Rethinking Capital Structure Arbitrage

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Abstract

We found that the so-called capital structure arbitrage strategy generated negative Sharpe ratios over the period 2005-2009, in line with hedge fund industry benchmark. In this paper we introduce four new capital structure arbitrage strategies that take time-varying price discovery into account. These, while still based on the discrepancy between the CDS market spread and its equity-implied spread, exploit the information provided by the time-varying price discovery of the equity and CDS markets. We find that these new strategies outperform the traditional version of the strategy. They generate positive Sharpe ratios, especially during the financial crisis that started in mid-2007, which clearly signal the diversification benefits of these new strategies for hedge fund portfolios at times when diversification, and hence risk reduction is hardly achievable.

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

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

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1. Introduction

"The number one reason why investors are getting involved in capital structure arbitrage now is because of the development of the credit default market. Even with the right theoretical models and the right views, investors were not able to go long equity and short debt. Default swaps changed that. Credit is now much more tradable." This is what an executive director at Morgan Stanley stated in 2002, when capital structure arbitrage was thought like one of the most promising and popular strategies within fixed income arbitrage[1]. Over the last decade, the credit default swap (CDS) market has experienced an impressive growth which has reached its peak at the end of 2007 with a notional amount outstanding of about USD 62 trillion. Since then, the market hit by the "Great Recession" undertook a downward trend which, however, has not compromised the massive size of a market that, as of June 2010, still boasted an outstanding value of USD 26 trillion[2]. Driven by this huge growth in the CDS market, fixed income arbitrage has benefited from steady growth in total assets. According to Lipper Tass (2009) Asset Flows Report, the outstanding total assets were almost USD 59 billion at the end of 2008. However, the last quarter of 2008 corresponding to the Lehman collapse and the peak of the financial crisis has seen assets extremely reduced by about USD 23.5 billion.

Historically, fixed income arbitrage has consistently generated losses during periods of crisis in the financial markets. Those losses have caused the closure of many hedge funds and trading divisions of large investment banks[3]. Periods of crisis are associated with a decrease of assets invested in fixed income arbitrage, as it can be seen in Figure 1 (Lipper Tass (2009)). Since hedge funds are known for being market neutral (so able to deliver positive returns no matter how markets trend), why haven't traditional strategies generated profits during the crisis? Ideally, trading strategies should be built so that they are profitable in both stable and distressed times. Thus, the main question that arises is which fixed income arbitrage strategies are capable of generating profits in both periods of growth and instability of the financial markets?

This paper addresses this issue by focusing on one of the commonly used fixed income strategies, capital structure arbitrage (CSA). An important study which analysed CSA is that of Yu (2006), examining the profitability of the strategy over the period 2001-2004 in the US. It showed that a portfolio of individual CSA trades generates positive Sharpe ratios, in line with those of hedge fund industry benchmarks.[4] Interestingly, he also found that hedging strategies used to offset CDS positions with equities are

[1] For a very general and non-technical introduction on capital structure arbitrage, see Currie and Morris (2002).
[2] See ISDA Market Survey (2010).
[3] The most cited example is the story of LTCM, narrated, for instance, by Lowenstein (2000).
[4] Similar results were obtained by Duarte et al. (2007) and Cserna and Imbierowicz (2008).

ineffective. Alexander and Kaeck (2008) argue that a reason for these ineffective hedge ratios may be the fact that they do not capture different market regimes. 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 (lack of) liquidity of the equity market becomes a determinant factor.

Typically, when implementing the CSA strategy, a trader would look at a significant divergence between the CDS spread and the implied spread and trade accordingly; that is he 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 a equity hedge to offset the CDS position. The CSA strategy (including hedging) would work well if both markets are equally efficient in the sense that none leads the other one, i.e. any discrepancy between them is random and short lived, and price discovery occurs simultaneously in both of them. Given that hedging is not working well for the CSA strategy, and given that several studies document a lead-lag relationship between equity and CDS markets, it might be a better idea to trade in one market only, namely the market that is being led.

There is a vast literature analyzing the price discovery in equity markets; additionally, in the last decade, a growing number of studies have focussed on lead-lag relations and price discovery in credit spreads. For these the main references are Hull et al. (2004), Zhu (2004), Blanco et al. (2005), Norden and Weber (2009), Longstaff et al. (2003), Forte and Peña (2009), Avino et al. (2011), Acharya and Johnson (2007) and Berndt and Ostrovnaya (2008). Only the latter six studies focused on the information flow between CDS and equity markets by implementing various methodologies. Even if their findings are mixed, all show evidence of time variation in the price discovery of credit-related information. In particular, Avino et al. (2011) showed how to use volatility models to generate time-varying estimates (at daily frequency) of price discovery for the credit spreads obtained from different markets. In this paper we use both the Vector Error Correction Model (VECM) for changes in spreads, and time-varying price discovery measures to derive new strategies for trading the CDS and equity markets.

Previous studies on the CSA strategy have shown that its profitability is obviously 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), Huang and Huang (2003) focussed on credit spreads obtained from bonds and found that, on average, 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[5]. Bajlum and Larsen (2008) discussed how the profitability of CSA depends on the choice of the credit risk model and the volatility estimation model. They found that using option-implied volatility (rather than historical volatility) generates higher excess returns. Also, they conclude that the choice of the credit risk model is of secondary importance and does not affect returns significantly.

Having these in mind, in this paper we propose four new trading strategies and compare them with the traditional CSA strategy, evaluating their performance over the period 2005-2009. The four strategies are based on four possible flaws of the CSA strategy, namely: (1) it is characterized by ineffective hedging, so it might be better to omit it; (2) it is not being sensitive to the informational efficiency of different markets (i.e. the release of information), meaning that if market A informationally leads market B then it makes perfect sense to trade in market B only, based on the information released in market A; (3) it doesn't take into account the exact form of cointegration between the two markets, if this exists – i.e. if a long-term relationship between two markets exists and the market that is being lead wanders away from this long-term relationship then it is expected to move back; and (4) it ignores the existence of the error correction term, meaning that based on the long-term relationship between the two markets and the error correction term, the direction of the move in the informationally less efficient market can be anticipated.

The implementation of the strategies is based on information coming from two time series of spreads, namely the CDS spread observed in the market and an equity implied spread which is obtained from a Merton-like structural credit risk model[6]. CreditGrades (for details see the Appendix) is the model used to generate the theoretical spreads and it is also used by earlier studies which focussed on the analysis of capital structure arbitrage[7]. Similar to previous studies, we assume that structural credit risk models can generate reasonable estimates of both implied spreads and hedge ratios.

The new strategies are in first instance based on an additional layer of information which can be obtained from the lead-lag relationship or the price discovery process of the CDS and equity markets. Using knowledge on the interaction between the two markets should enhance profitability. The methodology to incorporate information on price discovery derives from the literature on the common factor models, pioneered by Hasbrouck (1995) and Gonzalo and Granger (1995). These studies introduce two measures

[5] This study is linked to the growing literature on limits of arbitrage. Equity arbitrage is discussed in Mitchell et al. (2002), Abreu and Brunnermeier (2002), Brunnermeier and Pedersen (2009), Kondor (2009), Liu and Longstaff (2004), Shleifer and Vishny (1997) etc. Some studies, for example Das and Hanouna (2009) and Kapadia and Pu (2008), specifically focus on the link between credit and equity markets.

[6] Structural credit risk models are based on the seminal paper of Merton (1974).

[7] See CreditGrades Technical Document (2002) for details on the model's implementation. Other structural credit risk models often used in the credit risk literature are the ones from Leland and Toft (1996) and Zhou (2001).

of price discovery for every market, namely the information share (IS) and the Gonzalo-Granger (GG) measures, and these are used to infer on the price discovery process in the two markets. The innovation of the paper is that the newly introduced strategies are based on forecasts of (time-varying) price discovery measures, which are built on volatility forecasts.

The rest of the paper is organised as follows: Section 2 discusses the pricing of CDS contracts and the price discovery process which underlie the trading strategies; Section 3 describes the trading strategies we implement; the data used in our analysis is presented in Section 4. Section 5 explains the construction of the return indexes for the trading strategies and analyses their monthly returns. Section 6 presents robustness checks and Section 7 concludes.

