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IMPACT OF FINANCIAL CRISIS ON THE PROFITABILITY OF CAPITAL STRUCTURE ARBITRAGE IN AUSTRALIA

Jiri Svec
Nicholas Reeves
The University of Sydney

Abstract

We evaluate the performance of a convergence style capital structure arbitrage trading strategy using Australian CDS spreads estimated by the Credit Grades model. By comparing a number of volatility inputs, we find that although option-implied volatility inputs produce biased spreads compared to historical measures, their correlation with medium-term changes in market spreads generate significantly more profitable trades during the financial crisis, even after the inclusion of transaction costs. While the strategy is risky at both the individual obligor and the iTraxx Index level, combining positions into an equally-weighted index of arbitrage trades reduces risk.

Keywords:
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1. Introduction

Using Credit Default Swap (CDS) spread estimates derived from the CreditGrades model, we develop a convergence-style capital structure arbitrage trading strategy to exploit possible mispricing between each obligor's estimated spreads and market spreads. If the model and market CDS spreads diverge significantly, a position is taken in the CDS market and a corresponding position is taken in the equity market as a hedge. The trade will be profitable if the model and the market spreads subsequently converge. While loosely based on Yu (2006), we make a number of modifications in the implementation of the strategy. Firstly, we analyse a range of volatility inputs. Secondly, while still conducting all estimation out-of-sample, we set aside a longer in-sample period from which to estimate each firm's default boundary level. Thirdly, we include additional stop loss and profit taking trading rules to terminate trades. Finally, in contrast to previous work, we retain financial firms in the sample to test the arbitrage strategy at both the individual obligor's level and the CDS index level.

A CDS is a credit derivative under which the buyer of protection makes a series of payments to the seller of protection and, in return, receives payment if the reference entity over which the CDS is written experiences a credit event such as bankruptcy, failure to pay or restructuring. CDS contracts allow parties to isolate and trade credit risks, with buyers able to reduce counterparty exposure and sellers able to enhance returns (Skinner and Townend, 2002). While the risk profile of a CDS is similar to that of a corporate bond, it offers numerous advantages; both long and short positions can be taken relatively easily without payment of any initial capital and the bond of the reference entity does not need to be liquidly traded. By transferring risk off balance sheets, they can also allow financial institutions to reduce capital requirements (Batten and Hogan, 2002)).

While mainly used for risk management throughout the 1990s, the global CDS market grew significantly in the 2000s as the derivatives became increasingly used for speculation. Through 2007 alone, the notional value of outstanding CDS contracts increased by 36% to US$58 trillion (Baba and Gallardo, 2008). However, following a period of severe strains in the credit market and increased multilateral netting of offsetting positions by market participants, the outstanding values of contracts fell to US$42 trillion by the end of 2008 and to US$33 trillion by the end of 2009 (Mallo & Kleist, 2010).

Notwithstanding recent market contractions, the International Swaps and Derivatives Association (2010) estimates that credit default swaps alone still make up approximately 8% of the entire global derivatives market. In Australia, the notional turnover of single name credit default swaps has grown from $45 billion in 2004-2005 to $186 billion in 2008-2009 (Australian Financial Markets Association, 2010). Given its recent growth and the lack of capital structure literature on Australian data, we focus on the Australian CDS market.

We estimate the CDS spreads using the CreditGrades model, developed by Finger *et al.* (2002). Bedendo, Cathcart and El-Jahel (2009) claim the model has become an industry standard for pricing CDS contracts and is used by most capital structure arbitrage professionals (Yu, 2006). In the original specification, and probably a consequence of the benign economic conditions throughout their estimation sample from May 2000 to August 2001, Finger *et al.* (2002) restricted their volatility inputs to estimators that rely solely on historical equity prices. However, Stamicar and Finger (2005) and Blanco, Brennan and Marsh (2005) find that credit spread risk volatility can be decomposed not only to a component linked to equity prices but also to one driven by equity option volatility. Using a Markov switching model, Alexander and Kaeck (2008) show that although CDS spreads are usually more sensitive to stock returns, in times of market turbulence, they become extremely sensitive to stock volatility. While the use of historical volatility allows the CreditGrades model to be applied to firms which may not have options liquidly traded, Benkert (2004) and Cao, Yu and Zhong (2010) show that option-implied volatility is a timelier and more efficient forecast of future realised volatility. These findings combined with the recent significant equity and debt market volatility, provide a rationale to examine the performance of the CreditGrades model using timelier volatility inputs.

The remainder of this paper is structured as follows: Section 2 reviews previous literature on CDS spreads and capital structure arbitrage. Section 3 introduces the CreditGrades model, while section 4 describes the dataset. Section 5 presents the results while section 6 concludes the paper.

2. Capital structure Arbitrage

2.1 Credit Instruments

While few papers deal specifically with the CreditGrades model or capital structure arbitrage, vast amounts of literature examine credit instruments and the pricing of credit risk. From the early work of Jones, Mason and Rosenfeld (1984), researchers have struggled to model bond default premiums. Elton et al. (2001) show that expected default only accounts for a small fraction of the premium in corporate bond rates over treasury rates while Collin-Dufresne, Goldstein and Martin (2001) show that bond spread changes are impacted by local demand and supply shocks which are independent of credit risk.

Literature demonstrates that the CDS market provides a timelier measure of credit risk than the bond market. In particular, Zhu (2006) finds that deviation of CDS and bond spreads is largely due to the higher responsiveness of CDS spreads to credit conditions. According to Norden and Weber (2009), the CDS market contributes more to price discovery than the bond market. As well as suggesting that CDS is a cleaner indicator of credit risk than bond spread, Blanco, Brennan and Marsh (2005) show that in firms where CDS spreads and bond spreads form a valid equilibrium relationship, the CDS market contributes around 80% of price discovery. Furthermore, even in the few cases where they do not, CDS spreads are still more likely to Granger-cause bond spread changes than the reverse. Similarly, Longstaff, Mithal and Neis (2005) suggest that CDS spreads provide a relatively precise measure of the default component of corporate spreads while a significant non-default component relates to bond-specific and macroeconomic measures of bond market liquidity. Considering other financial instruments, Norden and Wagner (2008) demonstrate that changes in CDS spreads are the dominant determinants of loan spreads, explaining loan rates much better than bonds of the same rating and other traditional explanatory factors.

2.2 CDS Pricing Models

From the initial work of Altman (1968) which identified firm characteristics associated with corporate bankruptcy, a great deal of empirical work has focussed on methods of predicting default probabilities. One approach to credit assessment involves reduced form models, first introduced by Litterman and Iben (1991), which assume market participants hold the same level of information, and default time is thus unpredictable. Further development undertaken by a number of researchers, including Jarrow and Turnbull (1995), aimed to provide a methodology for pricing and hedging derivatives involving credit risk. While reduced form models can compare credit risk, they do not specify the economic medium behind the default process (Zhou, 2001) or explicitly explain structural elements of firms which contribute to default.

The CreditGrades model belongs to a different class of models known as structural models. These models are generally based on the Black and Scholes (1973) and Merton (1974) contingent claims framework, under which equity and debt represent an option on the firm's assets with default probabilities predominantly estimated from market and balance sheet parameters. Although originally specified so that default occurs at maturity, both Black and Cox (1976) and Longstaff and Schwartz (1995) extended the analysis such that a firm defaults when its value first crosses an exogenous default threshold. This principle also underlies the dynamics of the CreditGrades model.

By introducing uncertainty into the default barrier, the CreditGrades model matches the observed CDS spreads more closely than the Merton (1974) model which underestimates short-dated spreads given its assumption that changes in asset values follow a geometric Brownian- motion diffusion process. Modelling uncertain default barriers is consistent with Duffie and Lando's (2001) argument that around the time of default, accounting information updates revealed to the market create uncertainty in the value of the assets. The authors also use the notion that investors are unable to directly a observe firm's assets to provide a link between reduced form and structural-based models. While the use of an uncertain default barrier offers one solution, jumps can also explain sudden changes in market values (Zhou, 2001). Upward and downward jumps are often modelled asymmetrically, for example, Hilberink and Rogers (2002), use a L´evy process which only permits downward jumps in a firm's value.

