Credit Market Final Report

Capital Structure Arbitrage Strategies with Price Discovery Augment

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Introduction

Capital structure arbitrage refers to trading strategies that take advantage of the relationship of mispricing between different security classes issued from the same company's capital structure. Mainly, the arbitrage opportunities appear between equity-linked and debt-linked securities. Structural models treat equity and debt as claims on the value of the firms, thus, the temporary mispricing often arises from equity and debt markets having different participants and market structures that create the discrepancy of price discovery process and speeds. A typical example would be an after-effect of a firm's earnings reports. If a firm surprises the market with disappointing earnings, a company's stock possibly drops 10 percent immediately, yet that same information may not be reflected in the company's bond price until a few days later, and possibly only result in a 2 percent drop in the bond price. However, this scenario can be exploited and make a profit systematically from mispricings and divergent intermarket dynamics.

These capital structure strategies (CSA) are usually implemented by offsetting the positions of an issuer's debt, CDSs, swaps, and equity option securities. The core of making an arbitrage is to go long the undervalued securities linked to one part of the company's capital structure, at the same time hedging the position by going short overvalued securities linked to another part of the capital structure to create a floor or ceiling. It is essentially like a convertible arbitrage strategy where we go long the convertible bond and short the company's stock.

In homework 3, we visited a more sophisticated capital structure arbitrage using the empirical capital structure of Boeing and the 5 year at-market CDS spread. The trading strategies use implied volatilities from the equity options markets against default probabilities implied by the credit spreads, effectively arbitraging the default probability predicted by the CDS market and the equity options market. CDS rate is equivalent to a prox of default probability. Thus, the interrelationship between volatility skew, CDS rate, and credit spreads creates capital structure arbitrage opportunities. More specifically, the implementation of the strategies is based on information coming from two time series of spreads, the 5-year at-market spread and an equity-implied spread which is obtained from CreditGrades, a Merton extension structural credit model. When implementing the CSA strategy, we look at a significant divergence between the CDS spread and its implied spread. Hence, a trader would short (long) a CDS contract if the CDS spread is significantly higher (lower) than the implied spread and short (long) a given number of shares as an 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. The assumptions let structural credit risk models generate good estimates not only on implied spreads but also hedge ratios.

Yet, our homework study showed that the gains of the strategy are not very consistent and profitable across real-world Boeing datasets. We performed data-mining on different parameters (both time-dependent or trigger thresholds) to try to maximize the profits. As the below figure and table shows, the results are not very ideal, and the cumulative returns/sharpe are negative across all data mining.

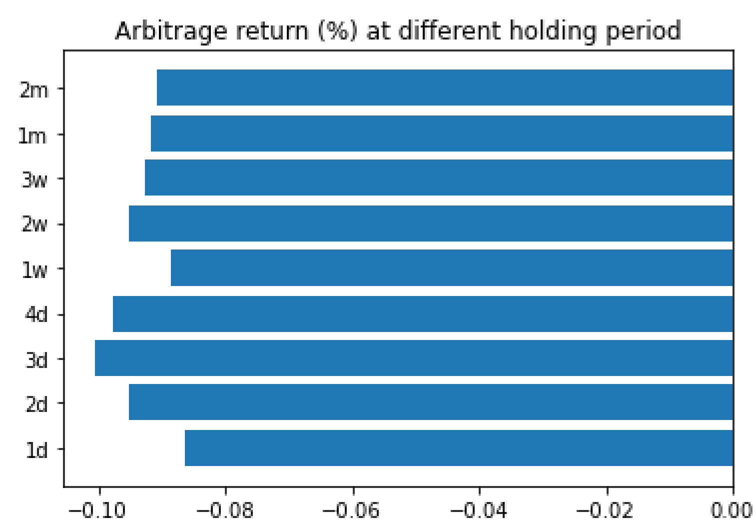


Table. Mean Arbitrage Return (%) of holding periods and thresholds

z-score	1w	2w	3w	1m	3m	6m
3	-0.20	-0.38	-0.38	-0.90	-1.57	-1.07
1	-0.15	-0.47	-0.80	-0.04	-0.10	-0.14
0.5	-0.16	-0.37	-0.57	-0.04	-0.07	-0.09

There are several reasons that account for the loss of expectation of the CSA strategy. The study by Yu (2006) showed that hedging strategies used to offset CDS positions with equities can be ineffective and expensive. 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 another determinant factor would be the lack of liquidity of the equity market.

