the CDS and equity markets, section 3 describes the data followed by the methodology and the results sections. The final section concludes.

1. **Price discovery in the CDS and equity markets**
   1. **Price discovery of spreads**

Lehmann (2002) defines the price discovery as the “efficient and timely incorporation of the information implicit in investor trading into market prices”. Hence, when two price series are closely linked by arbitrage considerations, quantifying the contribution of a price series to the price discovery is equivalent to measuring the extent to which it is the first to reflect new information about the “true” underlying asset value.

For the purpose of this paper, any trader who could produce accurate estimates of price discovery for both CDS and equity-implied spreads, would be in an advantageous position (relative to her/his peer traders), as she/he could be able to better predict the future direction of movements of the spreads which are slower at reflecting new information.

We use the IS measure defined in Hasbrouck (1995) to quantify the price discovery of CDS and equity-implied spreads. If CDS spreads and equity-implied spreads are cointegrated, then the two time series of spreads would share the same efficient price. Hasbrouck (1995) decomposes the variance of this efficient price innovations and defines the IS of a market as the proportion of variance of the efficient price innovations that is attributable to innovations in that market. In order to compute the IS measure we first need to estimate the following VECM of changes in CDS spreads () and equity-implied spreads () for the series of spreads which are non-stationary:

(1a)

(1b)

where and are the speed-of-adjustment parameters which define the adjustment of each series of spreads towards the long run equilibrium implied by the model, the *β* and *γ* coefficients represent the short run dynamics of the system, and and are i.i.d. error terms. The cointegrating equation is defined as:

(1c)

where the *α* coefficient defines the long run dynamics of the system. The estimated parameters of the VECM are then used to compute the IS measure. Due to potential non-zero correlation of the VECM residuals ( and ), Hasbrouck (1995) suggests to use the Cholesky decomposition to remove this contemporaneous correlation. This gives an upper and lower boundary for the price discovery measure; the formulae for these boundaries for the CDS market are

, (2)

where , , and give the time-invariant covariance matrix of and . Baillie et al. (2002) show that the midpoint of these IS bounds, denoted by *IScds*, can be considered a reasonable estimate of the price discovery of a given market, and we use this in the following analysis.

Ideally, a capital structure arbitrageur would be interested in having an estimate of the price discovery of the CDS and equity markets every day, based on which she/he can define and execute her/his trades. We apply a bivariate GARCH model to the residuals of the VECM estimated in (1).[[6]](#endnote-6) In particular, we use the BEKK specification of Engle and Kroner (1995):

(3)

where , , , and .

We define the time dependent (daily) IS measure by replacing the unconditional error volatilities and covariance in (2) with the conditional volatilities and covariance obtained with (3). The first step is to estimate (1) and (3) for all companies by using a rolling window of 1 year of data (250 observations)[[7]](#endnote-7), starting from January 2004. We use the one step ahead covariance matrix of the error terms obtained with (3) to compute the IS measure[[8]](#endnote-8), and we use the latter as a forecast of the price discovery for the following day. The next day we roll over the 1-year window and we re-estimate (1) and (3) to get a new IS estimate for the following day. We follow this procedure till the end of our sample period. Hence we have a series of estimates of price discovery for the CDS and equity markets for each obligor.

* 1. **Trading strategies**

We describe the main features of the 4 strategies implemented. The trading rules are summarised in Exhibit 1.

***Strategy 1: Standard CSA***

Capital structure arbitrage is originally based on the market CDS spread and the equity-implied spread of a given entity. When these two series of spreads deviate from each other by a threshold value (set by the trader), a trading opportunity arises. In particular, if the CDS spread is higher (or lower) than the equity-implied spread by a defined trading trigger *θ*, a trader would short (long) a CDS position with a notional amount of USD 1[[9]](#endnote-9) and shares of the common stock. These positions are typically kept for a fixed holding period.

***Strategy 2***

We augment Strategy 1 by introducing a price discovery trigger. We filter Strategy 1 trades and execute them only if our price discovery estimates suggest that one market strongly leads the other one.[[10]](#endnote-10) However, we still hedge the positions. Hence, if the CDS spread is higher (lower) than the equity-implied spread by a defined trading trigger *θ* and the price discovery of the CDS market is either lower than or higher than , a CDS position with a notional amount of USD 1 and shares of the common stock are shorted (bought). Thus, trades are filtered not only on the basis of the deviation between the spreads, but also according to the informational efficiency of the markets.

***Strategy 3***

Here we explore the possibility to trade one market only, namely the one that is being led and is responsible for the adjustment towards the long-run equilibrium implied by the error correction term of the VECM. In particular, if the CDS spread is higher than the equity-implied spread by a defined trading trigger *θ* and the price discovery of the CDS market is lower than a benchmark (meaning that the CDS market is being led), a trader would sell a CDS contract with a notional of USD 1. On the other hand, he would short the equity market if the CDS spread is higher than the equity-implied spread by a defined trading trigger *θ* and the price discovery of the CDS market is higher than (in which case the equity market is being led). Similarly, if the equity-implied spread is higher than the CDS spread by a defined trading trigger *θ* and the price discovery of the CDS market is lower than , a CDS contract with a notional of USD 1 would be bought. Finally, shares are bought if the equity-implied spread is higher than the CDS spread by a defined trading trigger *θ* and the CDS market is leading the equity market.

***Strategy 4***

We use the estimated parameter in the cointegrating equation (1c) in order to define the minimum deviation between the market and model spreads necessary to generate a trading opportunity. In cointegrated systems, we would expect the coefficient on the equity-implied spread to equal 1 in the cointegrating vector; and this is assumed in Strategies 1, 2 and 3. However, while from a statistical perspective may not be significantly different from 1, in practice the actual values of the estimated coefficient are different from 1 and could be economically significant, providing the trader with valuable information. The trading is then done similarly to Strategy 3, except that is not assumed to be 1 but estimated from the VECM.

Exhibit 2 summarises the main features of the strategies. It is worth highlighting that only Strategy 1 and 2 assume hedging and all new strategies we propose (2 to 4) are based on a price discovery trigger.