An alternative structural model proposed by Leland (1994) and Leland and Toft (1996) considers an endogenous default threshold where the optimal capital structure for each firm and the value of long-term risky debt is explicitly linked to each firm's risk, taxes, bankruptcy costs, interest rates, payout rates and bond covenants. For example, Fan and Sundaresan (2000) assume that shareholders and creditors of distressed firms negotiate to avoid inefficient liquidation and may inject new equity before debt maturity.

By comparing a reduced-form model to two structural models, Arora, Bohn and Zhu (2005) show that a Hull-White reduced-form model largely underperforms sophisticated structural models in default prediction and estimation of CDS spread levels. Using the CreditGrades model with lagged stock returns, Byström (2006) shows that structural models are also effective at predicting CDS spread changes. This is consistent with Norden and Weber (2009) who consider monthly, weekly and daily co-movements between markets and conclude that stock returns tend to lead changes in both CDS spreads and bond spreads.

Ericsson, Jacobs and Oviedo (2009) find that by regressing structural-model inputs such as firm volatility, firm leverage and the risk-free rate on CDS spreads, they can explain approximately 60% of the levels and 23% of the daily changes in CDS spreads of investment grade obligors. Pu's (2008) results are broadly consistent with 22% of the variation of the changes in CDS spreads of investment grade and 35% of speculative grade obligors being explained by a set of market factors.

2.3 Capital Structure Arbitrage Trading Strategies

Our capital structure arbitrage strategy is a form of fixed-income arbitrage that exploits mispricing between firm's debt and equity. Duarte, Longstaff and Yu (2007) note that it is one of the five most widely used-fixed income arbitrage strategies used by market participants. However, the ability of traders to profit from relative mispricing has been previously restricted by the difficulties in taking short positions in a firm's debt and a lack of liquidity in parts of the bond market. While not focussing specifically on the CreditGrades model, Ericsson, Reneby and Wang (2007) show that the emergence of the CDS market overcomes many of these difficulties. They show that Leland's (1994), Leland and Toft's (1996) and Fan and Sundaresan's (2000) structural models fit market CDS spreads much more closely than bond spreads with any difficulties encountered in estimating default risk caused by illiquidity in the bond market.

Although Currie and Morris (2002) note that many market participants see capital structure arbitrage strategies as the most significant development since the invention of the CDS itself, Yu (2006) notes a complete lack of prior academic research providing evidence either for or against capital structure arbitrage strategies. Using the 5-year North American daily CDS spreads from 2001 to 2004, he implements a convergence-style strategy which uses the CreditGrades model to identify trades in the CDS market and hedges the positions in the equity market. His results indicate that while substantial losses can occur at individual trades level, an equally weighted portfolio of arbitrage trades produces returns similar to other fixed-income hedge fund benchmarks. Duarte, Longstaff and Yu (2007) extend the work of Yu (2006) and conduct a review of the risk and return of a number of widely used fixed-income strategies using a larger dataset. They conclude that the potential profitability of a convergence-style capital structure arbitrage strategy is the highest of all fixed-income strategies considered, yet it also involves the highest level of risk.

Extending the analysis of Yu (2006) and Duarte, Longstaff and Yu (2007), Cserna and Imbierowicz (2009) consider the profitability of a similar capital structure arbitrage strategy, but utilise the models of Leland and Toft (1996) and Zhou (2001) in addition to the CreditGrades model. Once transaction costs were taken into account, they found that the strategy produced significant positive returns over the sample period from 2002 to 2006 when CDS spreads were estimated using the CreditGrades or the Leland and Toft model, but not the Zhou model. They do, however, concede that their analysis was conducted over a period of low volatility and suggest it would be interesting to analyse the strategy in a more volatile market.

Byström (2006) also exploits inefficiencies in the CDS market using the CreditGrades model. However, his trading strategy is based on the autocorrelation in the CDS data and thus ignores fundamental changes in the obligor's assets. Furthermore, his study is predominantly based on short-term autocorrelation and not medium-term relative mispricing, with positions only held for a single day and not hedged in the equity market.

3. Model Description

To compute theoretical CDS spreads, the CreditGrades model requires equity price (S), debt per share (D), the mean global recovery rate ($\bar{L}$), the standard deviation of the global recovery rate (λ), a bond-specific recovery rate (R), equity volatility (σ_S) and a risk-free rate (r). The asset value (V_t) is assumed to follow geometric the Brownian motion such that:

$$dV_t = \sigma V_t dW_t + \mu_D V_t dt \tag{1}$$

where σ is the asset volatility and the asset drift μ_D is assumed to be zero. [1] To correct for underestimation of short-term default probabilities by structural models and to reflect uncertainty arising from incomplete accounting information, the CreditGrades model introduces uncertainty into the default boundary. A firm is assumed to default if its asset value falls under a default threshold (LD) given by:

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2} \tag{2}$$

The global recovery rate (L) follows a log-normal distribution with mean $\bar{L}$, Z is a standard normal random variable and λ^2 is the variance of $ln(L)$. To relate asset value and asset volatility to an obtainable equity value and equity volatility, CreditGrades uses a linear approximation:

$$V = S + \bar{L}D \tag{3}$$

$$\sigma = \sigma_s \frac{S}{S + \bar{L}D} \tag{4}$$

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[1] The asset value has a zero drift because it is not the drift itself, but the drift relative to the default boundary that is relevant to the calculation of default probabilities. By issuing debt and paying dividends, the model assumes that each firm will maintain a steady leverage ratio such that the drift of the assets relative to the default boundary will be zero.

Given that default is defined as the first passage of V_t below *LD*, a closed-form solution is then obtained for the survival probability, *P(t)*, up until time *t*:

$$P(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln(d)}{A_t}\right) - d\Phi\left(-\frac{A_t}{2} - \frac{\ln(d)}{A_t}\right) \tag{5}$$

where $\Phi(\cdot)$ represents the cumulative normal function and:

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L}D} \tag{6}$$

$$A_t^2 = \sigma^2 t + \lambda_2 \tag{7}$$

P(t), can then be used to obtain a theoretical CDS spread ($c*$) such that the initial CDS price equals zero:

$$c* = r(1-R)\frac{1-P(0)+H(t)}{P(0)-P(t)e^{-rt}-H(t)} \tag{8}$$

where:

$$H(t) = e^{r\varepsilon}\left(G(t+\varepsilon) - G(\varepsilon)\right) \tag{9}$$

$$G(t) = d^{z+1/2}\Phi\left(-\frac{\ln(d)}{\sigma\sqrt{t}} - z\sigma\sqrt{t}\right) + \tag{10}$$

$$\varepsilon = \frac{\lambda^2}{\sigma^2} \tag{11}$$

$$z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma^2}} \tag{12}$$

3.1 Model Implementation and Calibration

3.1.1 Calibration and model inputs

The CreditGrades model requires the estimation of three parameters. As recommended by Finger et al. (2002), we set λ to 0.3 and *R* to 0.5 with the optimal $\bar{L}$ value of each firm determined by minimising the mean squared error (MSE) between the estimated and the actual spreads in the in-sample period. Consequently, the expected default boundary (LD) for each firm depends on both the level of the firm's debt and an implied estimate of L. Given the importance of an accurate estimation of each firm's L, we extend Yu's (2006) 10-day calibration period to two-months.

We focus on the 5-year CDS as they offer the highest level of liquidity (Ericsson, Jacobs and Oviedo, 2009). Consistent with previous research conducted in other markets, such as Finger et al. (2002), we use the 5-year Australian interest rate swap as a risk-free proxy as it matches the maturity of the contracts. Moreover, derivative traders regard the swap zero curve as the risk-free rate (Hull, Predescu and White, 2004).