2. The theory underlying the trading strategies

2.1 The pricing of a CDS contract

A CDS is an insurance contract against the occurrence of credit events (such as the default on a corporate bond) related to a specific obligor (also called reference entity). In the occurrence of the credit event indicated in the stipulated contract, the counterparty who sold insurance has the obligation to pay the face value of the underlying bond to the protection buyer. In order to be insured against credit events, the protection buyer has to pay to the protection seller a quarterly premium until the maturity of the contract or the credit event, whichever takes place first. Under a continuous-time framework, the present value of the premium leg of the contract is equal to

$$E\left(c \int_0^T \exp\left(-\int_0^s r_u du\right) 1_{\{\tau>s\}} ds\right) \tag{1}$$

where c represents the CDS spread, T is the maturity of the CDS contract, r is the risk-free interest rate and τ is the time of default of the obligor. If we assume independence between τ and r, we can simplify the above as

$$c \int_0^T P(0,s) q_0(s) ds \tag{2}$$

where $P(0,s)$ is the price of a default-free zero coupon bond with maturity s and $q_0(s)$ is the risk-neutral survival probability of the issuer, $P(\tau > s)$, at $t = 0$.

The present value of the protection leg of the CDS contract can be defined as

$$E\ \left((1-R)\exp\left(-\int_0^{\tau} r_u du\right) 1_{\{\tau<T\}}\right) \tag{3}$$

where R is the recovery rate of the corporate bond in the event of default. Under the assumption of a constant recovery rate and of independence between τ and r, we can write the above as follows

$$-(1-R)\int_0^T P(0,s)q_0'(s)ds \tag{4}$$

where $-q_0'(t) = -dq_0(t)/dt$ is the probability density function of the default time. By setting the initial value of the contract to zero, we are able to determine the CDS spread as

$$c = -\frac{(1-R)\int_0^T P(0,s)q_0'(s)ds}{\int_0^T P(0,s)q_0(s)ds} \tag{5}$$

Equation (5) gives the CDS spread for a new stipulated contract. If an investor who went long a CDS contract at time 0 holds it until time t, then its market value will be given by

$$\pi(t,T) = \big(c(t,T) - c(0,T)\big)\int_t^T P(t,s)q_t(s)ds \tag{6}$$

where $c(t,T)$ is the CDS spread on a contract initiated at time t with a maturity of T. The survival probability $q_t(s)$ depends on the equity price S_t via the structural model. The latter is also used to generate the hedge ratio defined as

$$\delta(t,T) = \frac{\partial\pi(t,T)}{\partial S_t} \tag{7}$$

2.2 Time-varying Information Share (IS)

The main novelty of this study is the introduction of trading strategies based on the information flow of the markets which are being traded. The information flow of a given market can be quantified by measures of price discovery. The two most popular measures used in the market microstructure literature are the IS and GG measures, and are defined in Hasbrouck (1995) and Gonzalo and Granger (1995), respectively. In order to compute these measures of contribution to price discovery, we first need to estimate the following VECM of changes in CDS spreads (cds) and equity implied spreads (eis) for the series of spreads which are non-stationary:

$$\Delta cds_t = \lambda_1 CE_{t-1} + \sum_1^p \beta_{1j}\Delta cds_{t-j} + \sum_1^p \delta_{1j}\Delta eis_{t-j} + \varepsilon_{1t} \tag{8a}$$

$$\Delta eis_t = \lambda_2 CE_{t-1} + \sum_1^p \beta_{2j} \Delta cds_{t-j} + \sum_1^p \delta_{2j} \Delta eis_{t-j} + \varepsilon_{2t} \quad (8b)$$

where ε_{1t} and ε_{2t} are i.i.d. error terms. The cointegrating equation is defined as:

$$CE_t = cds_t - \alpha_1 eis_t \quad (8c)$$

We focus on the IS measure because, unlike the GG measure, it takes account of the volatility of the error terms of the VECM. However, only an upper and lower boundary can be defined, at every time *t*, so that we do not have a point estimate of price discovery[8]. However, Baillie et al. (2002) showed that the midpoint of these IS bounds can be considered a reasonable estimate of the price discovery of a given market at a certain point in time[9]. The contributions of the CDS market to price discovery are given by the following relations:

$$IS_{cds,1} = \frac{\lambda_2^2\left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2}, \qquad IS_{cds,2} = \frac{\left(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2} \quad (9)$$

where $IS_{cds,1}$ and $IS_{cds,2}$ give the bounds of the IS measure of the CDS market[10]. σ_1^2, σ_{12}, and σ_2^2 give the covariance matrix of ε_{1t} and ε_{2t}.

Ideally, a capital structure arbitrageur would be interested in having an estimate of the price discovery of the CDS and equity markets every day, and based on those estimates he can place his trades. Following Avino et al. (2011), we apply a bivariate GARCH model to the residuals of the VECM estimated in (8).[11] In particular, we use the BEKK specification of the GARCH model as introduced by Engle and Kroner (1995):

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon_{t-1}')A + B'H_{t-1}B \quad (10)$$

where $H_{\mathrm{t}} = \begin{pmatrix} \sigma_{1,\mathrm{t}}^2 & \sigma_{12,\mathrm{t}} \\ \sigma_{12,\mathrm{t}} & \sigma_{2,\mathrm{t}}^2 \end{pmatrix}$, $C = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}$, $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, $B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$.

[8] There has been a lively debate on the correct interpretation of the GG and IS measures. Generally, the IS measure seems to be the proper measure to assess the amount of information generated by each market. For more on this topic, see the special issue (issue 3, 2002) of the *Journal of Financial Markets*.

[9] To give support to our choice, we also calculated the average range of the upper and lower bounds of the IS measure. The average range is about 12% for investment grade obligors, whereas it is about 14% for speculative grade obligors. These ranges are in line with past microstructure studies; for example, Blanco et al. (2005) report an average range of 8%.

[10] The GG measure would be given simply by $\frac{\lambda_2}{\lambda_2 - \lambda_1}$.

[11] A different way to obtain daily estimates of price discovery would be based on intraday prices so that a daily VECM could be estimated using data for a given day. However, for the CDS market, high frequency trading is still in its infancy.

Because the IS is defined as a function of the volatility of the error terms in the VECM, a time dependent (daily) IS can be produced by replacing the unconditional error volatilities in (9) with the conditional volatilities obtained with (10). As a result, we can explore the time varying behaviour of the information flow among markets and use it for trading purposes. In order to achieve this aim, for all companies for which we find evidence of cointegration over the whole sample period and even for those which do not show cointegration, we estimate (8) and (10) by using a rolling window of 1 year of data (250 observations)[12], starting from January 2004. We use the covariance matrix of the error terms (obtained with (10)) at the end of the year to compute the IS measure (the midpoint of the bounds)[13], and we use the latter as an estimate of the price discovery of the CDS market for the following day. The next day, we roll over the 1-year window, we re-estimate (8)[14] and (10) to get a new IS estimate for the following day. We follow this procedure till the end of our sample period, that is 31st December 2009. Hence, starting from January 2005 till the end of 2009, we have a series of estimates of price discovery for the CDS and equity markets for each reference entity. In the next section, we show how to use these estimates to trade both markets.

3. Description of the trading strategies

This section describes the main features of the 5 strategies (the first one being the standard CSA and 4 new strategies) implemented. The trading rules for each strategy are summarised in Table 1.

3.1 Strategy 1: Standard CSA

Capital structure arbitrage is generally implemented on individual entities. It is originally based on two different time series of data, namely the market CDS spread and the model spread obtained from equity-based information 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 than the equity implied spread by a defined trading trigger θ, a trader would short a CDS position with a notional amount of USD 1[15] and $-\delta_{t-1}$ shares of the common stock. Instead, if the equity implied spread

[12] 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 we analyse) because they are pricing the same risk, even though the Pearson correlation between changes in CDS prices and stock prices is low.

[13] $(1 - IS_{cds})$ will give the price discovery estimate for the equity market.

[14] The number of lags we include for the VECM estimation in (8) is chosen according to the Akaike criterion for the whole sample.