Given that hedging may be ineffective for the CSA strategy, and several studies have shown that a lead-lag relationship between equity and CDS markets would affect the forecasting power of the Credit models. We found some paper proposed trading CSA with Price Discovery on the market that is being led would generate positive Sharpe ratios and can be more easily to forecast.

We implemented this trading strategy at homework 3, using the empirical capital structure of Boeing and the 5 year at-market CDS spread. USing the CreditGrade implied CDS spread to observe the discrepancy of mispricing opportunity of CDS spread.

The price discovery in the equity market is being widely analyzed and there is a vast literature that can be found, including professor Longstaff (2003) as well. These studies focused on the information flow between CDS and equity markets and most the paper we reviewed shows evidence of time variation in the price discovery of credit-related information. Therefore, we took the similar approach presented in these papers, using both the Vector Error Correction Model (VECM) for changes in spreads, and time-varying price discovery measures to combine with the CSA strategies for trading CDS and equity markets.

In this report, we analyze two different trading strategies and compare them with standard CSA strategy, using the same Boeing dataset to evaluate the performance over the same period of time. The two strategies are based on the flaws of the CSA we observed, namely (1) not sensitive to the information efficiency, meaning that if lead-lag relationship is presented, the leading market information, says market A, makes perfect sense to trade on market B based on information released in market A; (2) the ineffective hedging position might lead to extensive consumption of the profits. We analyzed the risk and returns of these strategies and investigated the different holding periods and trigger moments to maximize the performance of the strategy.

Price Discovery

Information has a fundamental role in the formation of prices in secondary markets. Understanding how prices efficiently incorporate information about fundamentals has been, and remains, one of the main interests of the market microstructure literature. Moreover, increased market fragmentation means that the same asset may be trading simultaneously in multiple markets. Therefore, to measure the relative degree of efficiency of these markets it is important to estimate the speed at which related prices incorporate news. This process is called price discovery, and there are currently two main measures that are widely used in the literature. They both base their analysis on structural models of cointegrated price series that share a common random-walk efficient price. The first metric aims at quantifying how much of the variance of the efficient price can be attributed to the different markets. Hasbrouck (1995) refers to this proportion as the Information Share (IS). The second measure is the Component Share (CS), applied by Booth et al. (2002), Chu et al. (1999) and Harris et al. (2002) on the basis of the econometric work of Gonzalo and Granger (1995). It focuses on the decomposition of the price series into a permanent component, that reflects the contribution of the efficient price, and a transitory component, that represents the deviation from the efficient price due to market microstructure frictions.

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:

$$\Delta cds_t = \alpha_1 CE_{t-1} + \sum_1^p \beta_{1,j} \Delta cds_{t-j} + \sum_1^p \delta_{1,j} \Delta eis_{t-j} + \varepsilon_{1t}$$
$$\Delta eis_t = \alpha_2 CE_{t-1} + \sum_1^p \beta_{2,j} \Delta cds_{t-j} + \sum_1^p \delta_{2,j} \Delta eis_{t-j} + \varepsilon_{2t}$$

where e1 and e2 are i.i.d. error terms. The cointegrating equation is defined as:

$$CE_t = \alpha(cds_t - eis_t)$$

We focus on the IS measure because, unlike the GG measure, it takes account of the volatility of the error terms of the VECM. We calculate IS1, IS2, CS1 and CS2 from the error correction parameters and variance–covariance of the error terms, following Baillie et al. (2002). The component shares are obtained from the normalized orthogonal to the vector of error correction coefficients, $\alpha\perp = (\gamma 1, \gamma 2)'$, thus:

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, \quad CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}.$$

Given the covariance matrix of the reduced form VECM error terms,

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix}$$

and its Cholesky factorization, Ω = MM′, where

$$M = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2\left(1-\rho^2\right)^{1/2} \end{pmatrix}$$

the IS are calculated then using:

$$IS_1 = \frac{\left(\gamma_1 m_{11} + \gamma_2 m_{12}\right)^2}{\left(\gamma_1 m_{11} + \gamma_2 m_{12}\right)^2 + \left(\gamma_2 m_{22}\right)^2}, \quad IS_2 = \frac{\left(\gamma_2 m_{22}\right)^2}{\left(\gamma_1 m_{11} + \gamma_2 m_{12}\right)^2 + \left(\gamma_2 m_{22}\right)^2}.$$