While Finger et al. (2002) suggest using all of the short-term and long-term debts and half of all other liabilities except accounts payable as a proxy of the firm's debts, recent studies on capital structure arbitrage including Yu (2006), Duarte, Longstaff and Yu (2007) and Cserna and Imbierowicz (2009) use total liabilities. We also choose total liabilities as it represents a more parsimonious input and is consistent with Vassalou and Yuhang's (2004) argument that total liabilities affect the ability of firms to refinance short-term debts. Moreover, the calibration steps detailed above ensure that firm defaults when its asset value drops below a market-implied proportion of total liabilities, not its entire value.

3.1.2 Equity volatility measures

Extending the 1000-day volatility (*1000_VOL*) input used by most researchers, we examine the effect of the 250-day volatility (*250_VOL*), exponentially-weighted moving average (EWMA) volatility (*EW_VOL*) and option-implied equity volatility (*IMP_VOL*) measures on the accuracy of the CreditGrades model and its subsequent profitability when used in the context of a capital structure arbitrage strategy.

The *EW_VOL* measure follows the approach of Ericsson, Jacobs and Oviedo (2009)[2]. For a more generalised result we fix the weighting parameter in the EWMA equation across all firms in the estimation. The MSE is minimised such that only a 0.07% weighting is placed on the most recent observation. Similarly, weights on the most recent 250 observations and the most recent 1000 observations sum to only approximately 16% and 50%, respectively, resulting in an extremely long-term historical volatility measure.

Stamicar and Finger (2005) argue that using the forward-looking *IMP_VOL* instead of historical volatility may provide a timelier credit signal during market turmoil. Similarly, Cao, Yu and Zhong (2010) choose the 30-day at-the-money put option volatility over historical volatility to value CDS contracts. However, as our objective is to estimate the 5-year volatility, we use a longer-dated measure. Constrained by the relative illiquidity of the Australian options

2 While not used in the context of the CreditGrades model, the authors use an average EWMA volatility measure as a determinant of CDS spreads.

market, our *IMP_VOL* measure is a combination of the 30-day, 90-day and 200-day at-the money option implied volatility measures, with the greatest weight placed on those with around 90 days to expiry.[3]

4. Data

The data set consisted of the daily CDS spreads, equity prices, equity volatility, swap rates and financial statements information covering a period from 1 November 2005 to 31 December 2009. The first two months between 1 November 2005 and 30 December 2005 were used to estimate the model parameter $\bar{L}$ for each firm over each volatility input. Long-term historical equity volatility was estimated over 5 years between 1 July 2000 and 31 December 2005. The remaining four years from 3 January 2006 and 30 December 2009 were used to evaluate the model and test the capital structure arbitrage.

The firms used in the analysis comprised the iTraxx Australia Series 13 CDS Index. The constituents and their GIGS (Global Industry Classification Standard) Sectors and Industry Groups are listed in Table 1.[4] The Index is compiled and published by the Markit Group and comprises 25 investment grade entities listed on the Australian Securities Exchange (ASX). The CDS quotes are collected from a number of contributors and filtered by Markit to validate that spreads are reflective of possible trades on each day. Inclusion in the Index is determined predominantly based on the liquidity of each obligor's CDS contracts, with the Markit Group aggregating volume-ranked lists from market makers to compute liquidity rankings for each entity. The index, based on 5-year credit default swaps, is itself tradable and is rolled every six months. Option-implied volatilities and 5-year interest rate swap rates were sourced from IRESS, equity closing prices and the number of shares on issue from Bloomberg and liabilities from Aspect Huntley.

Table 1: Sample Firms

Reference Entity	GIGS Sector	GIGS Industry Group
Amcor Limited	Materials	Materials
AMP Limited	Financials	Insurance
Australia and New Zealand Banking Group	Financials	Banks

(continued)

[3] The weighted average is calculated daily by IRESS. In the very few cases where this information was not available a shorter-dated, 30-day at-the-money option-implied volatility was used.

[4] The iTraxx Australia Series 13 Index was released in March 2010. The list of constituents is available from the Markit website (http://www.markit.com). We omitted Crown Limited from the analysis as it was only listed in mid- 2007 and therefore long-term historical volatility estimates were not available.

Reference Entity	GIGS Sector	GIGS Industry Group
BHP Billiton Limited	Materials	Materials
Coca-Cola Amatil Limited	Consumer Staples	Food, Beverage & Tobacco
Commonwealth Bank of Australia	Financials	Banks
CSR Limited	Industrials	Capital Goods
Foster's Group Limited	Consumer Staples	Food, Beverage & Tobacco
GPT Group	Financials	Real Estate
Lend Lease Group	Financials	Real Estate
Macquarie Group Limited	Financials	Diversified Financials
National Australia Group Limited	Financials	Banks
QANTAS Airways Limited	Industrials	Transportation
QBE Insurance Group Limited	Financials	Insurance
Rio Tinto Limited	Materials	Materials
Singapore Telecommunications Limited	Telecommunication Services	Telecommunication Services
Tabcorp Holdings Limited	Consumer Discretionary	Consumer Services
Telecom Corporation of New Zealand Limited	Telecommunication Services	Telecommunication Services
Telstra Corporation Limited	Telecommunication Services	Telecommunication Services
Wesfarmers Limited	Consumer Staples	Food & Staples Retailing
Westfield Group	Financials	Real Estate
Westpac Banking Corporation	Financials	Banks
Woodside Petroleum Limited	Energy	Energy
Woolworths Limited	Consumer Staples	Food & Staples Retailing

We addressed potential illiquidity of contracts with the Lesmond, Ogden and Trzcinka's (1999) simple Zeroes measure, which identifies the proportion of days with zero returns. We based our selection on the evidence of Goyenko, Holden and Trzcinka (2009) that securities with lower liquidity are characterised by a greater number of zero-return days. The results showed that liquidity increased throughout the sample with most zero-return days occurring in the first half of the sample with relatively low and stable spreads. In the more volatile second-half of the sample, following the deterioration of credit conditions in March 2008, the number of zero-return days did not exceed 2%. We also collected the number of contributors to Markit's composite spreads to verify the quotes were indicative of the overall market. The mean number of contributors in our sample was ten, with more than 90% of the quotes compiled by at least seven contributors.

While many studies such as Yu (2006), Bajlum and Larsen (2008) and Bedendo, Cathcart and El-Jahel (2009) exclude financial firms from structural models due to difficulties in interpreting their capital structure, we elected to include financial firms, in accordance with Cserna and Imbierowicz (2009).

To ensure a consistent barrier across the three models in their analysis, Cserna and Imbierowicz (2009) base the default boundary of financial firms on the capital adequacy requirements, that is, 8% of total liabilities. As their approximation only explicitly considers the capital structure of banks, and may not hold for other non-bank financials in the sample (Real Estate, Diversified Financials and Insurance Industry Groups), we did not specify a fixed default boundary. Instead, we utilised the CreditGrades model to calibrate the default boundary of each firm based on actual market spreads. As a robustness check, we also considered a sample of 14 firms which excluded those comprising the GIGS Financial Sector.

5. Trading Strategy Results

5.1 Model Performance

An effective trading strategy ensures that model spreads do not lag actual CDS spreads and are generally close fitting and correlated with the market spreads so that significant deviations can be attributed to potentially profitable trading opportunities and not simply a badly specified and calibrated model. The differences between actual and model spreads determine market-entry decisions while the sensitivity of model spreads to changes in the equity price determine the equity hedge ratios. We split the hold-out sample into two periods – a low volatility 'pre-crisis' period with stable spreads from January 2006 to December 2007 and a high volatility 'crisis' period from January 2008 to December 2009 with elevated spreads caused by the Global Financial Crisis. The performance is presented in Table 2. We used three accuracy measures, mean error (ME), root mean squared error (RMSE) and mean absolute deviation (MAD) consistent with Bowerman, O'Connell and Koehler (2005).[5]

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5 Mean Absolute Percentage Error (MAPE) was not utilised, given that it imposed a significantly heavier penalty on positive errors than negative errors and had an extremely skewed distribution if the actual series was close to zero (Hyndman and Koehler (2006)), which was the case with the CDS spread data.