1. **Data description**

We use daily mid-market CDS quotes provided by CMA[[11]](#endnote-11) on senior unsecured debt for non-financial companies with 5-year maturity, both North American and European obligors with a modified restructuring and modified-modified restructuring clause, respectively, and currencies denominated in USD and EUR, from 2005 to 2009. The recent financial crisis had its biggest impact between mid-2008 and April 2009, hence the inclusion of 2008 and 2009 in the study period will help us understand the markets during the crisis period. We match the CDS data with information required by the CreditGrades model to get the equity-implied spreads. We focus our attention on a sample comprising the most capitalised companies in the US and Europe with CDS and equity data available.

In order to implement CreditGrades, we need the following inputs for each company: daily stock prices and market capitalisations; accounting data including short- and long-term liabilities, minority interest, and preferred shares (downloaded from Bloomberg). Also, we need the mean global recovery rate and its standard deviation (assumed to be 0.3 as reported in the CreditGrades Technical Document, 2002); the recovery rate of the firm’s senior unsecured debt (estimated as the Moody’s average historical recovery rate on senior unsecured debt over the period 1982-2009, and equal to 0.326[[12]](#endnote-12)); the annualized equity volatility and the 5-year risk-free interest rate. We follow Yu (2006) to define the value of the global recovery rate and, for each reference entity, we use the first 10 daily CDS spreads to minimize the sum of squared pricing errors. The implied value is then used in the credit model together to generate theoretical CDS spreads. We also download rating data for each company from Bloomberg.

The most important input of the model is the equity volatility. Our main findings are based on a 250-day moving average of past equity stock returns. However, we also employ a 1,000-day moving average as suggested in the CreditGrades Technical Document (2002). From a trading perspective it would be interesting to see how the profitability of the strategies would change when we alter the length of the volatility estimation window. In fact, using a 1000-day moving average, especially during the crisis, might result in spreads which underestimate the market spreads. As a robustness test, we repeat our analysis using equity volatilities estimated as 1000-day moving averages.

The following step is to make sure that we have a fairly continuous time series of CDS quotes. For each reference entity we ensure that consecutive daily quotes are no more than 14 days apart and we check that we have all the information needed for the computation of model spreads. After applying these filters, our final sample includes 70 companies (35 are US-based and 35 are European obligors) with 101,799 composite daily quotes starting from January 2005 till the end of 2009. We actually use a total of 120,000 CDS quotes starting from January 2004, but the first year quotes are used to estimate the inputs for the new trading strategies. As a result, trading starts from January 2005.

Our sample includes highly capitalized firms whose CDS contracts are actively traded. In untabulated results, we compare our sample of firms to the Depository Trust and Clearing Corporation (DTCC) universe in terms of CDS trading activity and find that, on average, our sample of firms have larger transaction amounts and a higher number of traded contracts. Liquid and actively traded securities are important to mitigate any concern related to the uncertainty of the parameter estimates which define our trading strategies.

Exhibit 3 presents summary statistics for the 70 obligors. Over 80% of the obligors are rated investment grade. We report averages over time and through firms, for the rating categories of investment grade and speculative grade. As a structural credit risk model would predict, we find a positive relationship between the CDS spread and the level of leverage and volatility. The average correlation between changes in CDS spreads and equity prices is negative but very low, which could raise concerns on the effectiveness of the equity hedge. Based on this evidence, we suggest that trading of CDS and equity markets should be based on the cointegration of the two prices (the exact form of the long-run relationship of the variables).

It is evident that two regimes can be distinguished, the period preceding the recent financial crisis and the crisis period itself. The level of spreads, their volatility and leverage increase substantially during the crisis (especially for speculative grade companies) whilst the equity market capitalisation of the obligors shrinks. Surprisingly, the correlation between CDS spreads and equity prices is reduced, especially for speculative grade obligors. This is in contrast with past studies which have reported more negative correlations for this category of obligors. This may be due to several factors: (1) our sample includes a very small number of B-rated and CCC-rated obligors and for these categories the relationship between CDS and equity markets is stronger; (2) the divergence of views of the two markets on the price of credit risk increased in times of financial instability; (3) Pearson’s correlation coefficient does not capture the non-linear relationship between changes in CDS spreads and equity prices.

1. **Methodology**

After computing the equity implied spreads for all companies we run ARCH tests and we find that 94% of the companies have spreads characterized by autoregressive variance. After fitting the BEKK model in (3) to the CDS spreads and the equity implied spreads we compute the time-varying IS measure (given as the midpoint of the boundaries in (2)) of the equity and CDS markets for all the companies. Then we implement the trading strategies summarized in Exhibit 1 for the 70 obligors. As we have thousands of open trades every day, we construct a monthly index return for each strategy, which would facilitate the comparison of our results with returns reported by hedge fund industry benchmarks.

1. **Results**
   1. **Analysis of the returns of the strategies**

As the CDS position has a value of zero at initiation, we assume USD 0.5 initial capital[[13]](#endnote-13) for every trade we make. If hedging is not required, then only one market is traded and the entire initial capital is invested in that single market. If hedging is required then we use the capital to finance the equity hedge. For instance, if the trade involves buying equity, a trader will invest USD 0.5 initial capital to buy equity, whereas if he has to sell equity, he will sell shares for USD 0.5 of capital. In the case of buying/selling CDS, USD 0.5 initial capital represents the trader’s deposit into a margin account.

All cash flows arising from the positions in the CDS and equity such as CDS premiums and cash dividends are deducted from or credited to the initial capital. We assume, for all strategies, a 10% bid-ask spread for trading CDS. Similarly to Yu (2006), we ignore transaction costs on common stocks[[14]](#endnote-14), which should be minimal due to the use of static hedging.

Using CreditGrades, we can track the daily market value of the CDS positions and hence compute the daily excess returns for every trade. After that, we compute an equally-weighted average daily return across all trades which are open, for every day of our sample. We finally compound the daily returns into monthly returns. Hence, we end up having a total of 60 monthly excess returns which are generated by holding an equally-weighted portfolio of all available trades for each of the 4 strategies we implement. For Strategy 4, in case of speculative grade obligors for which we have a small sample, we do not have individual trades available for some months, in which case we assume a zero monthly excess return.