[15] For European obligors we assume EUR 1 of notional for the CDS contract.

is higher than the CDS spread, a trader would buy a CDS position with a notional of USD 1 and, at the same time, buy $-\delta_{t-1}$ shares. These positions are typically kept for a fixed holding period or for a shorter period of time if convergence occurs between the two spreads.

3.2 Strategy 2

We augment Strategy 1 by introducing a price discovery (PD) trigger. x_l and x_u represent, respectively, the lower and upper thresholds of IS price discovery for the CDS market selected by the trader. We are filtering Strategy 1 trades and execute them only if there is clear evidence of one market leading the other one. However, we still hedge the positions.[16] Hence, 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 either lower than x_l or higher than x_u, a CDS position with a notional amount of USD 1 and $-\delta_{t-1}$ shares of the common stock are shorted. On the other hand, if the equity implied spread is higher than the CDS spread and the price discovery of the CDS market is either lower than x_l or higher than x_u, a CDS position with a notional amount of USD 1 and $-\delta_{t-1}$ shares of the common stock are bought. Thus, trades are filtered not only on the basis of the deviation between the two spreads, but also according to the informational efficiency of the markets, captured by the IS measure of price discovery.

3.3 Strategy 3

According to Yu (2006), hedging CDS positions with equity shares can be ineffective due to the low correlation observed between changes in CDS spreads and stock prices. A trader could be better off if he trades just one market. In particular, a trader would sell a CDS contract with a notional of USD 1 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 x_l, meaning that the CDS market is being led. On the other hand, he would short the equity market only 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 x_u, so the equity market is being led. Similarly, a CDS contract with a notional of USD 1 would be bought 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 x_l. 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. Hence, a trader would trade only one market, namely the least efficient one (with a low value of price discovery).

[16] A valid criticism of this strategy is that if one market leads the other one, then one should trade only in the inefficient market, and ignore hedging. This is what Strategy 3 will be, and we look at Strategy 2 in order to differentiate between the effect of (1) omitting hedging altogether and (2) filtering the trades based on the price discovery of the markets.

We expect to improve capital allocation by not trading the efficient market, that is the market which is difficult to forecast.

3.4 Strategy 4

We use the estimated parameters in the cointegrating equation (8c) in order to define the minimum deviation between market and model spreads necessary to generate a trading opportunity. In fact, in cointegrated systems, we would expect the coefficient on the equity-implied spread α_1 to equal 1 in the cointegrating vector; and this is assumed in Strategies 1, 2 and 3. However, while from a statistical perspective α_1 is not often significantly different from 1, in practice, the actual values of the 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 α_1 is not assumed to be 1).

3.5 Strategy 5

Similarly to Strategy 3 and 4, this strategy does not require the equity hedge. We only use a price discovery trigger and the error correction term (CE_{t-1}) of the VECM of changes in spreads, namely the first part of equations (8a) and (8b). A trader would sell a CDS contract with a notional of USD 1 if the product $sign(\lambda_1) * CE_{t-1}$ is lower than the negative of a multiplier (the trading trigger θ) times yesterday's CDS spread, and the price discovery of the CDS market is lower than x_l; whereas he would go long such a CDS contract if the product $sign(\lambda_1) * CE_{t-1}$ is higher than the product between the trading trigger θ and yesterday's CDS spread, and the price discovery of the CDS market is lower than x_l. Similarly, a trader would short equity if the product $sign(\lambda_2) * CE_{t-1}$ is higher than the product between the trading trigger θ and yesterday's CDS spread, and the price discovery of the CDS market is higher than x_u, while he would go long equity if the product $sign(\lambda_2) * CE_{t-1}$ is lower than the negative of the trading trigger θ times yesterday's CDS spread, and the price discovery of the CDS market is higher than x_u[17].

Table 2 presents the main features of the 5 strategies. It can be noticed that only Strategy 1 and 2 use a hedge ratio and all new strategies we propose (2 to 5) are based on a price discovery trigger.

4. Data

[17] For Strategy 5, we also tried to include the lagged changes in the spreads from the VECM into the trading rule so that in the trading rule condition we replace $\lambda_i * CE_{t-1}$ with $\lambda_i * CE_{t-1} + \sum_1^p \beta_{ij}\Delta cds_{t-j} + \sum_1^p \delta_{ij}\Delta eis_{t-j}$, for i = 1 and 2. However, the additional terms are of small magnitude and economically insignificant as they almost never change the sign of a trade. Hence, adding them would not change the profits of this strategy.

We use CDS quotes provided by the CMA database.[18] We only use daily mid-market quotes on senior unsecured debt for non-financial companies with 5 year maturity and a modified restructuring (MR) clause. We include both North American and European obligors with currencies denominated in USD and EUR, respectively. The data used for the strategies' execution are from 2005 to 2009. We match the CDS data with information required by the CreditGrades model to get the equity implied spreads.

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, preferred shares; the mean global recovery rate $\bar{L}$ and its standard deviation λ; the recovery rate of the firm's senior unsecured debt, R; the annualized equity volatility σ_S and the 5-year risk-free interest rate r.

Stock prices, market capitalisations, accounting data and 5-year swap rates for both USD and EUR are downloaded from Bloomberg. For λ we take the value of 0.3 as reported in the CreditGrades Technical Document (2002). The recovery rate R is estimated as the Moody's average historical recovery rate on senior unsecured debt over the period 1982-2009 (see Moody's, 2011) and is equal to 0.326. We follow Yu (2006) to define the value of $\bar{L}$ and, for each reference entity in our sample, we use the first 10 daily CDS spreads to minimize the sum of squared pricing errors over $\bar{L}$. The implied value of $\bar{L}$ is then used in the credit model together with the other inputs to generate theoretical CDS spreads.

The most important input of the model is the equity volatility σ_S. For this we use a 250-day moving average of past equity stock returns, in order to have a volatility estimate that is responsive to changing market conditions (very important during the financial crisis, when most entities experienced a sharp increase in credit spreads). However, we also employ a 1,000-day moving average as suggested in CreditGrades Technical Document (2002), which would, most likely, determine a lagged response of the model spreads. 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 market spreads, which would alter the trade to be executed (for example, a 'buy CDS' trade might be changed into a 'sell CDS' trade). Thus, as a robustness test, in Section 6 we compute the returns of the strategies 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 search for the longest string of more than 100 daily quotes which are no more than 14 days apart and we check that we have all the information needed for the computation of model spreads.

[18] According to Mayordomo et al. (2010), 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.

Applying these filters renders a final sample of 70 companies[19] with 101,799 composite daily quotes starting from January 2005 till the end of 2009[20]. Even though the number of companies in our sample is less than in previous studies, we analyse a larger time span which allows us to generate a total number of available quotes very close to 136,000 quotes reported in Yu (2006) and Duarte et al. (2007).

Table 3 presents the 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. Also, 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, consistent with structural models, but very low, which would raise concerns on the effectiveness of the equity hedge; and this is one of the reasons why we also propose new strategies which do not involve hedging.

Moreover, it is evident that we can distinguish two different regimes, the period preceding the recent financial crisis and the crisis period itself. In fact, the level of spreads, volatility and leverage increase substantially during the crisis and this is especially true for speculative grade companies. The equity market capitalisation of the obligors shrinks too due to the downtrend in the equity markets. 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 found higher correlations for this category of obligors, and some possible explanations are: (1) our sample includes a very small number of B-rated and CCC-rated obligors and for these two categories the negative relationship between CDS and equity markets is stronger; (2) the dissimilarity of views between the CDS and equity markets on the price of credit risk increased in times of financial instability; (3) Pearson's correlation coefficient does not fully capture the non-linear relationship between CDS and equity markets.

5. Results

We implemented the 5 strategies for the 70 obligors in our final sample for the period January 2005-December 2009. The procedure we follow is similar to the one used in Yu (2006) and Duarte et al. (2007). 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

[19] Of these, 36 are US-based while 34 are European obligors.