Table 2: Model Performance

Cross-sectional averages of accuracy measures across sample firms. ME signifies the average mean-error, RMSE the average root-mean-square-error and MAD the average mean-absolute-deviation. 1000_VOL, 250_VOL, EW_VOL and IMP_VOL represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively.

	ME	RMSE	MAD
Panel A: Entire Sample			
1000_VOL	-7.3	93.5	62.8
250_VOL	-90.5	167.3	109.3
EW_VOL	17.0	83.3	57.0
IMP_VOL	-80.6	128.7	101.3
Panel B: Jan 2006 – Dec 2007			
1000_VOL	-1.9	26.1	19.1
250_VOL	-11.8	29.9	22.8
EW_VOL	-3.9	28.0	21.1
IMP_VOL	-16.0	36.7	27.1
Panel C: Jan 2008 – Dec 2009			
1000_VOL	-12.7	127.5	106.5
250_VOL	-169.3	232.8	195.9
EW_VOL	37.9	111.5	92.9
IMP_VOL	-145.2	220.6	175.6

In the pre-crisis period, estimated spreads using the conventional *1000_VOL* deviated from actual spreads by an average of approximately 19 basis points (bps). This was a closer fit than many previous international studies, with Cserna and Imbierowicz (2009), for example, finding that CreditGrades model spreads deviated from actual spreads by an average of 32 bps across a range of countries between January 2002 and December 2006. The MAD for the *1000_VOL* rose to 107 bps during the crisis period, a substantial increase over the previous period. Comparing the range of volatility inputs across the sample, spreads estimated using the two long-term historical volatility inputs (*1000_VOL* and *EW_VOL*) were most accurate, with MAD of 63 bps and 57 bps, respectively. In contrast, spreads estimated using *IMP_VOL* and *250_VOL* had a MAD of 101 and 109 bps, respectively. The conclusions using RMSE, which more heavily penalises large deviations, were broadly similar. The *250_VOL* and *IMP_VOL* performed substantially worse as they overestimated the actual spreads by approximately 91 and 81 bps, respectively. In contrast *1000_VOL* and *EW_VOL* measures were largely unbiased with ME of -7 bps and 17 bps, respectively. Average cross-sectional accuracy measures calculated without financials in the sample yielded similar conclusions.

5.2 Correlation analysis

The Spearman rank correlations between daily changes in actual CDS spreads, equity prices, volatility inputs and estimated CDS spreads for each firm are presented in Table 3. As expected, CDS spread changes have a significant negative correlation with equity price changes, with an average correlation of -0.21. Consequently, we anticipated that equity should provide a reasonable hedge against changes in CDS spreads driven by market sentiment. Although increases in equity volatility signal increased risk and should be associated with a greater probability of default, we observed that only changes in *IMP_VOL* had a significant positive relationship with changes in CDS spreads, with an average correlation of 0.13. Changes in historical volatility inputs were only correlated with changes in CDS spreads by 0.03 to 0.05, on average, depending on the calculation method. Finally, we found a significant positive correlation between changes in the CreditGrades model CDS spreads and the changes in actual CDS spreads, confirming the model had explanatory power. The average correlation ranged between 0.19 and 0.22, but interestingly, the *IMP_VOL* correlation coefficient was smaller than the historical volatility coefficients.

Table 3: Daily correlations

Cross-sectional average Spearman rank correlations between daily changes in estimated CDS spreads, daily changes in equity volatilities and daily changes in actual CDS spreads. We used the non-parametric Spearman rank correlation coefficient instead of the Pearson product-moment correlation coefficient due to heteroscedasticity and the presence of non-linear relationships between changes in many of the variables of interest. *CDS* represents actual CDS spreads, *1000_VOL*, *250_VOL*, *EW_VOL* and *IMP_VOL* represent 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. Cross-sectional average t-statistics are reported in brackets with 1% and 5% significance levels indicated by ** and *, respectively. Given strong a-priori expectations regarding the interaction between the variables, the reported statistics are based on one-tail tests.

Correlation (t-statistic)	ΔEquity price	ΔEquity Volatilities				ΔEstimated CDS spreads using			
		1000_VOL	250_VOL	EW_VOL	IMP_VOL	1000_VOL	250_VOL	EW_VOL	IMP_VOL
ΔCDS	-0.21	0.04	0.03	0.05	0.13	0.22	0.21	0.22	0.19
	(-7.10)**	(1.39)	(1.07)	(1.57)	(4.32)**	(7.25)**	(7.04)**	(7.23)**	(6.38)**

Given the substantial noise present in the daily equity, CDS and option data, we also considered differences using weekly, monthly and two-monthly data. As expected, the correlations between the estimated and the actual spreads increased as the sampling frequency decreased. While this is observed across all volatility inputs, it was most evident for *IMP_VOL*. Over the two-month periods, changes in actual spreads had a correlation of 0.56 with spreads estimated using *IMP_VOL*, compared to correlations of between 0.41 and 0.47 for spreads estimated using historical volatility. Excluding financial firms from the sample did not influence the results.

5.3 Granger causality analysis

The Granger causality tests examine whether actual spreads lead or lag estimated spreads. [6] Our lag structure was guided by Norden and Weber (2009) who suggest that two lags for weekly data and five lags for daily data are appropriate in capturing the overall information processing and aggregation time across the CDS, bond and stock markets. However, given that correlations between the actual and the CDS spreads increased substantially as sampling frequency decreased, we also considered monthly data with two lags.

The results presented in Table 4 provide little evidence of a lead-lag relationship. Although at the monthly level, estimates using *IMP_VOL* were more likely to lead actual spreads than estimates using historical volatility, the reverse was true at the daily and weekly level. As with previous sections, analysis was also conducted without financial firms, with results largely unchanged.

Table 4: Granger causality tests

Proportion of firms for which changes in estimates spreads Granger-cause changes in actual spreads, changes in actual spreads Granger-cause changes in estimated spreads, changes in actual and estimated spreads Granger-cause each other and no Granger-causality in either direction at the 5% level of significance. *1000_VOL*, *250_VOL*, *EW_VOL* and *IMP_VOL* represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. Figures may not add up to 100% due to rounding errors.

[6] To avoid spurious Granger-causality conclusions, we tested for stationarity of differenced actual CDS spreads, stock price returns, volatility inputs and the estimated differenced CreditGrades model CDS spreads using the Augmented Dickey-Fuller (ADF) and the Kwiakowski-Phillips-Schmidt-Shin (KPSS) tests. We tested each firm using differences over daily, weekly and monthly intervals. All series were stationary across all frequencies using both the KPSS and the ADF tests, except the ADF test at the monthly frequency which founds 88% of the series to be stationary.

	1000_VOL	250_VOL	EW_VOL	IMP_VOL
		Daily changes (5 lags)		
Estimate causes actual	17%	42%	13%	13%
Actual causes estimate	21%	8%	21%	38%
Bidirectional	42%	25%	38%	38%
No granger causality	21%	25%	29%	13%
		Weekly Changes (2 lags)		
Estimate causes actual	17%	21%	21%	13%
Actual causes estimate	13%	13%	17%	13%
Bidirectional	13%	13%	13%	13%
No granger causality	58%	54%	50%	63%
		Monthly Changes (2 lags)		
Estimate causes actual	8%	8%	8%	25%
Actual causes estimate	25%	17%	21%	17%
Bidirectional	4%	0%	8%	17%
No granger causality	63%	75%	63%	42%

5.4 Trading Strategy Implementation

Without a clear lead-lag relationship between the equity and the CDS markets, we implemented a relatively simple convergence-style trading strategy to profit from any mispricing between the two securities. The strategy involved taking a simultaneous position in both the equity and the CDS markets to profit from medium-term relative mispricing between the markets. Although similar to the strategy implemented by Yu (2006), we made a number of modifications.