To implement the new strategies, a trader needs to choose a reasonable price discovery trigger, which can be used to filter strong signals. Selecting higher triggers should generate higher profits because a stronger evidence of a market’s inefficiency should make that market more predictable. However, too high triggers would lead to less profit due to the sharp decrease in the number of potentially profitable transactions. We choose a value of 80% for the price discovery trigger. Hence, in the trading rules and will be equal to 20% and 80%, respectively.

Exhibit 4 shows the number of trades executed for each strategy over the whole sample period. It is interesting to notice how the use of the price discovery trigger substantially reduces the frequency of trading. The implementation of Strategies 2 and 3 allows a reduction in the number of trades of almost 40% if compared with the traditional CSA. Comparing Strategy 4 with the first strategy, the number of trades is reduced by about 65%.

An interesting point refers to Strategies 1 and 2, both requiring hedging. For these the equity hedge becomes very expensive, especially during the crisis period. For some days, if the trade involves buying equity, we notice that a USD 0.5 initial capital is not sufficient to meet the trader’s hedging need. This anomaly is a limit of arbitrage and, as shown in Brunnermeier and Pedersen (2009), the potential lack of funding liquidity prevents arbitrageurs from exploiting mispricings. Our finding is supported by Das and Hanouna (2009), who explain that equity hedging costs increase when markets become more volatile, and Kapadia and Pu (2012), who show that limits to arbitrage can arise due to worsening market liquidity. From the point of view of implementation, we are not able to perform a complete hedge on the days when such an anomaly occurs.[[15]](#endnote-15) In these cases, we make sure that at least 10% of the notional amount of the CDS contract is left in the margin account and can be used for hedging.[[16]](#endnote-16)

Exhibit 5 shows the summary statistics of the monthly excess returns of the 4 strategies for the pre-crisis period and the crisis period. We implement the strategies separately for investment and speculative grade companies by using a holding period of 180 days[[17]](#endnote-17) and *θ* trading triggers of 0.5 and 2, to be consistent with previous studies. As in Yu (2006) and Duarte et al. (2007), increasing the trading trigger from 0.5 to 2 generates higher monthly mean returns and higher Sharpe ratios for Strategies 1 and 2. However, this relationship does not always hold for Strategies 3 and 4, because they avoid hedging. Furthermore, speculative grade entities produce higher Sharpe ratios than the investment grade obligors for Strategy 4.

Ranking strategies’ portfolios according to the Sharpe ratio when excess returns are negative can be counterintuitive. In order to avoid this anomaly, we also report the modified Sharpe ratio proposed by Israelsen (2005). Strategy 1 generates negative Sharpe ratios both before and during the crisis. In the pre-crisis period, with regard to the investment grade category, the un-hedged strategies (Strategy 3 and 4) underperform Strategies 1 and 2. An analysis of the speculative grade category reveals a less clear pattern. Based on the modified Sharpe ratio, we can clearly notice how, during the pre-crisis period, the new strategies (except for Strategy 2 in the case of investment grade obligors) show a higher volatility of returns and, for this reason, would be worse ranked compared to the CSA strategy. The higher level of volatility induced by the un-hedged strategies can also be observed more clearly in Exhibit 6, which shows the evolution of monthly excess returns for all strategies.

During the crisis period, all the new strategies outperform Strategy 1 for investment grade firms, whereas Strategy 3 is the only one to perform worse than Strategy 1 for speculative grade companies. In particular, focusing on the investment grade category, the un-hedged strategies (Strategy 3 and 4) give the highest Sharpe ratios for a trading trigger of 2, with Strategy 3 giving the highest Sharpe ratio of 1.24. Relative to the speculative grade category, Strategy 4 is the one with the highest Sharpe ratios for any trading trigger.

Exhibit 7 presents the evolution of monthly cumulative excess returns for all strategies. Strategies 3 and 4, while incurring bigger losses and substantial drawdowns than Strategy 1 and 2 during the pre-crisis period, stop making losses right at the start of the financial crisis, whereas Strategy 1 and 2 continue making losses until the beginning of 2009. It is worth noticing that the cumulative returns of Strategy 4 are almost always higher than those of Strategy 3. Most importantly, Strategy 4 generates the highest cumulative returns at the end of our sample period.

Strategies 3 and 4 show mostly positive skewness and low excess kurtosis, leading to a much lower tail risk than Strategies 1 and 2. To investigate this point in more depth, in Exhibit 8 we report, for each strategy, the monthly 95%, 99% and 99.5% Value-at-Risk (VaR) estimates based on the Cornish-Fisher approximation. During the pre-crisis period and relative to investment grade obligors, Strategy 3 and 4 have higher VaRs than Strategies 1 and 2. During the crisis period, for investment grade obligors, Strategy 3 provides the lowest VaR estimates. For speculative-grade obligors, the VaR estimates of Strategy 4 are the lowest, especially during the crisis period. This confirms the reduction in the tail risk borne by Strategy 4.

Finally, we compute the daily hedging errors of the two hedging strategies implemented for all firms during the whole sample period. We find that, for a theta trigger of 2, the root mean square error (RMSE) of the traditional CSA (Strategy 1) is equal to 1.12, whereas the RMSE of Strategy 2 is slightly lower at 0.97, confirming the main results about the overall superiority of Strategy 2.

* 1. **Comparison of the strategies’ returns with fixed income hedge fund returns**

Following Duarte et al. (2007), we compare the monthly returns indices of each strategy with fixed income arbitrage hedge fund return data. We download monthly return data from Credit Suisse First Boston (CSFB) for the AllHedge Fixed Income Arbitrage Index over the period 2005-2009. The construction of the index is based on the TASS database, which includes data on over 8,000 hedge funds.[[18]](#endnote-18) The characteristics of these hedge fund returns are very similar to the capital structure index returns we constructed and described in the previous section. Some of the strategies we propose show positive skewness and low kurtosis and are capable to give positive Sharpe ratios which, in some cases, are higher than 1.