We introduce the terminology “information leadership” to refer to this metric because it comes from an (unnamed) expression derived by Yan and Zivot (2010) to measure which price series leads the process of adjusting to innovations in the fundamental value. As described earlier, in Yan and Zivot's structural cointegration model CS measures the level of noise in one price series relative to the other, and IS measures a combination of relative level of noise and relative leadership in reflecting innovations in the fundamental value.

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 (2) with the conditional volatilities obtained with (3). 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 we estimate (1) and (3) by using a rolling window of 1 year of data (250 observations)11, starting from January 2004. We use the covariance matrix of the error terms (obtained with (3)) at the end of the year to compute the IS measure (the midpoint of the bounds)12, 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 (1)13 and (3) to get a new IS estimate for the following day. We follow this procedure till the end of our sample period, 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.

Trading Strategies

Strategy 1- Standard CSA

The standard CSA is like we mentioned above, it’s based on two different time series of data, here would be the market CDS spread and the model spread implied by the equity-based information of a given securities. Capital Structure arbitrage here is implemented on individual securities, also apply on common cases. When these two series of spreads deviate from each other by a threshold value, a trading signal arises. In particular, if the CDS spread is higher than the equity-implied spread by a defined trading trigger θ, we short a CDS position with a notional amount of USD 1 dollar and $-\delta_{t-1}$ shares of the common stock. Instead, if the equity-implied spread is higher than the CDS spread, we long a CDS position with a notional of USD 1 dollar and at the same time, buy $-\delta_{t-1}$ shares. We also kept the position for a fixed holding period typically unless a convergence occurs between the two time series spreads, then we closed our position and exited the trade.

Strategy 2 - Information Share Augment CSA

With the price discovery signals, x_{lower} and x_{upper} represent, respectively, the lower and upper thresholds of IS price discovery for the CDS market selected by the trade, we could augment the standard CSA. We are filtering CSA trades and executing them only if there is clear evidence of one market leading the other one. However, we still hedge the positions. 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 or higher than , a CDS position with a notional amount of USD 1 dollar 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 or higher than , we long CDS position with a notional amount of USD 1 dollar and $-\delta_{t-1}$ shares of the common stock. Thus, the signals 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.

Strategy 3 - Information Share Augment CSA without hedging

We also observed that hedging CDS positions with equity shares can be ineffective due to the low correlation observed between changes in CDS spreads and stock prices according to the paper by Yu (2006) during the class. A trade could be more efficient if it trades just one market. To be more specific, we 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_{upper}, so the equity markets are 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_{lower}.

On the other hand, we would sell a CDS contract with a notional of USD 1 if the CDS spread is higher than the CG model implied spread by a defined trading trigger θ and the price discovery of the CDS market is lower than a benchmark, meaning that the CDS market is being led.

Finally, we only long the shares if the CG model implied spread is higher than the CDS spread by the defined trading trigger θ and the CDS market is leading the equity market. Hence, we trade only on one market, the least efficient one (with a low value of price discovery). By not trading the efficient market, we expect to improve capital allocation due to the efficient market being difficult to forecast.

The following table provides a more formulated equation for understanding the trading trigger signal and which asset class are being traded.

Table. Trading rules of strategies

Type	Trading Rule (Trigger Condition)	Asset Class	
		CDS	Equity
Strategy 1	$C^o - C^m \geq \theta_t$	short	short
	$C^o - C^m \leq -\theta_t$	long	long

Strategy 2	$[C^o - C^m \geq \theta_t]$and $[(IS_{cds,t-1} \leq X_{lower})\ or\ (IS_{cds,t-1} \geq X_{upper})]$	short	short
	$[C^o - C^m \leq -\theta_t]$and $[(IS_{cds,t-1} \leq X_{lower})\ or\ (IS_{cds,t-1} \geq X_{upper})]$	long	long
Strategy 3	$[C^o - C^m \geq \theta_t]$and $[IS_{cds,t-1} \leq X_{lower}]$	short	-
	$[C^o - C^m \geq \theta_t]$and $[IS_{cds,t-1} \geq X_{wloer}]$	-	short
	$[C^o - C^m \leq -\theta_t]$and $[IS_{cds,t-1} \leq X_{lower}]$	long	-
	$[C^o - C^m \leq -\theta_t]$and $[IS_{cds,t-1} \geq X_{lower}]$	-	long

Data Description

Due to the fact that we couldn't get the access to any raw datasets from CDS markets, we reused the Boeing.csv from the homework3.