[20] In practice, we use a higher number of daily CDS quotes that start from January 2004. However, the quotes available for the first year are used to estimate some of the inputs for the trading strategies, whilst we start trading from January 2005. If we include the quotes starting from 2004, we end up with approximately 120,000 quotes.

industry benchmarks (discussed in the next section). As the CDS position has a value of zero at initiation, we assume USD 0.5 initial capital[21] for every trade we make and use the same capital to finance the equity hedge, if hedging is required by the strategy. If hedging is not required, then only one market is traded and the initial capital is invested in that single market. 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 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[22], which should be minimal given the fact that we use 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 5 strategies we implement. For Strategy 4, in the case of speculative grade obligors for which we have a smaller 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. The role of this price discovery trigger is at least twofold: (1) it can be used to filter strong signals (the price discovery of a given market should be reasonably high); (2) it can motivate not to hedge because trading in an informationally efficient market is risky, whilst it makes sense to trade in a market which is known to follow another market.

Thus, for the new strategies we compared different levels of price discovery triggers. Intuitively, selecting higher triggers (stronger price discovery in one market) should generate higher profits as the second market would follow the first one more closely, so the second market could be predicted more effectively. However, too high triggers would lead to less profit due to the sharp decrease in the number of transactions and due to profitable trades being left out. We chose a value of 80% for the price discovery

[21] For European entities, we assume EUR 0.5 initial capital.

[22] 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.

trigger in the CDS market (corresponding to a 20% trigger for the equity market). Hence, in the trading rules defined in Section 3, x_l and x_u will be equal to 20% and 80%, respectively.

Table 4 shows the number of trades executed for each strategy over the whole sample period. It is very interesting to notice how the use of an additional trigger such as the PD trigger substantially reduces the frequency of trading. The implementation of Strategies 2 and 3 for investment grade obligors allows a reduction in the number of trades of almost 40% if compared with the traditional capital structure arbitrage (Strategy 1). If we compare the latter with Strategy 4 and Strategy 5, a trader would reduce the number of trades by 66% and 84%, respectively, and the same is true for speculative grade obligors.

An interesting point to notice refers to Strategy 1 and 2, which require 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[23]. This anomaly is a limit of hedging, 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), whose study shows that equity hedging costs increase when markets become more volatile, and Kapadia and Pu (2010), who show that limits to arbitrage can arise because the liquidity in markets can worsen. From the point of view of implementation, we are not able to perform a complete hedge (as predicted by the hedge ratio calculated with the CreditGrades model) on the days when such an anomaly occurs. Hence, a trader would need more capital (which becomes a scarce resource) to implement these strategies when volatility in the market is high. A way to still accomplish these strategies would involve trading CDS contracts on smaller amounts of notional making sure that a given percentage (such as 10%) of the CDS notional be deposited as a margin account. In these cases, we make sure that at least 10% of the notional amount of the CDS contract stays deposited in the margin account and is not invested to buy the equity shares[24].

Tables 5, 6 and 7 show the summary statistics for the monthly excess returns of the 5 strategies for the whole sample period, the pre-crisis period (January 2005-July 2007) and the in-crisis period (August 2007-December 2009), respectively. We implement the strategies separately for investment and speculative grade companies by using holding periods of 30 days and 180 days 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 (denoted by α in their paper) from 0.5 to 2 generates higher monthly mean returns and higher Sharpe ratios for Strategy 1, and similarly for Strategy 2. However, this relationship doesn't

[23]As mentioned previously, the initial capital is used to finance the equity hedge.

[24]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.

always hold for Strategies 3, 4 and 5, mostly because they don't imply hedging. Furthermore, speculative grade entities produce higher Sharpe ratios than the investment grade obligors for Strategies 4 and 5. Figure 2 presents the evolution of monthly excess returns for all strategies.

Strategy 1 (the classical CSA strategy) generates negative Sharpe ratios both before and during the crisis. All the new strategies we propose outperform Strategy 1 in every period. In the pre-crisis period, Strategy 4 seems to give the best Sharpe ratios for investment grade obligors and it is also the best strategy for speculative grade obligors when a trading trigger of 0.5 is employed. However, for a trading trigger of 2, Strategy 5 overperforms it. Even during the crisis period, Strategy 4 gives the best Sharpe ratios for speculative grade companies but in the case of investment grade obligors Strategies 3 and 5 do better for a trading trigger of 2 and 0.5, respectively. Interestingly, the new strategies deliver highly positive Sharpe during the crisis period with Strategy 3 giving the highest Sharpe ratio of 1.24 in the case of a holding period of 180 days and a trading trigger of 2. In summary, we find that classical CSA underperforms all new strategies we propose for any holding period or trigger used.

While consistent with modern portfolio theory, ranking strategies' portfolios according to the Sharpe ratio when excess returns are negative can be counterintuitive. In fact, strategies which generate higher volatility of returns would be better ranked than low-volatility strategies. In order to avoid this anomaly, we also report a modified Sharpe ratio which has been proposed by Israelsen (2003, 2005). Based on this modified version of the Sharpe ratio, we can clearly notice how, during the pre-crisis period, the new strategies we propose (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.

5.1 *Comparison of strategies' returns with fixed income hedge fund returns*

Following Duarte et al. (2007), we compare the monthly returns indices constructed for each strategy with fixed income arbitrage hedge fund return data obtained from popular industry sources. 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[25].

The characteristics of these hedge fund returns are very similar to the capital structure index returns we constructed and described in the previous section. The annualised average return and standard deviation of the AllHedge Fixed Income Arbitrage Index are -4.84% and 12.82%, respectively. These values imply an annualised Sharpe ratio of -0.38, which is extremely similar to the Sharpe ratios reported in Table 5 for

[25] See www.hedgeindex.com for more details on index construction rules.

Strategy 1. The negative skewness of -3.1 and the excess kurtosis of 16.17 are also quite close to the values generated by our capital structure arbitrage returns. If we focus on the period including the financial crisis, the Sharpe ratio is even more negative at a level of -0.54. Hence, fixed income arbitrage hedge funds delivered a very bad performance during this period. Some of the strategies we propose show positive skewness and lower kurtosis over the same time period and are capable to give positive Sharpe ratios which, in some cases, are higher than 1.

Moreover, we look at the correlations between Strategy 1 and the CSFB index. They are high and positive over the whole sample period and over the subsamples of pre-crisis and in-crisis. For instance, the correlation between monthly returns of Strategy 1 (implemented with a 250-day historical volatility, holding period of 180 days and a trading trigger of 2) and the CSFB index monthly returns is about 0.40. This value is much higher than those reported by Duarte et al. (2007). A reason for that may be the increased popularity of the strategy among hedge funds over the recent years and this could also explain why profits turned negative eventually.

Instead, when we look at the correlations of the new strategies with the CSFB index, we find different patterns. Except for Strategy 2 (whose correlations are of the same order as Strategy 1), Strategy 3, Strategy 4 and Strategy 5 present correlations of -0.28, -0.39, -0.003. Table 8 shows the correlation of the monthly returns generated by the 5 strategies. It is evident that most of the new strategies are uncorrelated or even negatively correlated with the standard CSA. Overall, these new strategies could really help achieve the objective of portfolio risk diversification.

6. Robustness of the results

6.1 Test of strategies on theoretical spreads obtained from a 1000-day historical volatility

In this section 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 vary according to both the structural credit risk model used and especially, changes in 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 strategy's profitability; however, the choice of the volatility input can have a bigger impact on the profits of capital structure arbitrage. They state that using option-implied volatilities (rather than historical volatilities) as inputs to the structural model generates higher profits. As we do not have availability of option-implied volatilities, we compute theoretical spreads using 1000-day historical volatility, which was originally suggested in the CreditGrades Technical Document (2002) and considered as the best choice for volatility estimation because it could generate the most accurate estimates of model spreads. When changing the length of the moving window to compute volatility, the trade to be made can change (for example a buy trade might become a sell trade). We find that the results (available on request) look quite similar to the results shown in Tables 5, 6 and 7. Strategy 1 again proves to be the worst performing strategy. The only major difference concerns the outperformance of Strategy 3 in the pre-crisis period for investment grade obligors and holding period of 30 days. 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.

As in the previous section, we also compute the correlation between monthly returns of Strategy 1 (implemented with a 1000-day historical volatility, holding period of 180 days and a trading trigger of 2) and the CSFB index monthly returns and we find that it rises up to a value of 0.65. 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.