Exhibit 9 shows the correlation of the monthly returns generated by the 4 strategies and the CSFB index. The correlation between Strategy 1 and the CSFB index is high and positive, whilst Strategies 3 and 4 present correlations of -0.15 and -0.24 with the CSFB index. Also, it is evident that the new strategies show low or negative correlation with the standard CSA.

* 1. **Analysis of the risk-adjusted returns of the strategies**

Similarly to Duarte et al. (2007) and Yu (2006), we explore whether the returns of the strategies represent compensation for their exposure to systematic market risk factors. To this end, we regress the monthly excess returns of each strategy on a selected collection of equity and bond portfolios. In particular, we use the excess returns on the Fama-French (1993) market (MKT), small-minus-big (SMB), high-minus-low (HML) and winner-minus-loser (WML) global portfolios as proxies for equity market risk.[[19]](#endnote-19) We also include the excess returns on the MSCI World bank stock index (MSCIBank). We use the excess returns on the Bank of America/Merrill Lynch 5-year US Treasury bond portfolio (TRSY5Y) to proxy for bond market risk. We finally use two proxies to control for default risk, namely the excess returns on the Bank of America/Merrill Lynch indices for both the BBB-rated industrial (IND) and financial (FIN) global bond portfolios.

Exhibit 10 shows the regression results for each individual strategy, for an equally-weighted portfolio of the strategies and for the CSFB fixed income arbitrage hedge fund return index. First, we can observe a very high explanatory power of the market risk factors for the CSFB index returns (with R-squared of 60%), indicating that fixed income arbitrageurs were far from being market-neutral during the period 2005-2009, consistent with the findings of Patton (2009). Second, the CSA strategy also shows a high R-squared (49%) with significant positive loadings on the bank stock index. The new strategies show lower R-squared values. Strategy 3 presents a negative loading on the market portfolio, suggesting how this strategy is countercyclical and could be used as a hedge against macroeconomic risk (or major financial crises). The equally-weighted portfolio of the 4 strategies is substantially less correlated with market risk factors (R-squared of 30%) than both the CSA and CSFB index returns.

* 1. **The effect of the volatility estimation method**

We test if the results obtained by the new strategies are robust to changes to the model used to calculate theoretical spreads. Previous studies have shown that the profitability of CSA may depend on the structural credit risk model used and especially on the inputs used for a given model. As shown by Bajlum and Larsen (2008), the use of a different structural model is of secondary importance for the strategies’ profitability; however, the choice of the volatility input can have a big impact. They state that using option-implied volatilities (rather than historical volatilities) as inputs generates higher profits. Given our lack of data on option-implied volatilities, we compute spreads using 1000-day historical volatility, originally suggested in the CreditGrades Technical Document (2002) and repeat our analysis.

We find that the results (available on request) look quite similar to the ones shown in Exhibit 5. The new strategies outperform the CSA strategy in the crisis period, whereas in the pre-crisis period they perform worse than the CSA (except for Strategy 2). We also compute the correlation between the returns of Strategy 1 under a 1000-day and 250-day historical volatility, and find that it is extremely high (0.93) in the pre-crisis subsample, but it is lower than 0.5 during the crisis. These differences highlight how the price discovery measures produce different and better signals during the crisis period relative to the standard CSA. The correlation between the monthly returns of Strategy 1 (implemented with a 1000-day historical volatility) and the CSFB index monthly returns is 0.67. A reason for this higher value may be that market participants implementing the strategy tend to follow the guidelines included in the CreditGrades Technical Document (2002) and then choose a 1000-day historical volatility to estimate model spreads.

* 1. **The impact of asynchronous trading between CDS and equity markets**

In our study we assume that all the trades are performed at the closing time of the equity market, which can be different from the recording time of the CDS quotes. This discrepancy can have an effect on our results if the CDS market is very active between the CDS quote recording time and the equity market closing time. Previous studies did not consider the effect of asynchronous trading between the two markets on the strategies’ profitability, whilst in our view this is an interesting question worth considering.

In the US, the closing prices for equity markets are recorded at the closing time of the New York Stock Exchange (NYSE), which is at 21:00 (London time), whilst CDS quotes from CMA are recorded at 21:30 (London time). For European firms, CDS quotes are recorded at 16:30 (London time), while their equity closing prices are recorded at the closing time of the corresponding European exchanges, which is either at 16:30 (for the Italian Stock Exchange, the Stockholm Stock Exchange, the Helsinki Stock Exchange and the Zurich Stock Exchange) or later[[20]](#endnote-20). To analyse the impact of these time discrepancies, we use data on intraday CDS quotes from GFI (a leading CDS interdealer broker) between January 2006 and July 2009. This period covers about three-fourth of our trading period. We count how many CDS quote updates we find between 21:00 and 21:30 and between 16.30 and the later closing time of specific equity markets, for each of the US and European obligors in our sample. We assume that if the number of CDS quote updates over these time intervals is higher than 100, then information in the CDS market may affect the price discovery estimates.[[21]](#endnote-21)

We find that for the US market none of the companies in our sample has more than 100 updates between 21:00 (closing time for the equity market) and 21:30 (closing time of the CDS market). However, 6 European firms have more than 100 updates in the CDS market after the recording time of the CDS quotes and before the equity market closes. We then exclude these six reference entities from our original sample and re-run all the strategies. Results (available on request) are very similar to those reported in Exhibit 5, leading us to conclude that asynchronous trading has no major impact on our findings.

* 1. **The impact of credit event specification**

Standard CDS contracts on US and European obligors are based on two different specifications of the credit event, namely the modified restructuring and modified-modified restructuring clauses, respectively. The former requires delivery of bonds with maturity shorter than 30 months, whereas the latter requires delivery of restructured obligations with maturity shorter than 60 months together with other obligations with maturity shorter than 30 months. Because of the different way the credit event is specified for US and European CDS contracts, we split our sample in two, looking at US and European obligors separately and run all trading strategies again for the two sub-samples. This way we are able (1) to evaluate whether differences in the specifics of the CDS contracts affect the profitability of the strategies, and also (2) to analyse the performance of the trading strategies separately for US and Europe. The latter point is particularly interesting as previous studies have not reported specific results on the profitability of the CSA strategy for European reference entities.