Preliminary Result

The below table shows the average return from our trading strategy 2. The use of an additional trigger on price discovery triggers substantially reduces the frequency of trading by the PD thresholds. Our expectation is that the reduced trade could generate a higher average returns percentage by reducing the risk of large hedging costs against volatile markets and having better forecasting power released from the leading market.

Thus, 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 initially chose a value of 80% for the price discovery trigger in the CDS market (corresponding to a 20% trigger for the equity market). And due to the adjustment for the crisis period, we also raised the restriction on the trigger threshold to 5% and 95 % respectively to compare.

The preliminary result of Strategy 2 although didn't produce very significant improvement, yet still has better performance compared to the original CSA strategy. And if we also take into account the transaction cost in reality, we would have a greater impact on reducing the amount of redundant cost to maximize the profit.

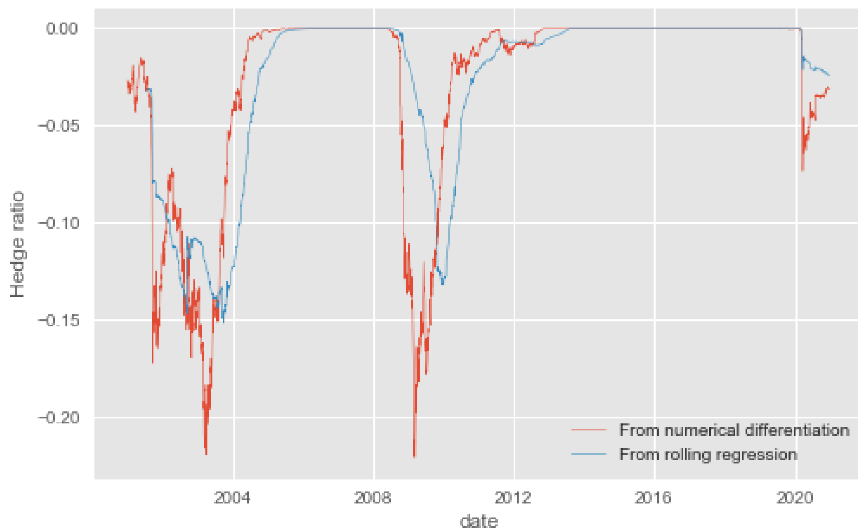
Table. Mean Arbitrage Return (%) of Strategy 2 - PD threshold 0.2

z-score	$x_{lower} = 0.2$; $x_{upper} = 0.8$					
	1w	2w	3w	1m	3m	6m
3	-0.17	-0.26	-0.58	-1.03	-1.93	-1.37
1	-0.21	-0.62	-0.96	-0.06	-0.12	-0.16
0.5	-0.20	-0.37	-0.53	-0.04	-0.10	-0.10

Table. Mean Arbitrage Return (%) of Strategy 2 - PD threshold 0.05

z-score	$x_{lower} = 0.05$; $x_{upper} = 0.95$					
	1w	2w	3w	1m	3m	6m
3	-0.60	-1.43	-1.12	-1.10	-1.86	-1.62
1	0.10	-0.52	-0.58	-0.05	-0.10	0.01
0.5	0.04	-0.58	-0.74	-0.04	-0.08	-0.05

The Strategy 1 and 2 both require hedging positions. For these equity hedges become very expensive, especially during the crisis period, such as 2008 or covids. The figures from homework shows the hedging ratio spike in those periods. Equity hedging costs increase when markets become more volatile and the 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, we would need more capital (which becomes a scarce resource) to implement these strategies when volatility in the market is high.

The below table shows the trading strategy 3. The resulting performance is what we're looking for, positive average returns.