6.2 Excluding companies for which the CDS and equity markets are not cointegrated

For some of the 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. Thus, we tried to remove the companies which were not cointegrated from our sample[26] and, as expected, we obtained an improvement in the strategies' profitability. Hence, the strategies we propose in this paper seem to work much better for cointegrated series and ideally, a trader should trade obligors for which the equity and CDS markets are cointegrated. This could substantially reduce the risk of losses which are more likely to derive from entities whose equity and CDS markets do not show a long run relationship. However, these strategies seem to work even when cointegration is not achieved.

7. Conclusions

Exploiting the mispricings between the CDS and equity markets is the main objective of the so-called "capital structure arbitrage" strategy. Despite its popularity over the last decade, the strategy has undergone a clear decrease in profitability over the period 2005-2009. The main reasons for this fall in

[26]Out of 70 companies, only 7 companies reject cointegration between CDS and equity markets over the whole sample period.

profits lie in (1) the arrival of the financial crisis around the middle of 2007 and (2) the great development of the CDS market, which in recent years has become a mature market now widely used by professional investors.

Given the need for innovative strategies which can help diversify investors' portfolios particularly in periods of higher market volatility, this paper proposes new trading strategies involving the CDS and equity markets which are based on the use of the information flow between the markets. Triggers based on daily price discovery estimates for the two markets are introduced, which allow traders to filter the most profitable trades and give traders a solid motivation not to hedge and hence not to trade the efficient market. The new strategies outperform capital structure arbitrage and, more importantly, are able to do that by substantially reducing the frequency of trading. For instance, one of the strategies we propose would involve about 84% less trades and still would deliver better returns. The new strategies generate the highest profits and positive Sharpe ratios especially during the recent financial crisis and, except for Strategy 2, deliver monthly returns which show low or even negative correlation with both the returns of capital structure arbitrage and fixed income hedge fund returns. However, in the period preceding the financial crisis, the new strategies show a higher volatility of the monthly returns, apart from Strategy 2 which shows the lowest volatility among all strategies. Interestingly, we find that the results are robust to the length of the window used to estimate the volatility in the structural model that is an essential input to the trading rules generated.

We introduced innovative and theoretically sound trading ideas which can be used to diversify hedge funds portfolios' risk at times when achieving diversification becomes a harder job. It would be interesting to see how the profitability of the new strategies would change if option implied volatilities are used as input. Further research should also focus on innovative strategies based on more advanced methodologies to forecast price discovery measures.

Appendix

CreditGrades Model

According to the model, the recovery rate L follows a lognormal distribution with mean $\bar{L}$ and standard deviation λ where

$$\bar{L} = EL \text{ and} \tag{A1}$$

$\lambda^2 = Varlog(L)$, such that (A2)

$$LD = \bar{L}De^{\lambda z - \frac{\lambda^2}{2}}, \quad \text{(A3)}$$

z is a standard normal random variable which is known at the time of default only. The company's asset value is assumed to follow a geometric Brownian motion:

$$\frac{dV_t}{V_t} = \mu dt + \sigma dW_t \quad \text{(A4)}$$

where μ is the asset drift, σ is the asset volatility and W is a standard Brownian motion.

The survival probability of the company at any time *t* is given by the probability that the asset value (A4) does not hit the barrier defined in (A3) before time *t*:

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln d}{A_t}\right) - d\Phi\left(-\frac{A_t}{2} - \frac{\ln d}{A_t}\right) \quad \text{(A5)}$$

where

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L}D} \text{ and} \quad \text{(A6)}$$

$$A_t^2 = \sigma^2 t + \lambda^2 \quad \text{(A7)}$$

The asset value and asset volatility can be proxied by market observables parameters. In fact, it can be assumed that at time *t* = 0:

$$V = S + \bar{L}D \text{ and} \quad \text{(A8)}$$

$$\sigma = \sigma_S \frac{S}{S + \bar{L}D} \quad \text{(A9)}$$

where S is the stock price, σ_S is the stock volatility, D is the debt-per-share, $\bar{L}$ is the global recovery rate and λ is the percentage standard deviation of the default barrier. Finally, the survival probability is converted to a credit spread as follows:

$$c(0,T) = r(1-R)\frac{1 - q(0) + H(T)}{q(0) - q(T)e^{-rT} - H(T)} \quad \text{(A10)}$$

where $\xi = \frac{\lambda^2}{\sigma^2}$ (A11)

and, following Rubinstein and Reiner (1991),

$$G(u) = d^{z+\frac{1}{2}}\Phi\left(-\frac{\log(d)}{\sigma\sqrt{u}} - z\sigma\sqrt{u}\right) + d^{-z+\frac{1}{2}}\Phi\left(-\frac{\log(d)}{\sigma\sqrt{u}} + z\sigma\sqrt{u}\right) \tag{A12}$$

$$H(T) = e^{r\xi}\big(G(T+\xi) - G(\xi)\big) \tag{A13}$$

with $z = \sqrt{\frac{1}{4} + 2r/\sigma^2}$. (A14)

Following Yu (2006), we approximate the value of a CDS contract by:

$$\pi(t,T) = \big(c(t,T) - c(0,T)\big)\int_t^T P(t,s)q_t(s)ds$$

$$= \frac{c(0,T)-c}{r}\Big(q(0) - q(T)e^{-rT} - e^{r\xi}\big(G(T+\xi) - G(T)\big)\Big) \tag{A15}$$

where c is the CDS spread of the contract at initiation and $C(0,T)$ is function of the equity price S as shown in equation (A10). Combining (A10) with (7), we obtain the hedge ratio implied by the model:

$$\delta(0,T) = \frac{1}{r}\frac{\partial c(0,T)}{\partial S}\Big(q(0) - q(T)e^{-rT} - e^{r\xi}\big(G(T+\xi) - G(T)\big)\Big) \tag{A16}$$

where c is numerically equal to $c(0,T)$ evaluated at an equity price of S. We then differentiate $c(0,T)$ numerically with respect to S to find the hedge ratio.

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Table 1. Trading rules of the strategies.

Summary of the trading rule conditions and the corresponding trades (long or short) in CDS and equities for the 5 strategies.

Type	Trading rule condition	Trade	
		CDS	equity
Strategy 1	$cds_{t-1} > (1+\theta) * eis_{t-1}$	short	short
	$eis_{t-1} > (1+\theta) * cds_{t-1}$	long	long
Strategy 2	$[cds_{t-1} > (1+\theta) * eis_{t-1}]$ and $\left[(IS_{cds,t-1} \leq x_l) \text{ or } (IS_{cds,t-1} \geq x_u)\right]$	short	short
	$[eis_{t-1} > (1+\theta) * cds_{t-1}]$ and $\left[(IS_{cds,t-1} \leq x_l) \text{ or } (IS_{cds,t-1} \geq x_u)\right]$	long	long
Strategy 3	$[cds_{t-1} > (1+\theta) * eis_{t-1}]$ and $[IS_{cds,t-1} \leq x_l]$	short	-
	$[cds_{t-1} > (1+\theta) * eis_{t-1}]$ and $[IS_{cds,t-1} \geq x_u]$	-	short
	$[eis_{t-1} > (1+\theta) * cds_{t-1}]$ and $[IS_{cds,t-1} \leq x_l]$	long	-
	$[eis_{t-1} > (1+\theta) * cds_{t-1}]$ and $[IS_{cds,t-1} \geq x_u]$	-	long
Strategy 4	$[cds_{t-1} > (1+\theta) * \alpha_1 * eis_{t-1}]$ and $[IS_{cds,t-1} \leq x_l]$	short	-
	$[cds_{t-1} > (1+\theta) * \alpha_1 * eis_{t-1}]$ and $[IS_{cds,t-1} \geq x_u]$	-	short
	$[eis_{t-1} > (1+\theta) * cds_{t-1}/\alpha_1]$ and $[IS_{cds,t-1} \leq x_l]$	long	-
	$[eis_{t-1} > (1+\theta) * cds_{t-1}/\alpha_1]$ and $[IS_{cds,t-1} \geq x_u]$	-	long
Strategy 5	$(sgn(\lambda_1) * CE_{t-1} < -\theta * cds_{t-1})$ and $(IS_{cds,t-1} \leq x_l)$	short	-
	$(sgn(\lambda_2) * CE_{t-1} > \theta * cds_{t-1})$ and $(IS_{cds,t-1} \geq x_u)$	-	short
	$(sgn(\lambda_1) * CE_{t-1} > \theta * cds_{t-1})$ and $(IS_{cds,t-1} \leq x_l)$	long	-
	$(sgn(\lambda_2) * CE_{t-1} < -\theta * cds_{t-1})$ and $(IS_{cds,t-1} \geq x_u)$	-	long

Table 2. Main features of the trading strategies.