Our results (available on request) are qualitatively similar to those reported in Exhibit 5. However, we notice that Sharpe ratios are higher for the US sample. In particular, during the crisis period, for US obligors even Strategy 1 and 2 generate positive Sharpe ratios, although their performance is worse off when compared with that of the remaining strategies.

* 1. **The effect of the lack of cointegration between the CDS and equity market**

For some obligors, the CDS and equity markets were not cointegrated but we still estimated a VECM model from which the price discovery measures were derived. It can be argued that for these companies the VECM was not the most correct econometric specification to use. To test the effect of the lack of statistical cointegration, we discard the companies (7 out of 70) which are not cointegrated. As expected, we obtain an improvement in the profitability of the strategies (results available on request). Hence, our proposed strategies seem to work better for cointegrated series and ideally, a trader should trade obligors for which CDS and equity-implied spreads are cointegrated.

1. **Conclusions**

Despite its popularity, capital structure arbitrage has undergone a clear decrease in profitability over the period 2005-2009. In this paper, we propose three new trading strategies involving the CDS and equity markets, which are based on the supposed cointegration of the CDS and equity implied spreads and their time-varying price discovery. In particular, a time-varying price discovery measure is employed as a new trading filter.

Our study sheds new light on the role of equity hedging of CDS contracts. Ineffective hedging can reduce the profitability of CSA, as shown by Yu (2006). We find that this role is dependent on the state of the economy. In particular, during tranquil periods hedging has a positive effect on the risk and returns of CSA. However, during the crisis period, the strategies that do not hedge perform much better than those which do. In particular, in the pre-crisis period (January 2005 to July 2007), the unhedged strategies (strategies 3 and 4) deliver a very poor performance (most negative modified Sharpe ratios), whereas strategy 2 achieves a similar performance to the standard CSA (strategy 1) with a much lower trading frequency (almost 40% less trading). During the crisis period (August 2007 to December 2009), the new trading strategies (2, 3 and 4) outperform the standard CSA: positive Sharpe ratios close to one are observed for the unhedged strategies.

Our contribution is even more valuable since the returns of the new strategies show a lower correlation with market risk factors than the CSA. At the same time, the new strategies deliver monthly returns which show low or even negative correlation with the returns of fixed income hedge fund returns, proving that they can be a risk-reducing diversification tool. Furthermore, we find strong evidence of risk (VaR) reduction for the returns generated by Strategy 4, especially for speculative-grade obligors. We find that the results are robust to (1) the length of the window used to estimate the volatility; (2) the time mismatch between the two markets; and (3) the contractual terms of the CDS. Finally, all strategies generate a better performance for US obligors and for obligors with cointegrated spreads.

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**Exhibit 1. Trading rules of the strategies**

|  |  |  |  |
| --- | --- | --- | --- |
| **Strategy** | **Trading rule condition** | **Trade** | |
| **CDS** | **equity** |
| Strategy 1 |  | short | short |
|  | long | long |
| Strategy 2 |  | short | short |
|  | long | long |
| Strategy 3 |  | short | - |
|  | - | short |
|  | long | - |
|  | - | long |
| Strategy 4 |  | short | - |
|  | - | short |
|  | long | - |
|  | - | long |

**Exhibit 2. Main features of the trading strategies**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Strategy** | **Trading trigger** | **Price discovery trigger** | **Hedging** | **Cointegrating equation** |
| Strategy 1 | √ | - | √ | - |
| Strategy 2 | √ | √ | √ | - |
| Strategy 3 | √ | √ | - | - |
| Strategy 4 | √ | √ | - | √ |

**Exhibit 3. Summary statistics of the obligors for rating categories**

*N* represents the number of obligors. *Spread* is the average daily CDS spread in basis points. *VOL250* and *VOL1000* are the 250-day and 1000-day historical equity volatility, respectively. *Lev* is the ratio of total liabilities over the sum of total liabilities and equity market capitalisation. *Size* is the equity market capitalisation in millions of dollars. *Corr* is the correlation between daily changes in the CDS spread and the equity price.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Category** | **N** | **Spread** | **VOL250** | **VOL1000** | **Lev** | **Size** | **Corr** |
| **A. Whole Sample (January 2005-December 2009)** | | | | | | | |
| Investment grade | 57 | 63 | 28.4% | 27.8% | 0.378 | 58,164 | -0.04 |
| Speculative grade | 13 | 217 | 37.2% | 35.0% | 0.507 | 6,657 | -0.10 |
| **B. Pre-crisis period (January 2005-July 2007)** | | | | | | | |
| Investment grade | 57 | 26 | 20.2% | 25.9% | 0.342 | 62,969 | -0.09 |
| Speculative grade | 13 | 90 | 24.1% | 31.0% | 0.449 | 8,025 | -0.32 |
| **C. Crisis period (August 2007-December 2009)** | | | | | | | |
| Investment grade | 57 | 92 | 35.0% | 29.4% | 0.407 | 54,263 | -0.08 |
| Speculative grade | 13 | 278 | 48.4% | 38.3% | 0.552 | 5,520 | -0.04 |

**Exhibit 4. Total number of trades executed**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Category** | **Strategy 1** | **Strategy 2** | **Strategy 3** | **Strategy 4** |
| Investment grade | 44,376 | 27,151 | 27,151 | 14,984 |
| Speculative grade | 8,861 | 5,506 | 5,506 | 2,728 |