5.4.1 Entering Positions

A position is taken in the CDS market if the model and the market spreads differ by more than a threshold percentage difference. Denoting α as the trading trigger, c_t as the observed market spread and c_t* as the estimated CreditGrades model spread, a long position was taken in the CDS market if the model estimated spreads lie significantly above the observed market spreads, i.e. $c_t^* > (1+\alpha)c_t$. Simultaneously, based on the negative correlation between the equity and the CDS markets, a long position was taken in the equity market as a hedge. The trade would become profitable if the market and the model spreads converged due to an increase in the market spreads or a decrease in the model spreads. Conversely, a short position was taken in the CDS market, and hedged with a short position in the equity market, if the observed spreads lie significantly above the model estimated spreads, i.e. $c_t > (1+\alpha)c_t^*$. This trade would be profitable if the market and the model spreads converged due to a fall in the market spreads or an increase in the model spreads. For robustness and to prevent data mining we considered α values of 0.5, 1 and 2 in the strategy.

To compute trading returns, we specified an initial capital level of $0.50 per trade per $1 nominal position taken either long or short in the CDS market. This capital was assumed to cover margin and financing costs for the CDS position and equity hedge and was consistent with previous capital structure arbitrage literature. To ensure its adequacy, we monitored the number of trades where the initial capital on a trade was completely depleted by losses.

5.4.2 Equity Hedging

Consistent with previous literature, and to reduce transaction costs associated with the size of a dynamic equity hedging on a daily basis, the size of the equity hedge was determined when a position was taken in the CDS market and maintained until the position was exited. While some studies such as Cserna and Imbierowicz (2009) use a rolling regression between CDS spreads and equity prices to estimate hedge ratios, such an approach disregards the current market conditions or recent structural changes which may impact the sensitivity of the equity price to changes in the firm's CDS spread. It also requires an arbitrary horizon to be specified over which the regression is estimated. Following the earlier work of Yu (2006) and the findings of Schaefer and Strebulaev (2008) that structural models can produce hedge ratios which are relatively accurate and cannot be rejected in empirical tests, we used the CreditGrades model to calculate the appropriate hedge ratio for each firm when a position was entered.

$$\delta_t = \frac{\partial \pi_t}{\partial S_t} \tag{13}$$

Where π_t represents the model CDS spread and S_t represents the equity value for the firm in question, the hedge ratio, δ_t , is determined by numerically solving the following differential equation for each sample firm at each point in time:

Since falling equity prices are associated with increases in model CDS spreads, δ_t is negative and represents the dollar value of shares to be purchased per dollar notional value in the CDS. Given that the average correlation between the daily changes in CDS spreads and the daily changes in equity prices from Table 3 is only -0.21, the effectiveness of the hedge would be reduced over short horizons. Nevertheless, such a hedging strategy should, in theory, allow for arbitrage profits, even in the face of significant changes in market sentiment. In particular, if a long position is taken in the CDS market and both the actual and the model spreads fall, the long equity position should provide some degree of protection.

Similarly, if a short position is taken in the CDS market and the both actual and the model spreads rise, the short equity position should provide protection. This ensures that given the volatility of the CDS market over the sample period, any profits are a result of identifying relative mispricing and implementing a capital structure arbitrage trading strategy, not simply a result of timing the entry into the CDS market. However, it should be noted that while changes in the two markets may offset one another, the use of an equity hedge increases leverage. The computation of the hedge ratio is also reliant on other variables in the CreditGrades model, so, as well as differing across each firm and each point in time, it also differs depending on the volatility input used to estimate the CDS spreads.

5.4.3 Exiting Positions

Both Yu (2006) and Duarte, Longstaff and Yu (2007) formulated a trading strategy that assumes trades will be terminated when the market and the model spreads converge, or in the case that this does not occur, after a set time period. Yu (2006) further concludes that the use of a maximum holding period of 180 days produces more converging trades and is more profitable than those of shorter time periods. However, given the leverage inherent in a capital structure arbitrage strategy, the use of these arbitrary rules alone could generate losses which are significantly greater than the initial capital invested in each trade.

To reduce risk and more accurately represent traders' behaviour, Cserna and Imbierowicz (2009) instead stipulate that positions are closed if the market and the model spreads converge, if losses on an individual trade amount to 50% of the initial capital or returns on an individual trade represents five times the initial capital. However, provided the model and the market spreads do not converge and significant profits or losses are not generated, these rules do not preclude trades from remaining open indefinitely. Recognising the problems associated with ignoring either the length or profitability of trades when determining the exit criteria, we combined the timing limit of Yu (2006), and Duarte, Longstaff and Yu (2007), the stop-loss and profit-taking rules of Cserna and Imbierowicz (2009) and the convergence rule common to all three papers. Consequently, individual trades are closed out if any of the following conditions hold; market and model spreads converge, losses amount to 50% of the initial capital, returns reach five times the initial capital, positions are open for 180 days, or positions are open at the end of the sample period. For completeness, we report the trading strategy without the use of the stop-loss and profit-taking rules in Section 5.8.1.

5.4.4 Transaction costs

Consistent with Yu (2006), Duarte, Longstaff and Yu (2007) and Cserna and Imbierowicz (2009), we assumed a 5% spread when trading credit default swaps, meaning that trades occur 2.5% away from Markit's composite midpoint

CDS spread on both the entry and the exit. For example, a CDS with a spread of 100 bps assumes a buyer purchases the CDS at 102.5 bps while a seller receives 97.5 bps. While Cserna and Imbierowicz (2009) note that such an assumption is conservative, it allows our results to be compared with prior research.

Unlike Cserna and Imbierowicz's (2009), dynamic hedging strategy that requires equity transaction costs to be considered, the cost of establishing static hedges are relatively small in comparison. Consistent with other capital structure arbitrage literature utilising a static hedging strategy such as Yu (2006) and Duarte, Longstaff and Yu (2007), we ignored these costs.

5.5 Results of individual CDS Arbitrage

We identified trading opportunities for all firms using three trading triggers (α) across four volatility inputs. Although increasing the size of α translates to fewer open trades, the number of trades for each α remains relatively constant through time. The summary statistics of holding period returns for α=0.5, 1 and 2 across the four volatility inputs are presented in Table 5. The total number of trades executed differs significantly across the simulations, ranging from 105 trades (*250_VOL* with α=2) to 541 trades (*IMP_VOL* with α=0.5). The trading strategy is profitable across all simulations before transaction costs are considered, on average, with returns for each trade ranging from a mean of 0% (*1000_VOL* with α=2) to a mean of 44% (*IMP_VOL* with α=2). However, with transaction costs, a third of the simulations produce a loss. Furthermore, using only $0.50 of the initial capital to cover each $1 nominal position in the CDS market results in transaction costs of approximately 10% of the initial capital per trade where the spread at entry and exit is relatively similar but can exceed 10% if spreads increase significantly while positions are held.

Nevertheless, trades based on the *IMP_VOL* input (average holding period return ranging from 17% to 27% depending on α) and to a lesser extent *250_VOL* input (average holding period returns ranging from 9% to 13% depending on α) are still profitable. Although smaller α results in a larger number of trades; the effect on profitability is unclear with enhanced profitability under some volatility inputs and reduced profitability under others. The *IMP_VOL* input generated a greater number of trades for each α, consistent with conclusions from section 5.1 that market CDS spreads lie further away from the estimated spreads using *IMP_VOL* input than those estimated spreads using the historical volatility inputs.

It is evident that regardless of the volatility input or α, the capital structure arbitrage strategy can be very risky at the individual trade level. In each of the simulations detailed in Table 5, there is at least one trade in which losses exceed the amount of initial capital allocated as collateral for that trade. Such losses can result from the continuing divergence between CDS and equity markets following the identification of a trading opportunity and an inadequate hedge to offset changes in CDS spreads. However, the number of trades in each simulation in which the initial capital was completely depleted was relatively low (1 to 16 before ,and 4 to 23 after transaction costs were incorporated) compared to the total number of trades made (148 to 541).