Table. Mean Arbitrage Return (%) of Strategy 3 -- PD threshold 0.2

z-score	$x_{lower} = 0.2$; $x_{upper} = 0.8$					
	1w	2w	3w	1m	3m	6m
3	-0.04	-0.04	-0.18	0.01	-0.86	-1.18

1	-0.02	0.11	0.02	-0.02	-0.02	-0.02
0.5	-0.01	0.03	-0.06	-0.01	-0.01	-0.01

Table. Mean Arbitrage Return (%) of Strategy 3 -- PD threshold 0.05

z-score	$x_{lower} = 0.2$; $x_{upper} = 0.8$					
	1w	2w	3w	1m	3m	6m
3	0.10	0.04	0.09	0.03	-0.93	-1.27
1	0.00	0.09	0.02	-0.01	-0.03	0.01
0.5	0.01	0.09	0.03	-0.01	0.00	0.02

Due to the fact that we also don't need to provide hedging, it gives us the dynamics to proxy the market with lower volatility. The below figure also shows the historical arbitrage return across financial crisis and covid periods, we can see that the volatility of strategy compared to CSA strategy decreases significantly especially in these periods. The returns of the strategy were also observed with positive profits more consistently over the time.

Figure. Arbitrage Return of different strategy over periods 2018 - 2021

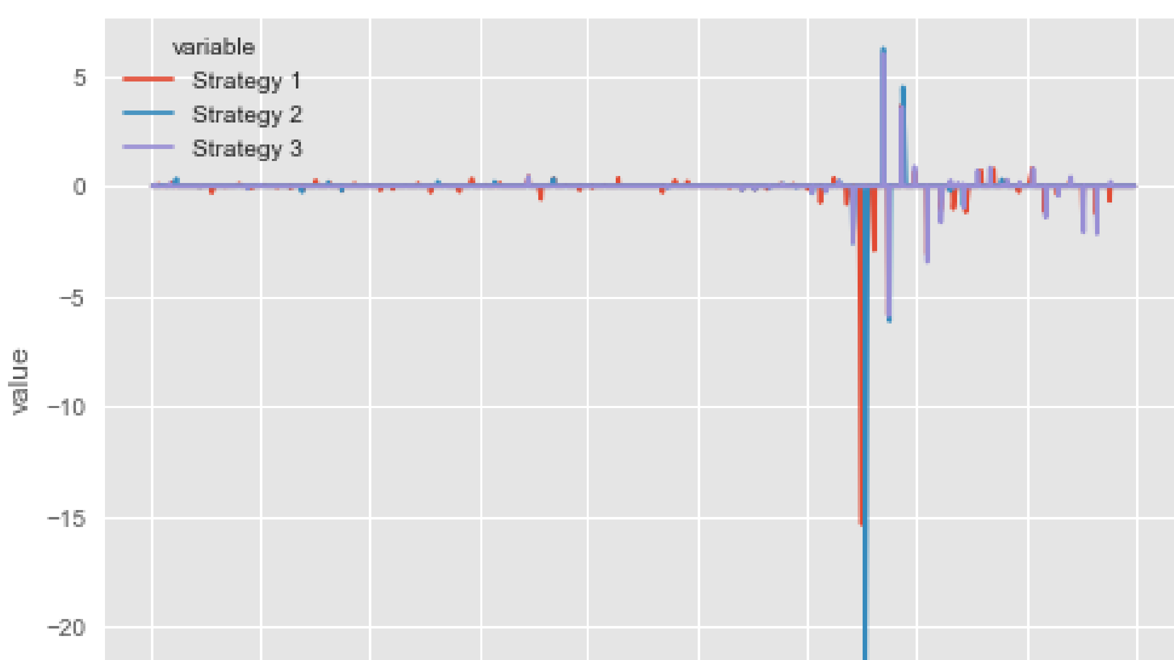
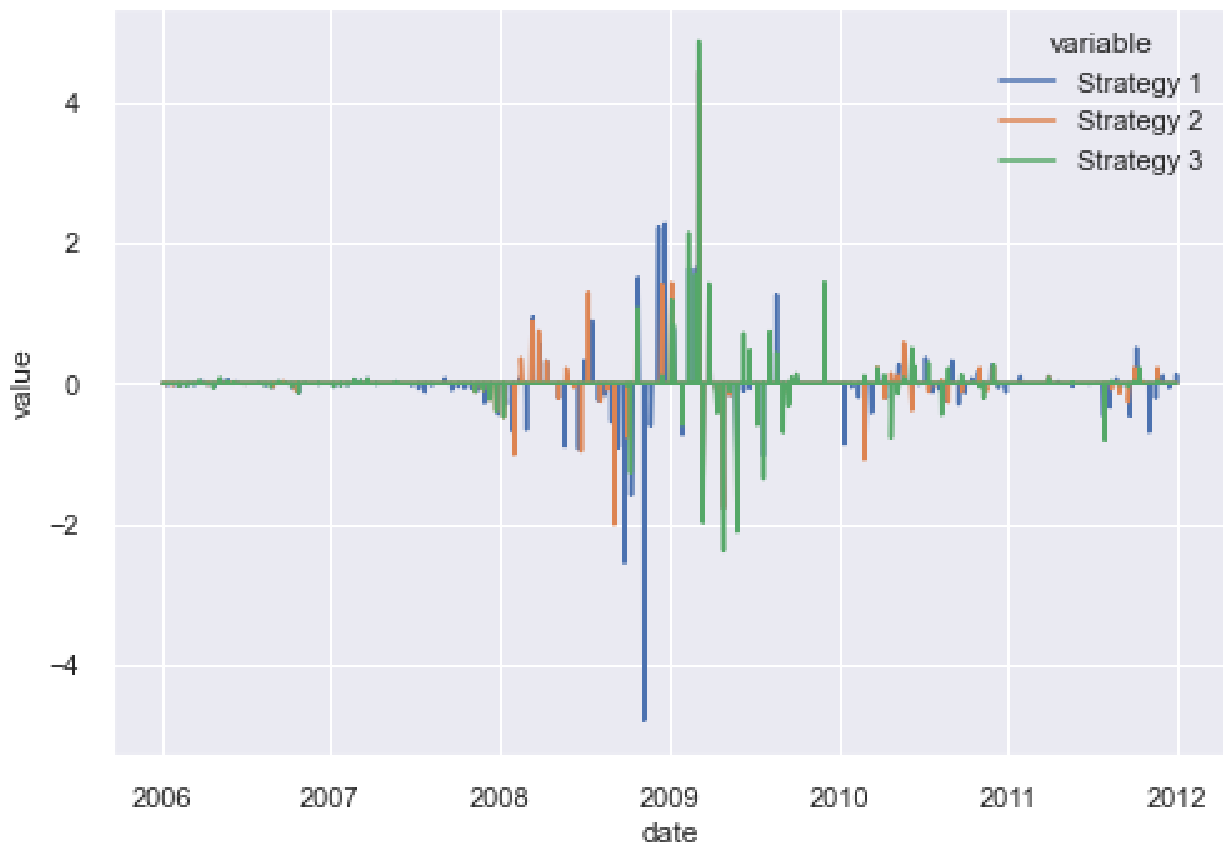


Figure. Arbitrage Return of different strategy over periods 2006 - 2012



Conclusion and Future Application

From the above results, we verify that by combining with the IS factor from price discovery could extend the original limitations of Capital Structure Arbitrage Strategy, such as hedging ratio, anomaly position and trading frequency. Specifically, triggers based on daily price discovery estimates for the two markets are introduced, which allow a filtration framework to be built for more profitability.

Further robustness testing could be investigated through the implementation of applying strategies on different yield and rating grade securities. We could also look into the economy factor, in particular, the TED spread or VIX index to see if our strategy related to dealer funding costs or market volatility.

In sum, the trading strategy that we introduced is based on the information flow and cointegration of the market movement. It can be used to diversify risk in investment fund portfolios at times. Further data mining and variation on the prediction model could also advance the profitability of these strategies. Further research could also focus on innovative strategies based on more advanced price discovery measures.

Literature Review

Risk and Return in Fixed-Income Arbitrage : Nickels in front of a steamroller?