**Exhibit 5. Summary statistics of the strategies’ returns**

Summary statistics for the monthly excess returns (%) of the 4 strategies. *θ* is the trading trigger which defines the distance between CDS and equity-implied spread. *Strategy* defines the strategy implemented, which are summarized in Table 1. *N* is the number of monthly excess returns. *Corr* is the first-order serial correlation of the monthly returns. *Neg* represents the fraction of negative returns. *Sharpe* and *MSharpe* are the annualised Sharpe ratio and modified Sharpe ratio (adjusted for autocorrelation if significant) of the strategy, respectively. \* indicates significance at 5% level of the autocorrelation coefficient.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **θ** | **Strategy** | **N** | **Mean** | **Median** | **Min** | **Max** | **Std** | **Skew** | **Kurt** | **Corr** | **Neg** | **Sharpe** | **MSharpe** |
| 1. **Pre-crisis period (Jan 05 – July 07)** | | | | | | | | | | | | |  |
| *Investment Grade* | | | | | | | | | | | | |  |
| 0.5 | Strategy 1 | 31 | -0.23 | -0.19 | -1.23 | 0.11 | 0.23 | -2.63 | 11.27 | 0.18 | 0.90 | -3.51 | -0.00002 |
|  | Strategy 2 | 31 | -0.23 | -0.20 | -1.20 | 0.13 | 0.23 | -2.42 | 9.76 | 0.18 | 0.87 | -3.45 | -0.00002 |
|  | Strategy 3 | 31 | -0.94 | -1.09 | -4.26 | 2.87 | 1.73 | 0.43 | 0.30 | -0.31 | 0.81 | -1.89 | -0.00057 |
|  | Strategy 4 | 31 | -0.76 | -0.84 | -3.65 | 3.18 | 1.61 | 0.46 | 0.59 | -0.20 | 0.77 | -1.63 | -0.00042 |
| 2 | Strategy 1 | 31 | -0.23 | -0.21 | -1.33 | 0.13 | 0.25 | -2.62 | 11.22 | 0.12 | 0.90 | -3.11 | -0.00002 |
|  | Strategy 2 | 31 | -0.23 | -0.19 | -1.30 | 0.16 | 0.26 | -2.50 | 10.08 | 0.15 | 0.90 | -3.09 | -0.00002 |
|  | Strategy 3 | 31 | -1.08 | -1.15 | -4.89 | 3.45 | 1.94 | 0.52 | 0.48 | -0.28 | 0.77 | -1.93 | -0.00073 |
|  | Strategy 4 | 31 | -0.63 | -0.63 | -4.10 | 3.06 | 1.85 | 0.18 | -0.69 | -0.15 | 0.68 | -1.18 | -0.00041 |
| *Speculative Grade* | | | | | | | | | | | | |  |
| 0.5 | Strategy 1 | 31 | -0.32 | -0.04 | -5.47 | 0.78 | 1.13 | -3.29 | 14.20 | 0.38\* | 0.55 | -0.69 | -0.00009 |
|  | Strategy 2 | 31 | -0.37 | -0.08 | -5.05 | 0.86 | 1.06 | -3.07 | 12.63 | 0.42\* | 0.61 | -0.82 | -0.00009 |
|  | Strategy 3 | 31 | -0.68 | -1.16 | -5.26 | 5.99 | 2.26 | 0.94 | 1.71 | -0.39\* | 0.74 | -1.52 | -0.00077 |
|  | Strategy 4 | 31 | -0.32 | -0.22 | -4.13 | 2.37 | 1.56 | -0.44 | 0.21 | -0.15 | 0.61 | -0.70 | -0.00017 |
| 2 | Strategy 1 | 31 | -0.26 | 0.00 | -5.04 | 0.93 | 1.10 | -2.84 | 11.40 | 0.35\* | 0.48 | -0.58 | -0.00007 |
|  | Strategy 2 | 31 | -0.29 | -0.07 | -4.27 | 0.90 | 0.99 | -2.26 | 7.93 | 0.40\* | 0.52 | -0.69 | -0.00007 |
|  | Strategy 3 | 31 | -0.80 | -1.27 | -5.14 | 5.86 | 2.31 | 0.99 | 1.57 | -0.39\* | 0.68 | -1.76 | -0.00093 |
|  | Strategy 4 | 31 | -0.45 | -0.61 | -3.19 | 2.88 | 1.46 | 0.22 | -0.18 | -0.31 | 0.61 | -1.06 | -0.00023 |
| 1. **Crisis Period (Aug 07 – Dec 09)** | | | | | | | | | | | | |  |
| *Investment Grade* | | | | | | | | | | | | |  |
| 0.5 | Strategy 1 | 29 | -0.24 | -0.12 | -7.11 | 5.88 | 2.20 | -0.39 | 4.15 | 0.23 | 0.55 | -0.38 | -0.00018 |
|  | Strategy 2 | 29 | -0.18 | -0.27 | -6.34 | 5.65 | 2.16 | -0.07 | 2.87 | 0.20 | 0.55 | -0.29 | -0.00014 |
|  | Strategy 3 | 29 | 0.62 | 0.22 | -6.46 | 6.82 | 2.60 | -0.11 | 1.38 | -0.03 | 0.38 | 0.83 | 0.83 |
|  | Strategy 4 | 29 | 0.41 | 0.43 | -4.07 | 6.19 | 2.18 | 0.50 | 1.05 | -0.32 | 0.41 | 0.66 | 0.66 |
| 2 | Strategy 1 | 29 | -0.17 | -0.25 | -5.77 | 5.68 | 2.06 | 0.13 | 2.65 | 0.10 | 0.62 | -0.28 | -0.00012 |
|  | Strategy 2 | 29 | -0.13 | -0.23 | -4.86 | 5.30 | 1.95 | 0.28 | 1.93 | 0.13 | 0.55 | -0.23 | -0.00009 |
|  | Strategy 3 | 29 | 0.86 | 0.54 | -2.65 | 7.75 | 2.39 | 1.06 | 1.56 | -0.30 | 0.38 | 1.24 | 1.24 |
|  | Strategy 4 | 29 | 0.66 | 0.48 | -3.87 | 6.54 | 2.35 | 0.77 | 1.03 | -0.24 | 0.45 | 0.97 | 0.97 |
| *Speculative Grade* | | | | | | | | | | | | |  |
| 0.5 | Strategy 1 | 29 | -0.38 | -0.20 | -16.3 | 11.28 | 6.32 | -0.45 | 0.24 | -0.51\* | 0.52 | -0.35 | -0.00138 |
|  | Strategy 2 | 29 | -0.08 | -0.25 | -20.0 | 15.92 | 7.67 | -0.22 | 0.86 | -0.45\* | 0.52 | -0.06 | -0.00033 |
|  | Strategy 3 | 29 | -0.54 | 1.78 | -38.5 | 11.62 | 9.54 | -2.50 | 8.43 | -0.08 | 0.34 | -0.20 | -0.00180 |
|  | Strategy 4 | 24 | 1.95 | 0.62 | -27.0 | 35.41 | 10.78 | 0.64 | 4.83 | 0.09 | 0.33 | 0.63 | 0.63 |
| 2 | Strategy 1 | 29 | -0.08 | -0.03 | -14.5 | 19.50 | 7.86 | 0.57 | 0.91 | -0.22 | 0.52 | -0.03 | -0.00021 |
|  | Strategy 2 | 29 | 0.26 | -0.16 | -18.8 | 24.85 | 9.33 | 0.72 | 1.74 | -0.19 | 0.52 | 0.10 | 0.10 |
|  | Strategy 3 | 29 | -0.66 | 1.53 | -51.3 | 23.62 | 13.22 | -2.17 | 7.46 | -0.03 | 0.31 | -0.17 | -0.00300 |
|  | Strategy 4 | 24 | 3.62 | 0.00 | -17.0 | 53.08 | 12.45 | 2.60 | 8.80 | 0.28 | 0.42 | 1.01 | 1.01 |