Table 5: Summary of returns on individual trades

1000_VOL, 250_VOL, EW_VOL and IMP_VOL represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. α represents the trading trigger, N1 represents the total number of trades and N2 represents the number of trades in which the initial capital was completely depleted. Mean, Min and Max represent the average, minimum and maximum holding period returns, respectively.

			Returns before transaction costs				Returns after transaction costs			
Volatility	α	N1	N2	Mean	Min	Max	N2	Mean	Min	Max
1000_VOL	0.5	365	10	13%	-225%	694%	17	2%	-241%	668%
	1	255	6	15%	-188%	694%	12	3%	-206%	668%
	2	148	2	0%	-188%	518%	10	-12%	-206%	500%
250_VOL	0.5	332	5	27%	-222%	567%	14	13%	-238%	526%
	1	222	4	29%	-222%	577%	9	12%	-238%	555%
	2	105	5	31%	-222%	607%	11	9%	-238%	554%
EW_VOL	0.5	359	16	8%	-224%	525%	23	-3%	-240%	503%
	1	243	10	2%	-187%	542%	15	-9%	-202%	520%
	2	156	4	2%	-167%	711%	9	-9%	-186%	688%
IMP_VOL	0.5	541	9	31%	-193%	700%	20	17%	-206%	677%
	1	362	5	36%	-232%	740%	13	21%	-245%	716%
	2	203	1	44%	-167%	573%	4	27%	-182%	532%

5.6 Results of Index Arbitrage

Given the riskiness of individual trades, we followed the lead of Yu (2006) in creating a capital structure arbitrage index consisting of an equally weighted portfolio of all the individual trades across all obligors open each day. The portfolio returns, compounded and analysed at the monthly frequency are presented in Table 6. While it would be difficult to invest in such an index, it allows us to analyse the risk and return in a portfolio context and determine how closely returns are linked to common market risk factors. Given the substantial number of trades across the entire sample, trades occurred in all 48 months. While still risky, returns are substantially less volatile compared to the previous section, with the capital allocated to the index not depleted in any individual month in any of the simulations.

Table 6: Summary of monthly index returns

1000_VOL, *250_VOL*, *EW_VOL* and *IMP_VOL* represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. α represents the trading trigger, *N1* represents the total number of months with non-zero returns, *N2* represents the number of months in which the initial capital was completely depleted and *N3* represents the number of months which generated positive returns. *Mean*, *Min* and *Max* represent the average, minimum and maximum monthly returns, respectively. *Stdev* represents the standard deviation of monthly returns. The *Sharpe Ratio* is the annualised Sharpe Ratio for the index returns.

Model spreads	α	N1	N2	N3	Monthly returns			Stdev	Sharpe Ratio
					Mean	Min	Max		
1000_VOL	0.5	48	0	24	3%	-39%	113%	27%	0.39
	1.0	48	0	22	1%	-37%	120%	28%	0.17
	2.0	48	0	20	-3%	-74%	103%	33%	-0.35
250_VOL	0.5	48	0	30	9%	-43%	111%	29%	1.05
	1.0	48	0	29	8%	-61%	93%	31%	0.87
	2.0	48	0	30	11%	-81%	234%	48%	0.83
EW_VOL	0.5	48	0	24	2%	-38%	107%	27%	0.21
	1.0	48	0	19	0%	-41%	111%	29%	-0.06
	2.0	48	0	22	-2%	-46%	129%	34%	-0.16
IMP_VOL	0.5	48	0	36	17%	-38%	190%	37%	1.63
	1.0	48	0	30	14%	-41%	146%	33%	1.43
	2.0	48	0	28	12%	-54%	94%	31%	1.31

Consistent with the analysis of individual trades, simulations based on *IMP_VOL* (average monthly returns of 12% to 17% depending on α) and to a lesser extent those based on *250_VOL* (average monthly returns of 8% to 11% depending on α) were significantly more profitable than those based on long-term historical volatility. Interestingly, those based on the *1000_VOL* input, as recommended by Finger et al. (2002) and used by Yu (2006), Duarte, Longstaff and Yu (2007) and Cserna and Imbierowicz (2009) in testing capital structure arbitrage trading strategies in more stable market conditions, performed relatively poorly. Taking into account the variability of returns and considering the annualised Sharpe Ratios for each strategy led to similar conclusions, with Sharpe Ratios of between 1.31 and 1.63 using the *IMP_VOL* input and between 0.83 and 1.05 using the *250_VOL* input. Again, the effect of the particular α used was uncertain, with the use of smaller α leading to enhanced profitability under some volatility inputs and reduced profitability under others.

The distribution of the daily index returns follow a similar distribution, with 11 of the 12 series exhibiting positive skewness. This mitigates some of the common criticism of fixed income arbitrage strategies described in Duarte, Longstaff and Yu (2007) that arbitrage returns frequently have negative skewness such that small positive returns are often completely eroded by a few dramatic losses. All simulations exhibited positive kurtosis, suggesting dramatic profits and losses might occur.

Finally, to determine whether index returns are driven by common market risk factors, the series of monthly returns for each volatility input and α was regressed on a set of common market factors. Changes in the iTraxx Australia and S&P/ASX 200 Indices were used to proxy for credit and equity market risk, respectively. Given the use of *IMP_VOL* in the estimation of spreads in this study, changes in the implied volatility of the S&P/ASX 200 Index were also used to proxy for market-wide volatility risk.[7]

As shown in Table 7, changes in the three market factors account for between 0% and 46% of the variation in returns on the capital structure arbitrage index, depending on α. It should be noted that neither the coefficient for the S&P/ASX 200 Index nor its implied volatility was significant in any of the scenarios. While the coefficient for the iTraxx Australia Index was significant in half the returns series, its sign fluctuated, with positive capital structure index returns associated with increases in the level of the iTraxx Index in some scenarios and decreases in others. We thus conclude that a significant proportion of the arbitrage profits cannot be explained by changes in market risk factors. Adjusting for such factors and considering the intercepts for each of the regressions also left the relative profitability of the trading strategy between different trading triggers and volatility inputs largely unchanged from previous results.

Table 7: Regression of monthly index returns on market variables

Coefficients and Adjusted R^2 statistics for regressions of monthly index returns on changes in market variables. *1000_VOL*, *250_VOL*, *EW_VOL* and *IMP_VOL* represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. α represents the trading trigger. *iTraxx* represents the iTraxx Australia CDS Index, *ASX200* represents the S&P/ASX 200 Index and *ASX200 IV* represents the implied volatility of the S&P/ASX 200 Index. t-statistics are reported in brackets. Without any strong a-priori expectations regarding the interaction of each variable and arbitrage profits, the 1% and 5% significance levels indicated by ** and *, respectively, assume a two-tailed test.

Model spreads	α	Adj R^2	Intercept	iTraxx	ASX200	ASX200 IV
1000_VOL	0.5	0.0199	0.0300	-0.0019	0.0001	-0.0025
			(26.65)**	(-1.27)	(0.42)	(-0.21)
	1.0	0.1780	0.0200	-0.0025	0.0001	-0.0108
			(26.74)**	(-1.76)	(0.04)	(-0.92)
	2.0	0.2732	0.9753	-0.0046	0.0001	-0.0131
			(24.21)**	(-3.02)**	(0.26)	(-1.05)

(continued)

[7] Similarly to individual stock IMP_VOL, the S&P/ASX 200 Index vol was supplied by IRESS.