The main characteristics of the 5 trading strategies based on the usage of a θ trading trigger, a price discovery (PD) trigger, hedging, cointegrating equation and error correction term.

	trading trigger	PD trigger	Hedging	CE	λCE
Strategy 1	√	-	√	-	-
Strategy 2	√	√	√	-	-
Strategy 3	√	√	-	-	-
Strategy 4	√	√	-	√	-
Strategy 5	-	√	-	-	√

Table 3. Summary statistics of the 70 obligors for rating categories.

Summary statistics for each rating category (Investment and Speculative) for the whole sample period, the pre-crisis period (January 2005-July 2007) and in-crisis period (August 2007-December 2009). *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							
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							
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. In-crisis							
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

Table 4. Total number of trades executed.

The total number of trades executed for each of the 5 strategies separately for investment grade and speculative grade obligors. Each strategy is implemented for a holding period of 180 days and a trading trigger of 2.

Category	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5
Investment grade	44,376	27,151	27,151	14,984	7,016
Speculative grade	8,861	5,506	5,506	2,728	1,658

Table 5. Summary statistics for the 5 strategies over the whole sample period.

Summary statistics for the monthly excess returns (%) of the 5 strategies. θ is the trading trigger which defines the distance between CDS and equity implied spread. *Type* defines the strategy implemented. *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. Panel A and Panel B show results for investment grade and speculative grade obligors, respectively. * indicates significance at 5% level of the autocorrelation coefficient.

θ	Type	N	Mean	Median	Min	Max	Std	Skew	Kurt	Corr	Neg	Sharpe	MSharpe
A. Investment Grade													
Holding Period: 30 days													
0.5	Strategy 1	60	-0.39	-0.23	-10.70	5.25	1.96	-2.65	15.65	0.24	0.78	-0.69	-0.00026
	Strategy 2	60	-0.25	-0.22	-7.15	5.02	1.62	-0.69	7.65	0.15	0.78	-0.54	-0.00014
	Strategy 3	60	-0.60	-0.64	-8.40	6.80	2.42	-0.33	2.59	0.23	0.67	-0.86	-0.00051
	Strategy 4	60	-0.41	-0.18	-4.50	4.13	1.71	0.02	0.30	-0.47*	0.58	-1.32	-0.00040
	Strategy 5	60	-0.31	-0.30	-4.54	4.11	1.65	0.28	0.70	0.08	0.57	-0.64	-0.00017
2	Strategy 1	60	-0.20	-0.19	-11.56	5.41	2.00	-2.57	18.28	0.03	0.75	-0.34	-0.00014
	Strategy 2	60	-0.08	-0.19	-6.96	5.10	1.65	0.05	7.23	0.00	0.73	-0.17	-0.00005
	Strategy 3	60	-0.23	-0.73	-4.22	8.10	2.44	1.07	1.45	0.10	0.67	-0.33	-0.00020
	Strategy 4	60	-0.62	-0.49	-8.67	7.90	2.53	-0.25	3.13	-0.44*	0.60	-1.30	-0.00084
	Strategy 5	60	-0.62	-0.40	-13.18	3.89	3.11	-1.36	3.63	0.19	0.57	-0.70	-0.00067
Holding Period: 180 days													
0.5	Strategy 1	60	-0.24	-0.19	-7.11	5.88	1.53	-0.55	10.64	0.23	0.73	-0.54	-0.00013
	Strategy 2	60	-0.21	-0.20	-6.34	5.65	1.50	-0.05	8.25	0.20	0.72	-0.48	-0.00011
	Strategy 3	60	-0.19	-0.63	-6.46	6.82	2.31	0.38	1.03	0.03	0.60	-0.28	-0.00015
	Strategy 4	60	-0.19	-0.48	-4.07	6.19	1.98	0.68	1.17	-0.16	0.60	-0.34	-0.00013
	Strategy 5	60	-0.16	-0.33	-3.12	4.41	1.45	0.40	0.74	-0.04	0.60	-0.38	-0.00008
2	Strategy 1	60	-0.20	-0.22	-5.77	5.68	1.43	0.24	7.80	0.10	0.77	-0.48	-0.00010
	Strategy 2	60	-0.18	-0.19	-4.86	5.30	1.36	0.48	6.47	0.12	0.72	-0.45	-0.00008
	Strategy 3	60	-0.14	-0.60	-4.89	7.75	2.36	0.87	1.46	-0.05	0.58	-0.21	-0.00012
	Strategy 4	60	-0.01	-0.24	-4.10	6.54	2.19	0.68	0.98	-0.09	0.57	-0.01	-0.00001
	Strategy 5	60	-0.37	-0.28	-13.93	7.14	3.13	-1.59	6.13	-0.01	0.53	-0.41	-0.00041
B. Speculative Grade													
Holding Period: 30 days													
0.5	Strategy 1	60	-0.81	-0.14	-18.42	9.73	4.68	-1.19	3.49	-0.44*	0.53	-0.92	-0.00201
	Strategy 2	60	-0.76	0.01	-20.38	12.83	5.78	-1.22	3.63	-0.45*	0.50	-0.70	-0.00234
	Strategy 3	60	-0.80	-0.08	-32.34	8.28	6.49	-2.82	11.12	-0.27*	0.53	-0.55	-0.00232
	Strategy 4	54	2.08	0.04	-43.63	117.3	16.6	5.54	41.54	-0.15	0.44	0.43	0.43
	Strategy 5	60	0.23	0.02	-15.96	22.41	5.13	0.68	8.21	-0.28*	0.50	0.20	0.20
2	Strategy 1	60	-0.71	0.06	-17.25	13.29	5.48	-0.54	1.95	-0.47*	0.48	-0.72	-0.00216
	Strategy 2	60	-0.56	0.03	-25.85	14.44	6.22	-0.95	4.85	-0.43*	0.48	-0.47	-0.00183
	Strategy 3	60	-1.31	0.00	-48.76	20.72	9.68	-2.56	11.08	-0.15	0.50	-0.47	-0.00440
	Strategy 4	54	1.23	0.00	-6.21	51.33	7.08	6.19	44.02	-0.06	0.50	0.60	0.60
	Strategy 5	60	-0.03	-0.18	-70.06	51.28	12.46	-1.88	21.13	-0.49*	0.52	-0.02	-0.00024
Holding Period: 180 days													
0.5	Strategy 1	60	-0.35	-0.09	-16.26	11.28	4.43	-0.65	3.21	-0.50*	0.53	-0.45	-0.00089
	Strategy 2	60	-0.23	-0.12	-20.04	15.92	5.34	-0.22	4.43	-0.44*	0.57	-0.23	-0.00066
	Strategy 3	60	-0.61	-0.17	-38.49	11.62	6.77	-3.16	16.46	-0.09	0.55	-0.31	-0.00144
	Strategy 4	55	0.78	0.00	-27.01	35.41	7.60	1.28	11.62	0.10	0.49	0.36	0.36
	Strategy 5	60	0.09	-0.20	-10.78	12.95	3.15	0.88	6.49	0.01	0.53	0.10	0.10
2	Strategy 1	60	-0.17	-0.01	-14.50	19.50	5.47	0.80	4.60	-0.22	0.50	-0.11	-0.00032
	Strategy 2	60	-0.02	-0.07	-18.80	24.85	6.47	1.12	6.35	-0.19	0.52	-0.01	-0.00005
	Strategy 3	60	-0.73	-0.07	-51.29	23.62	9.25	-2.86	15.82	-0.04	0.50	-0.27	-0.00234
	Strategy 4	55	1.52	0.00	-17.04	53.08	8.88	3.96	20.42	0.30*	0.53	0.44	0.44
	Strategy 5	60	0.05	-0.02	-11.27	17.36	4.25	0.89	4.46	0.28*	0.50	0.03	0.03

Table 6. Summary statistics for the 5 strategies during the pre-crisis period.