**Exhibit 6. The monthly excess returns of the 4 strategies**

**Exhibit 7. The monthly cumulative excess returns of the 4 strategies**

**Exhibit 8. The monthly Value-at-Risk estimates of the returns obtained by the strategies**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Pre-crisis period** | | | **Crisis period** | | |
| **95% VaR** | **99% VaR** | **99.5% VaR** | **95% VaR** | **99% VaR** | **99.5% VaR** |
| **Investment Grade** | | | | | | |
| Strategy 1 | 0.748 | 1.323 | 1.593 | 3.368 | 6.026 | 7.332 |
| Strategy 2 | 0.747 | 1.293 | 1.547 | 3.102 | 5.085 | 6.016 |
| Strategy 3 | 3.954 | 4.868 | 5.178 | 2.229 | 2.707 | 2.793 |
| Strategy 4 | 3.609 | 4.375 | 4.557 | 2.620 | 3.535 | 3.838 |
| **Speculative Grade** | | | | | | |
| Strategy 1 | 2.538 | 4.717 | 5.682 | 11.555 | 15.828 | 17.462 |
| Strategy 2 | 2.293 | 4.159 | 4.998 | 12.752 | 18.433 | 20.865 |
| Strategy 3 | 3.827 | 4.470 | 4.654 | 27.395 | 52.090 | 63.219 |
| Strategy 4 | 2.763 | 3.517 | 3.757 | 3.853 | 4.611 | 9.147 |

**Exhibit 9. The correlation matrix of the monthly returns of the strategies for investment grade and speculative grade obligors (above and below the main diagonal, respectively)**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Strategy 1 | Strategy 2 | Strategy 3 | Strategy 4 | Strategy 1\_1000 | CSFB Index |
| Strategy 1 | 1.00 | 0.92 | 0.03 | -0.22 | 0.39 | 0.37 |
| Strategy 2 | 0.98 | 1.00 | 0.03 | -0.20 | 0.41 | 0.39 |
| Strategy 3 | 0.45 | 0.41 | 1.00 | 0.89 | -0.15 | -0.15 |
| Strategy 4 | 0.03 | -0.10 | 0.31 | 1.00 | -0.25 | -0.24 |
| Strategy 1\_1000 | 0.15 | 0.17 | -0.34 | -0.48 | 1.00 | 0.67 |
| CSFB Index | 0.10 | 0.14 | -0.35 | -0.47 | 0.49 | 1.00 |

**Exhibit 10. Regressions of the strategies’ monthly returns on market risk factors**

This table reports estimated coefficients, White’s heteroskedastic consistent standard errors (in parentheses) and the R-squared of the regressions of the four strategies’ monthly excess returns (obtained by using a *θ* trading trigger of 2) on the excess returns of equity and bond portfolios:

*Ri* represents the excess returns using Strategy *i,* theCSFB fixed income arbitrage hedge fund return index and an equally weighted portfolio (EW) which includes the 4 strategies, and MKT is the excess return on the CRSP value-weighted portfolio. SMB, HML and WML are the Fama-French small-minus-big, high-minus-low and winners-minus-losers market factors, respectively. MSCIBank is the excess return on the MSCI (World) bank stock index. TRSY5Y, IND and FIN are the excess returns on the Bank of America/Merrill Lynch indices of the 5-year Treasury bond portfolios, the BBB-rated industrial global bond portfolios and the BBB-rated global bond portfolios for financial companies. \*, \*\* and \*\*\* indicate significance at the 10%, 5% and 1% levels.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Strategy** | **alpha** | **MKT** | **SMB** | **HML** | **WML** | **MSCIBank** | **TRSY5Y** | **IND** | **FIN** | **R2** |
| Strategy 1 | -0.06 | -0.08 | -0.19 | 0.06 | 0.09 | 0.15\*\* | -0.01 | 0.11 | 0.13 | 0.49 |
|  | (0.23) | (0.09) | (0.14) | (0.23) | (0.07) | (0.07) | (0.19) | (0.24) | (0.10) |  |
| Strategy 2 | 0.00 | -0.11 | -0.18 | 0.08 | 0.12\* | 0.15\* | -0.13 | 0.26 | 0.12 | 0.45 |
|  | (0.24) | (0.10) | (0.14) | (0.23) | (0.07) | (0.08) | (0.19) | (0.22) | (0.10) |  |
| Strategy 3 | 0.08 | -0.51\*\*\* | 0.07 | 0.03 | 0.02 | 0.07 | 0.25 | 0.05 | 0.24 | 0.45 |
|  | (0.30) | (0.18) | (0.18) | (0.22) | (0.12) | (0.13) | (0.24) | (0.34) | (0.16) |  |
| Strategy 4 | -0.14 | -0.17 | 0.03 | 0.09 | -0.11\*\* | -0.05 | -0.00 | -0.03 | 0.18\*\* | 0.45 |
|  | (0.16) | (0.11) | (0.08) | (0.12) | (0.05) | (0.08) | (0.13) | (0.16) | (0.07) |  |
| EW | -0.03 | -0.22\*\* | -0.07 | 0.07 | 0.03 | 0.08 | 0.03 | 0.10 | 0.17\* | 0.30 |
|  | (0.18) | (0.09) | (0.11) | (0.15) | (0.13) | (0.07) | (0.13) | (0.22) | (0.10) |  |
| CSFB Index | -0.57 | 0.21 | -0.01 | -0.01 | -0.08 | 0.06 | -0.73\* | 0.77 | -0.06 | 0.60 |
|  | (0.37) | (0.17) | (0.20) | (0.31) | (0.12) | (0.12) | (0.39) | (0.50) | (0.20) |  |