Model spreads	α	Adj R^2	Intercept	iTraxx	ASX200	ASX200 IV
250_VOL	0.5	0.0376	0.0800	0.0026	0.0001	0.0086
			(26.39)**	(1.69)	(0.53)	(0.68)
	1.0	0.0280	0.0700	0.0029	0.0002	0.0084
			(24.06)**	(1.71)	(0.79)	(0.43)
	2.0	0.0019	0.1100	0.0038	0.0001	0.0042
			(15.98)**	(1.46)	(0.19)	(0.20)
EW_VOL	0.5	0.2668	0.0200	-0.0035	0.0000	-0.0138
			(31.14)**	(-2.85)**	(0.08)	(-1.36)
	1.0	0.3330	0.0000	-0.0043	0.0000	-0.0152
			(28.89)**	(-3.28)**	(0.25)	(-1.41)
	2.0	0.4582	0.0000	-0.0070	-0.0002	-0.0178
			(27.21)**	(-5.09)**	(-1.04)	(-1.57)
IMP_VOL	0.5	0.1494	0.1700	0.0032	0.0000	0.0250
			(23.61)**	(1.74)	(0.17)	(1.64)
	1.0	0.2134	0.1300	0.0042	0.0001	0.0211
			(26.35)**	(2.61)*	(0.62)	(0.12)
	2.0	0.3339	0.1100	0.0050	0.0001	0.0166
			(30.12)**	(3.59)**	(0.30)	(1.46)

5.7 Performance of iTraxx Index Arbitrage

Given that we can identify relative mispricing between equity and CDS markets on an individual obligor basis, we extended this analysis to the index level. According to Byström (2006) the iTraxx CDS Indices are highly tradable and more liquid than contracts for individual obligors. Although they represent 44% of the turnover in the credit derivatives market (Australian Financial Markets Association (2010)), to the best of our knowledge no previous study has modelled CDS Indices using estimates of the constituents. We focused on the equally-weighted iTraxx Australia Index with 25 constituents.[8]

We found that the estimated index fits the actual index levels relatively well across all volatility inputs. For example, MAD between estimated and actual iTraxx levels was only 30 bps with the conventional *1000_VOL* input, which compared favourably to the 63 bps average cross-sectional MAD between the estimated and actual spreads of individual obligors documented in Table 2. Interestingly, due to the accurate fit, using α from the previous sections and in much of the earlier literature only identified extremely few (if any) trades. As such, and given the lack of any guidance from previous studies, we chose α of 0.1, 0.2 and 0.3 for the index analysis. As previously, to minimise data snooping, we did not optimise these values.

[8] We estimated the iTraxx Australia Index from 24 equally-weighted firms. Recently listed Crown Limited was omitted from the sample as long-term historical volatility was not available. However, its spreads were relatively close to that of the index.

Considering the proportion of the S&P/ASX 200 index capitalisation that the sample firms constituted, and the ease of taking futures positions in this index, we selected this index as an equity hedge to the iTraxx Index. The appropriate hedge ratio for the iTraxx Index at each point in time was calculated as an average of the model-estimated hedge ratios for each individual sample firm. Although the index bid-ask spread was lower than the spread for individual contracts, we maintained a 5% bid-ask spread to ensure consistency with previous sections.

Table 8 presents a summary of the holding period returns across each α and volatility input. Even after transaction costs, the strategy led to positive average returns across the majority of scenarios. Consistent with section 5.5, strategies using the timelier *IMP_VOL* and *250_VOL* inputs were significantly more profitable than those based on the *EW_VOL* and *1000_VOL* inputs. Interestingly, while the *IMP_VOL* input was most profitable before transaction costs, CDS spreads increased significantly while many of the positions were open, increasing transaction costs relative to initial capital and resulting in the *250_VOL* input generally being the most profitable after transaction costs.

Table 8. Summary of returns on iTraxx Australia Index trades

1000_VOL, *250_VOL*, *EW_VOL* and *IMP_VOL* represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. α represents the trading trigger, *N1* represents the total number of trades implemented and *N2* represents the number of trades in which the initial capital was completely depleted. *Mean*, *Min* and *Max* represent the average, minimum and maximum holding period returns, respectively.

			Returns before transaction costs				Returns after transaction costs			
Volatility	α	N1	N2	Mean	Min	Max	N2	Mean	Min	Max
1000_VOL	0.1	21	0	5%	-76%	138%	0	-5%	-89%	126%
	0.2	13	0	19%	-63%	136%	0	8%	-76%	123%
	0.3	12	0	22%	-77%	136%	0	11%	-90%	123%
250_VOL	0.1	15	0	42%	-80%	565%	0	31%	-93%	549%
	0.2	13	0	42%	-52%	442%	0	31%	-62%	428%
	0.3	9	0	49%	-57%	280%	0	38%	-66%	267%
EW_VOL	0.1	19	0	22%	-65%	138%	0	12%	-78%	126%
	0.2	12	0	20%	-65%	136%	0	10%	-78%	123%
	0.3	10	0	15%	-79%	136%	0	4%	-92%	123%
IMP_VOL	0.1	12	0	51%	-49%	272%	0	35%	-69%	257%
	0.2	12	0	44%	-52%	260%	0	27%	-75%	244%
	0.3	11	0	51%	-49%	294%	0	32%	-83%	278%

However, it is important to note that the index analysis was based on a smaller number of trades (9 to 21 depending on α and volatility input) compared to the analysis conducted on the individual obligor level (between 105 and 541 trades). While trading individual contracts may create a market neutral position with simultaneous long/short CDS trades (with an associated long/short equity position), in an index trade only one CDS position (and associated equity hedge) can be open at each point in time. Consequently, trading the iTraxx Index may be seen as being much closer to speculative trading than capital structure arbitrage. Nevertheless, the results were largely consistent with the findings of previous sections.

5.8 Sensitivity Analysis

5.81 Effectiveness of stop-loss and profit-taking trade out rules

We carried out a number of robustness checks to verify the sensitivity of our results to modifications in the trading strategy. To test the effectiveness of our additional stop-loss and profit-taking trade out rules, the trading profits were recalculated using only the convergence and timing trade-out rules of Yu (2006) and Duarte, Longstaff and Yu (2007). Table 9 contains a summary of the individual trade and index profitability, respectively.

Table 9: Trading Strategy Performance Without Stop-Loss and Profit Taking Trade-Out Rules

1000_VOL, *250_VOL*, *EW_VOL* and *IMP_VOL* represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. α represents the trading trigger, *N1* represents the total number of trades implemented and *N2* represents the number of trades in which the initial capital was completely depleted. *Mean*, *Min* and *Max* represent the average, minimum and maximum holding period returns, respectively.

Summary of returns on individual trades (without stop-loss and profit-taking trade-out rules)

			Returns before transaction costs				Returns after transaction costs			
Volatility	α	N1	N2	Mean	Min	Max	N2	Mean	Min	Max
1000_VOL	0.5	172	30	13%	-1327%	2397%	32	-1%	-1370%	2328%
	1.0	116	19	11%	-3213%	2397%	26	-5%	-3309%	2328%
	2.0	60	13	21%	-913%	2445%	14	5%	-947%	2347%

(continued)

			Returns before transaction costs				Returns after transaction costs			
Volatility	α	N1	N2	Mean	Min	Max	N2	Mean	Min	Max
250_VOL	0.5	177	25	45%	-1069%	2409%	28	27%	-1111%	2339%
	1.0	111	19	59%	-1069%	2409%	27	35%	-1111%	2339%
	2.0	58	6	118%	-312%	2455%	11	87%	-328%	2357%
EW_VOL	0.5	174	32	-18%	-3272%	1097%	34	-32%	-3370%	1087%
	1.0	104	24	-47%	-3272%	1097%	27	-61%	-3370%	1087%
	2.0	65	17	-45%	-3272%	1097%	19	-60%	-3370%	1087%
IMP_VOL	0.5	402	21	43%	-893%	2354%	28	29%	-928%	2284%
	1.0	259	14	53%	-902%	2354%	22	36%	-938%	2284%
	2.0	148	12	67%	-1022%	2354%	16	48%	-1061%	2284%

Summary of monthly index returns (without stop-loss and profit-taking trade-out rules)

N3 represents the number of months which generated positive returns. *Stdev* represents the standard deviation of monthly returns. The *Sharpe Ratio* is the annualised Sharpe Ratio for the index returns.