Summary statistics for the monthly excess returns (%) of the 5 strategies. θ is the trading trigger which defines the distance between CDS and equity implied spread. *Type* defines the strategy implemented. *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. Panel A and Panel B show results for investment grade and speculative grade obligors, respectively. * indicates significance at 5% level of the autocorrelation coefficient.

θ	Type	N	Mean	Median	Min	Max	Std	Skew	Kurt	Corr	Neg	Sharpe	MSharpe
A. Investment Grade													
Holding Period: 30 days													
0.5	Strategy 1	31	-0.23	-0.19	-1.26	0.10	0.24	-2.66	11.22	0.20	0.90	-3.38	-0.00002
	Strategy 2	31	-0.23	-0.18	-1.22	0.11	0.24	-2.34	8.95	0.13	0.94	-3.27	-0.00002
	Strategy 3	31	-0.84	-0.71	-3.66	1.87	1.33	0.12	0.27	-0.31	0.84	-2.18	-0.00039
	Strategy 4	31	-0.65	-0.73	-2.98	2.42	1.21	0.28	0.32	-0.22	0.68	-1.86	-0.00027
	Strategy 5	31	-0.63	-0.57	-2.67	1.51	1.04	-0.05	-0.37	-0.07	0.71	-2.12	-0.00023
2	Strategy 1	31	-0.23	-0.20	-1.44	0.12	0.27	-3.06	13.54	0.13	0.90	-2.88	-0.00002
	Strategy 2	31	-0.23	-0.18	-1.43	0.13	0.27	-2.91	12.34	0.09	0.87	-2.88	-0.00002
	Strategy 3	31	-0.96	-0.92	-4.22	2.25	1.48	0.18	0.48	-0.27	0.81	-2.23	-0.00049
	Strategy 4	31	-0.62	-0.63	-3.98	2.13	1.42	-0.23	0.19	-0.39*	0.65	-2.20	-0.00044
	Strategy 5	31	-1.34	-0.64	-13.18	3.88	3.31	-1.83	4.72	0.03	0.68	-1.40	-0.00154
Holding Period: 180 days													
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
	Strategy 5	31	-0.70	-0.70	-3.12	2.80	1.40	0.49	0.63	-0.21	0.74	-1.73	-0.00034
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	-0.22	-0.19	-1.30	0.16	0.26	-2.45	9.76	0.18	0.87	-3.01	-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
	Strategy 5	31	-1.02	-0.48	-13.93	7.14	3.84	-1.34	4.10	-0.14	0.65	-0.92	-0.00135
B. Speculative Grade													
Holding Period: 30 days													
0.5	Strategy 1	31	-0.33	-0.18	-5.00	0.59	1.04	-3.16	13.36	0.37*	0.52	-0.76	-0.00008
	Strategy 2	31	-0.41	-0.26	-5.03	0.62	1.03	-3.19	13.47	0.27	0.55	-1.38	-0.00015
	Strategy 3	31	-0.69	-1.15	-3.72	6.26	2.24	1.07	1.70	-0.33	0.68	-1.06	-0.00053
	Strategy 4	31	0.14	-0.04	-2.27	2.26	1.16	0.14	-0.49	0.26	0.55	0.41	0.41
	Strategy 5	31	-0.00	-0.28	-2.26	2.63	1.30	0.43	-0.25	-0.17	0.58	-0.001	-0.00000
2	Strategy 1	31	-0.29	0.02	-5.73	0.97	1.20	-3.20	13.79	0.37*	0.48	-0.59	-0.00009
	Strategy 2	31	-0.34	-0.16	-5.65	0.94	1.18	-3.17	13.78	0.26	0.52	-0.99	-0.00014
	Strategy 3	31	-0.81	-0.50	-5.37	6.26	2.46	0.74	1.11	-0.32	0.65	-1.14	-0.00069
	Strategy 4	31	-0.23	-0.21	-3.18	3.38	1.56	0.42	0.33	-0.07	0.65	-0.52	-0.00013
	Strategy 5	31	0.17	-0.34	-8.68	13.30	4.36	0.70	1.81	-0.01	0.55	0.13	0.13
Holding Period: 180 days													
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
	Strategy 5	31	-0.23	-0.52	-2.12	2.81	1.32	0.54	-0.50	-0.14	0.58	-0.59	-0.00010
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
	Strategy 5	31	-0.02	-0.43	-4.97	5.99	2.75	0.53	0.25	0.22	0.55	-0.02	-0.00002

Table 7. Summary statistics for the 5 strategies during the in-crisis period.

Summary statistics for the monthly excess returns (%) of the 5 strategies. θ is the trading trigger which defines the distance between CDS and equity implied spread. *Type* defines the strategy implemented. *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. Panel A and Panel B show results for investment grade and speculative grade obligors, respectively. * indicates significance at 5% level of the autocorrelation coefficient.

θ	Type	N	Mean	Median	Min	Max	Std	Skew	Kurt	Corr	Neg	Sharpe	MSharpe
A. Investment Grade													
Holding Period: 30 days													
0.5	Strategy 1	29	-0.56	-0.35	-10.7	5.25	2.82	-1.74	6.43	0.24	0.66	-0.69	-0.00054
	Strategy 2	29	-0.28	-0.42	-7.15	5.02	2.33	-0.47	2.50	0.15	0.62	-0.41	-0.00022
	Strategy 3	29	-0.35	0.05	-8.40	6.80	3.22	-0.53	1.04	0.31	0.48	-0.38	-0.00039
	Strategy 4	29	-0.15	0.01	-4.50	4.13	2.10	-0.31	-0.20	-0.61*	0.48	-0.46	-0.00020
	Strategy 5	29	0.05	0.15	-4.54	4.11	2.09	-0.10	-0.16	0.07	0.41	0.08	0.08
2	Strategy 1	29	-0.17	-0.18	-11.6	5.41	2.89	-1.89	8.35	0.03	0.59	-0.20	-0.00017
	Strategy 2	29	0.08	-0.26	-6.96	5.10	2.36	-0.17	2.45	-0.01	0.59	0.12	0.12
	Strategy 3	29	0.54	-0.15	-4.19	8.10	2.99	0.60	-0.14	0.05	0.52	0.62	0.62
	Strategy 4	29	-0.63	-0.45	-8.67	7.90	3.37	-0.21	1.26	-0.45*	0.55	-1.00	-0.00114
	Strategy 5	29	0.14	0.12	-5.63	3.89	2.72	-0.44	-0.47	0.33	0.45	0.18	0.18
Holding Period: 180 days													
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
	Strategy 5	29	0.42	0.47	-1.56	4.41	1.29	0.83	1.72	-0.21	0.45	1.12	1.12
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
	Strategy 5	29	0.31	0.69	-4.21	4.53	1.98	-0.18	0.15	0.27	0.41	0.55	0.55
B. Speculative Grade													
Holding Period: 30 days													
0.5	Strategy 1	29	-1.32	-0.10	-18.4	9.73	6.67	-0.64	0.18	-0.46*	0.55	-1.08	-0.00479
	Strategy 2	29	-1.13	0.58	-20.4	12.83	8.30	-0.75	0.23	-0.45*	0.45	-0.73	-0.00504
	Strategy 3	29	-0.92	1.57	-32.3	8.28	9.13	-2.20	5.09	-0.27	0.38	-0.35	-0.00292
	Strategy 4	23	4.15	0.23	-43.6	117.30	23.89	3.79	19.67	-0.16	0.30	0.60	0.60
	Strategy 5	29	0.48	0.54	-16.0	22.41	7.31	0.40	3.06	-0.29	0.41	0.23	0.23
2	Strategy 1	29	-1.17	0.26	-17.3	13.29	7.83	-0.21	-0.55	-0.49*	0.48	-0.84	-0.00514
	Strategy 2	29	-0.80	0.47	-25.9	14.44	8.94	-0.61	0.99	-0.43*	0.45	-0.47	-0.00376
	Strategy 3	29	-1.85	1.97	-48.8	20.72	0.14	-1.81	4.44	-0.15	0.34	-0.47	-0.00886
	Strategy 4	23	2.79	0.72	-6.21	51.33	9.90	4.44	22.26	-0.11	0.30	0.98	0.98
	Strategy 5	29	-0.25	0.31	-70.1	51.28	17.51	-1.45	11.23	-0.51*	0.48	-0.08	-0.00249
Holding Period: 180 days													
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
	Strategy 5	29	0.44	0.01	-10.8	12.95	4.34	0.49	2.73	0.01	0.48	0.35	0.35
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
	Strategy 5	29	0.13	0.18	-11.3	17.36	5.48	0.81	2.88	0.30	0.45	0.08	0.08

Table 8. Correlation matrix for the monthly returns of the strategies.