**Endnotes**

Davide Avino acknowledges financial support from Science Foundation Ireland (08/SRC/FMC1389). We are grateful to Simone Varotto, Alfonso Dufour, Fan Yu, Satchit Sagade, Luciano Machain, Chardin Wese Simen and seminar/conference participants at the Asia-Pacific Association of Derivatives 2012 Conference, Eastern Finance Association 2013 Annual Meeting, University College Dublin, Financial Management Association 2013 Annual Meeting, University of St. Andrews, National University of Ireland Maynooth, Midwest Finance Association 2014 Annual Meeting and Southern Finance Association 2014 Annual Meeting for their helpful comments and suggestions.

1. For a very general and non-technical introduction on capital structure arbitrage, see Currie and Morris (2002). [↑](#endnote-ref-1)
2. Similar results were obtained by Duarte et al. (2007) and Cserna and Imbierowicz (2008). [↑](#endnote-ref-2)
3. Another possible reason, according to Das and Hanouna (2009), is that equity hedges can be very expensive when markets become volatile because the hedge ratio varies very quickly and the reduction in the liquidity of the equity market becomes a determinant factor. [↑](#endnote-ref-3)
4. See CreditGrades Technical Document (2002) for details on the model’s implementation. [↑](#endnote-ref-4)
5. Previous studies on the CSA strategy have shown that its profitability is sensitive to the choice of the credit risk model (used to compute implied spreads) and the equity volatility estimation method. Early studies from Jones et al. (1984), Eom et al. (2004) and Huang and Huang (2012) focused on credit spreads obtained from bonds and found that credit risk models under-predict spreads. However, Ericsson et al. (2007) showed that credit risk models seem to perform better when applied to CDS spreads. Similarly, Schaefer and Strebulaev (2008) obtained evidence of good prediction of equity-to-debt hedge ratios using structural models. Bajlum and Larsen (2008) found that using option-implied (rather than historical) volatility generates higher excess returns. Also, they concluded that the choice of the credit risk model is of secondary importance and does not affect returns significantly. [↑](#endnote-ref-5)
6. A different way to obtain daily estimates of price discovery would be based on intraday prices. However, for the CDS market, high frequency trading is still in its infancy. [↑](#endnote-ref-6)
7. A careful observer may accuse us of “look-ahead bias” because we are using the future values of the spreads to detect the presence of cointegration. However, testing for cointegration requires many years of data, and a long run relationship between the two markets is very likely to exist (and we find it for the majority of the companies) because they are pricing the same risk, even though their Pearson correlation is low. [↑](#endnote-ref-7)
8. (1 – *IScds*) will give the price discovery estimate for the equity market. [↑](#endnote-ref-8)
9. For European obligors we assume EUR 1 of notional for the CDS contract. [↑](#endnote-ref-9)
10. In this paper, a “strong” evidence of a market leading the price discovery would occur when the estimated IS measure for that market is greater than 80%. [↑](#endnote-ref-10)
11. According to Mayordomo et al. (2013), CMA data on CDS lead the price discovery process if compared with other CDS databases such as GFI, Fenics, Markit, JP Morgan and Reuters EOD. [↑](#endnote-ref-11)
12. See Moody’s (2011). [↑](#endnote-ref-12)
13. For European entities, we assume EUR 0.5 initial capital. [↑](#endnote-ref-13)
14. As we are comparing the profitability of different trading strategies, the magnitude of transaction costs used is not that important as long as similar transaction costs are assumed for each strategy. Taking equity transaction costs into account would favour the strategies which trade less, especially Strategy 4. [↑](#endnote-ref-14)
15. A solution which would allow a full hedge (not explored in this paper) would consist in trading CDS contracts on smaller amounts of notional making sure that a given percentage (such as 10%) of the notional is deposited in a margin account. [↑](#endnote-ref-15)
16. This means that, for the strategies which require hedging (Strategy 1 and Strategy 2), we can buy shares for a maximum amount of USD 0.4. [↑](#endnote-ref-16)
17. We also implemented the strategies using a 30-day holding period (available from authors). Our results are quantitatively similar to the 180-day holding period results. [↑](#endnote-ref-17)
18. See [www.hedgeindex.com](http://www.hedgeindex.com) for more details on the construction of the index. [↑](#endnote-ref-18)
19. The Fama-French global factors are downloaded from Kenneth French’s website. [↑](#endnote-ref-19)
20. The closing prices of the remaining European equity markets for the firms in our sample are recorded at 16:35 from the London Stock Exchange, the Paris Stock Exchange, the Madrid Stock Exchange and the Amsterdam Stock Exchange. Lastly, the Frankfurt Stock Exchange records closing prices at 19:00 (London time). [↑](#endnote-ref-20)
21. Our choice of 100 updates is arbitrary, and results confirm that choosing a lower or higher threshold would not affect the strategies’ profitability. However, asynchronous trading would constitute a major issue for capital structure arbitrageurs as high frequency CDS trading develops. [↑](#endnote-ref-21)