Model spreads	α	N1	N2	N3	Monthly returns			Stdev	Sharpe Ratio
					Mean	Min	Max		
1000_VOL	0.5	48	0	23	1%	-39%	113%	25%	0.19
	1.0	48	0	21	1%	-42%	121%	29%	0.14
	2.0	48	0	21	-3%	-75%	100%	31%	-0.32
250_VOL	0.5	48	0	28	8%	-47%	93%	28%	0.94
	1.0	48	0	25	7%	-69%	85%	32%	0.73
	2.0	48	0	29	11%	-78%	231%	49%	0.79
EW_VOL	0.5	48	0	21	2%	-34%	110%	27%	0.23
	1.0	48	0	20	-1%	-43%	112%	28%	-0.14
	2.0	48	0	23	-2%	-48%	139%	34%	-0.18
IMP_VOL	0.5	48	0	36	17%	-41%	166%	36%	1.63
	1.0	48	0	29	14%	-45%	129%	34%	1.43
	2.0	48	0	26	10%	-54%	109%	34%	1.08

Table 10: Trading Strategy Performance Excluding Financials

1000_VOL, *250_VOL*, *EW_VOL* and *IMP_VOL* represent CreditGrades model spreads based on 1000-day historical, 250-day historical, exponentially-weighted historical and option-implied volatilities, respectively. α represents the trading trigger, *N1* represents the total number of trades implemented and *N2* represents the number of trades in which the initial capital was completely depleted. *Mean*, *Min* and *Max* represent the average, minimum and maximum holding period returns, respectively.

Summary of returns on individual trades (excluding financials)

			Returns before transaction costs				Returns after transaction costs			
Volatility	α	N1	N2	Mean	Min	Max	N2	Mean	Min	Max
1000_VOL	0.5	206	4	19%	-204%	694%	5	8%	-217%	668%
	1.0	144	3	18%	-188%	694%	3	7%	-206%	668%
	2.0	89	2	4%	-188%	518%	2	-7%	-206%	500%
250_VOL	0.5	194	1	22%	-103%	567%	4	10%	-148%	526%
	1.0	129	1	27%	-104%	577%	3	13%	-119%	555%
	2.0	63	2	22%	-118%	511%	5	4%	-143%	486%
EW_VOL	0.5	197	6	17%	-181%	516%	9	6%	-194%	494%
	1.0	136	4	14%	-167%	516%	5	3%	-186%	494%
	2.0	82	2	12%	-167%	521%	4	0%	-186%	483%
IMP_VOL	0.5	319	4	24%	-193%	584%	7	13%	-206%	542%
	1.0	221	3	27%	-232%	584%	6	14%	-245%	543%
	2.0	139	1	27%	-167%	573%	1	13%	-182%	532%

Summary of monthly index returns (excluding financials)

N3 represents the number of months which generated positive returns. *Stdev* represents the standard deviation of monthly returns. The *Sharpe Ratio* is the annualised Sharpe Ratio for the index returns.

Model spreads	α	N1	N2	N3	Monthly returns			Stdev	Sharpe Ratio
					Mean	Min	Max		
1000_VOL	0.5	48	0	20	6%	-49%	163%	35%	0.55
	1.0	48	0	19	2%	-45%	117%	32%	0.22
	2.0	48	0	17	-3%	-118%	137%	42%	-0.28
250_VOL	0.5	48	0	27	11%	-52%	243%	50%	0.79
	1.0	48	0	27	6%	-48%	103%	32%	0.67
	2.0	48	0	24	4%	-92%	215%	47%	0.29
EW_VOL	0.5	48	0	23	7%	-44%	150%	37%	0.64
	1.0	48	0	23	5%	-41%	153%	34%	0.50
	2.0	48	0	19	0%	-96%	147%	44%	-0.03
IMP_VOL	0.5	48	0	29	17%	-51%	287%	52%	1.11
	1.0	48	0	25	12%	-51%	225%	47%	0.90
	2.0	48	0	26	10%	-59%	162%	39%	0.86

As might be expected, when stop-loss and profit-taking trade out rules were excluded, the number of trades open at each point in time increased while the total number of trades decreased, reflecting positions being held open for significantly longer periods of time. While previous results indicated that the number of trades ranged from 105 to 541, when the stop-loss and profit-taking rules were excluded, it ranged from 58 (*250_VOL* with α=2) to 402 (*IMP_VOL* with α=0.5). Without stop-loss and profit-taking rules, the strategy was extremely risky at the individual trade level, with one particular trade based on the *EW_VOL* losing over 30 times the capital allocated to cover margin requirements for that trade. While this particular result was due to an unfortunate entry and exit timing, an increase in leverage of the trade and divergence in the CDS and equity market, this was by no means uncommon. The number of trades in each simulation in which the initial capital allocated to that trade was completely depleted represented a significant proportion (6 to 32 before and 11 to 34 after transaction costs) of the total number of trades made (58 to 402).

Interestingly, monthly returns on the capital structure arbitrage index were not influenced by the absence of stop-loss and profit-taking trade-out rules. Nevertheless, given the practical difficulties in daily trading and rebalancing to invest in such an index, we concluded that while the simple convergence and timing exit rules used by Yu (2006) and Duarte, Longstaff and Yu (2007) may be effective during times of market stability, they were not adequate in times of significant market volatility.

5.8.2 Inclusion of financials

To validate the inclusion of financial firms in the trading strategy, Table 10 contains a summary of individual trade and index profitability, respectively, when financials are excluded. The number of trades under each scenario ranged from 63 (*250_VOL* with α=2) to 319 (*IMP_VOL* with α=2), which was significantly lower than the previously discussed results.

The relative performance of strategies based on different volatility inputs after transaction costs was similar to previous results, with simulations based on the *IMP_VOL* (average returns on each trade of 13% to 14% depending on α) and, to a lesser extent, *250_VOL* (average returns of 4% to 13%) inputs performing much better than those based on long-term historical volatility inputs. Interestingly, while strategies based on the long-term historical volatility inputs were more profitable when financials were not included in the sample, those using the *IMP_VOL* and *250_VOL* inputs were more profitable when financials were included in the sample. Similar conclusions were reached when the returns on the capital structure arbitrage index were considered in addition to the returns on individual trades. We, thus conclude that the inclusion of financials in the trading strategy does not adversely affect its overall profitability.

6. Conclusion

We examined the ability of the CreditGrades model to predict CDS spreads of Australian obligors using factors such as equity prices, equity volatilities and leverage. Using the model, we implemented a convergence style capital structure arbitrage trading strategy to investigate the profitability of relative value opportunities across the two markets during the financial crisis.

We found that commonly used long-term, *1000_VOL* produced spreads which fit market spreads more closely than those produced using *IMP_VOL*. However, within the context of the trading strategy, the use of *IMP_VOL* resulted in a greater number of trades and higher average holding-period returns. Unlike previous studies conducted in the pre-crisis period, we found the average returns after transaction costs based on the *1000_VOL* disappointing, ranging from -12% to 2%, depending on α. In contrast, returns using the *IMP_VOL* input ranged from 17% to 27%, depending on α. Similar results held at the index level, with *IMP_VOL* producing significant annualised Shape ratios of between 1.31 and 1.63, again depending on α. We thus conclude that while model spreads based on *IMP_VOL* may not fit market spreads as closely as those based on historical volatility, they may be more relevant for practitioners engaging in capital structure arbitrage.

While previous literature incorporates trade-out rules which consider model convergence and either timing exits or profit and loss exits, we found these simple trade-out rules produced a significant number of trades where losses exceed the initial capital. Although these rules may be effective in stable markets, they are less reliable during periods of high market volatility. We propose a more complex set of trading rules which reduce large losses and may be of more interest to practitioners. By modelling the more liquid and highly traded iTraxx Index from the estimated spreads of the constituents, we offer a new direction in capital structure arbitrage which when hedged with an equity index is potentially profitable.

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