The paper introduces an analysis of the risk and return characteristics of a number of widely used fixed income arbitrage strategies. Fixed income arbitrage is a broad set of market-neutral investment strategies intended to exploit valuation differences between various fixed income securities or contracts. In this paper, the authors mainly focused on five of the most widely used fixed income arbitrage strategies in the market and used all of the five strategies to compute the alpha. The authors confirmed that most of the strategies are sensitive to various equity and bond market factors, for instance, the yield curve arbitrage returns are related to a combination of Treasury returns and capital structure arbitrage returns are related to factors that proxy for economy-wide financial distress. Above all, the strategies require “intellectual capital” to implement command positive excess returns even taking market risks and transaction costs into account.

- Swap Spread(SS) Arbitrage

Swap spread arbitrage has traditionally been one of the most popular types of fixed income arbitrage strategies. The importance of this strategy is illustrated by the historical facts. For instance, the hedge fund crisis of 1998 revealed that many other major investors such as Salomon Smith Barney, Goldman Sachs and Morgan Stanley had large sources of losses for Long Term Capital Market and experienced major losses in swap spread strategies. The swap spread arbitrage strategy has two legs. One is that an arbitrageur enters into a par swap and receives a fixed coupon rate CMS and pays the floating Libor rate. The other one is that the arbitrageur shorts a par Treasury bond with the same maturity as the swap at fixed coupon rate of the Treasury bond CMT and invests the proceeds in a margin account receiving the repo rate from the margin account.

- Yield Curve Arbitrage

Yield curve Arbitrage involves taking long and short positions at different points along the yield curve. There are many yield curve strategies depending on the specific details but most share a few common elements. First is that some type of analysis is applied to identify points along the yield curve which are either "rich" or "cheap." Second, the investor exploits these misvaluations by going long and short bonds in a way that minimizes the risk of the portfolio. Lastly, the portfolio is held until the trade converges and the relative values of the bonds come back into line.

- Mortgage Arbitrage

The mortgage-backed security strategy consists of buying MBS passthroughs and hedging their interest rate exposure with swaps. MBS passthrough is a MBS that passes all the interest and principal cash flows of a pool of mortgages to the passthrough investors, which is commonly implemented by hedge funds. The main risk of a MBS passthrough is prepayment risk. The timing of the cash flows of a passthrough is uncertain since homeowners have the option to prepay their mortgages generating the negative convexity of these securities. The overall logic of the strategy of buying MBS pass throughs, financing them with dollar rolls and hedging their duration with swaps.

- Fixed-Income Volatility Arbitrage

Fixed-Income volatility arbitrage is often implemented by selling options and then delta-hedging the exposure to the underlying asset. In doing this, investors hope to profit from the well-known tendency of implied volatilities to exceed subsequent realized volatilities. If the implied volatility is higher than the realized volatility, then selling options produces an excess return proportional to the gamma of the option times the difference between the implied variance and the realized variance of the underlying asset.

- Capital Structure Arbitrage

Capital structure arbitrage exploits mispricing between a company's debt and its other securities. The purpose is to analyze the risk and return of the strategy as commonly implemented in the industry. Using the information on the equity price and the capital structure of an obligor, the authors compute its theoretical CDS spread and the size of an equity position needed to hedge changes in the value of the CDS which is called the equity delta. Then the authors compared the theoretical CDS spread with the level quoted in the market. If the market spread is higher than the theoretical spread, short the CDS contract and vice versa.

How profitable is capital structure arbitrage?

The paper examines the risk and return of the "capital structure arbitrage" which exploits the mispricing between a company's debt and equity. Specifically, a structural model connects a company's equity price with its CDS spread. In essence, the capital arbitrageur uses a structural model to gauge the richness and cheapness of the CDS spread.

The model, a variant of Merton in general, predicts spreads based on a company's liability structure and its market value of equities. If the market spread is substantially larger than the predicted spread, there are two options. If arbitrageurs think that the equity market is more objective, they would sell credit protection. However, if arbitrageurs think that the market spread is right and there is a lag for the equity market to react to relevant information, they would sell equity. In practice, arbitrageurs take both actions and profit if the market spread and the model spread converge to each other. The size of the equity position relative to the CDS notional amount is determined by delta hedging. If the CDS spread widens or if the equity price rises, the best one could hope for is that the theoretical relation between the CDS spread and the equity price would prevail and the equity position can cushion the loss on the CDS position and vice versa. The lack of a close correlation between the CDS spread and the equity price suggests that there can be prolonged periods when the two markets hold diverging views on an obligor. If the strategy does not converge and the equity hedge works poorly, the strategy can experience large losses when marked to market, triggering margin calls and forcing an early liquidation of the positions.