The correlation matrix of the monthly returns generated by the five strategies and Strategy 1 implemented on theoretical spreads obtained by using a 1000-day historical equity volatility (denoted by Strategy 1_1000) for investment-grade obligors (above the main diagonal) and speculative-grade obligors (below the main diagonal). The strategies are implemented for a holding period of 180 days and a θ trading trigger of 2.

	Strategy 1	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 1_1000**
Strategy 1	1.00	0.98	0.39	-0.01	0.25	0.12
Strategy 2	0.98	1.00	0.40	0.00	0.27	0.16
Strategy 3	0.35	0.34	1.00	0.68	0.34	-0.06
Strategy 4	0.23	0.28	0.02	1.00	0.25	0.06
Strategy 5	0.09	0.08	0.32	0.06	1.00	0.14
Strategy 1_1000	0.16	0.14	-0.15	0.28	0.04	1.00

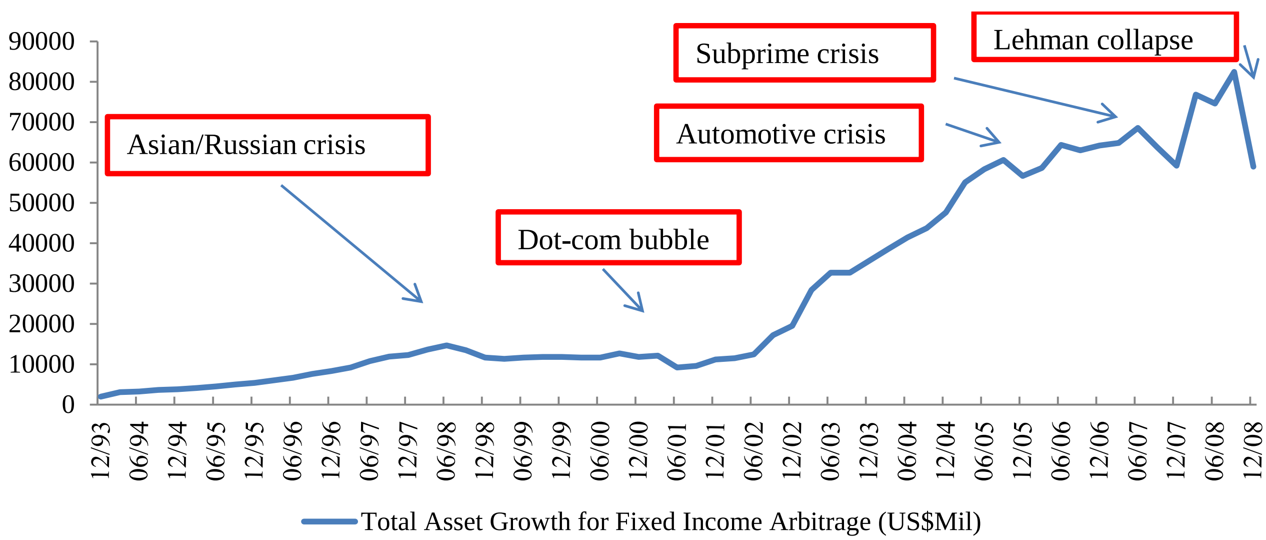

Figure 1. Asset growth for fixed income arbitrage during 1993 and 2008.

Asset growth in fixed income arbitrage is shown in US dollars starting from December 1993 until December 2008.

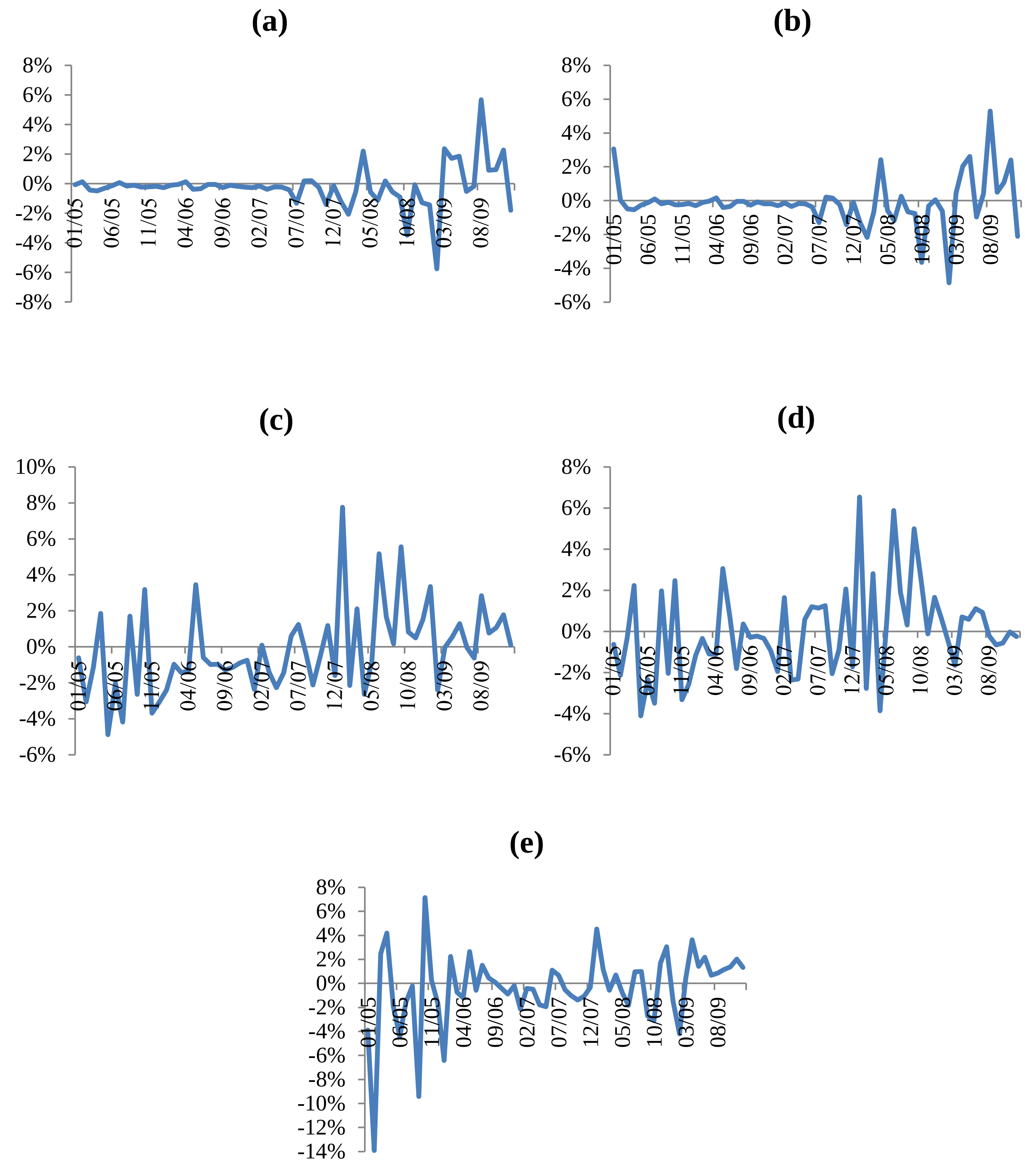

Figure 2. Monthly time series of excess returns for the 5 strategies.

Monthly time series of excess returns for Strategy 1 (a) and Strategy 2 (b) are shown in the top panel. The middle panel shows the evolution of excess returns for Strategy 3 (c) and Strategy 4 (d). The bottom panel plots the excess returns for Strategy 5 (e). The series of excess returns are shown for the strategies implemented on investment-grade obligors for a holding period of 180 days and a θ trigger of 2.