When implementing this strategy, the authors assumed that one has a time-series of observed CDS market spreads on freshly issued and fixed maturity contracts. Also, they assume a time series of observed equity prices with information about the capital structure of the obligor is available, which enables one to calculate a theoretical CDS spread. In these assumptions, the trader's belief that the difference between the observed CDS market spreads and the computed one will move predictably over time motivates the capital structure arbitrage trading. Lastly, assuming that the theoretical pricing consists of equity price, estimate of asset volatility and the other fixed parameters of the model such as the recovery rate, the actual CDS spread depends on the implied asset volatility. If the real market CDS spread is higher than the computed one, it may be that the implied volatility is too high and shall decline. In this case, the strategy would be to sell CDS and sell equity as a hedge, which is to sell overpriced stock options and use delta-hedging. Another possibility is that the CDS is priced fairly but the equity price reacts too slowly to new information. In this case, since the equity is overpriced, the trader should short CDS as a hedge against shorting equity. Different possibilities can exist accompanying the different strategies. However, the point in this strategy is that a CDS position is entered into whenever the two series diverge from each other by a fixed threshold level, with an accompanying equity position taken out as a hedge.

However, the authors warned of the possibilities of credit risk, which is that by varying the trading threshold level, the initial capital invested and the maximum holding period, the individual trades can be quite risky. In particular, the arbitrageur risks large losses if the CDS market spread rises rapidly resulting in a credit event. In this circumstance, the equity hedge can be completely ineffective, offering minimal resistance during a crisis period.

Evaluation of Conducting Capital Structure Arbitrage using the Multi-Period Extended Geske-Johnson Model

This paper uses a multi-period structural model which extends the Geske-Johnson compound option model to evaluate the performance of capital structure arbitrage under a multi-period debt structure. The extended Geske-Johnson model and the CreditGrades model shows that both models are similar in CDS spread calculation and are consistent with the market CDS spread. However, the extended Geske-Johnson model with a multi-period debt structure can predict default earlier than the CreditGrades model in extreme cases since it can exploit multi-period debt structure information to predict the default probability. In contrast, the CreditGrades model only considers total liability as the reference to predict the default probability. The Geske-Johnson model is the only model that accounts for the entire debt structure and imputes the default barrier to the asset value of the firm.

- Credit Grades Model

Credit Grades Model derives from the Merton structure model for assessing credit risk, including survival probability and credit spread. The model solves default points with an exogenous default barrier and calculates the CDS spread with uncertain recovery. The CreditGrades model is easy to implement in practice and to align with the credit derivatives market with historical volatility and debt. However, this model has its exogenous default barrier, which could cause negative equity value and incorrect survival probability.

- Extended Geske-Johnson Model

The Geske Johnson model extends the Black-Scholes-Merton mode where internal strikes are solved to guarantee positive equity value. The original Geske-Johnson model has three drawbacks; lack of stochastic interest rates, lack of an efficient implementation algorithm and lack of intuition provided by reduced form and barrier structural models. Hence, authors extended the model to n periods and incorporated random interest rates, since corporate bonds are sensitive to both credit and interest rate risks. With the extended Geske-Johnson model, the multi-variate normal probability functions cannot be implemented efficiently albeit it has a closed form to obtain the survival probabilities for multi-periods. Hence, the authors extended the binomial trees with different multi-period debt structures to solve the survival probabilities, zero bond values, and equity value.

From the CDS pricing model implementation, the arbitrageur sees an opportunity by the trading model based on the mispricing between market CDS spread and theoretical CDS spread. The arbitrageur should either buy CDS and equity or sell both when mispricing occurs due to the changes in capital structure or volatility. In other words, an arbitrage opportunity exists for co-movements of CDS spreads and stock prices, and the arbitrageur should obtain a profit from converging spreads or a loss from maintaining co-movements of CDS spreads and stock prices. The authors also followed this arbitrage strategy, capturing the mispricing. They conducted nine simulations and showed that the strategies have a few opportunities for positive mean returns

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