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Essays on Credit Default Swap

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Chapter 1

Introduction

1.1 Definition and Motivation

Credit derivatives are contracts which transfer credit risk of the underlying asset between two parties. With credit derivatives, investors can trade and hedge the credit risk. Compared with traditional debt market, investors no longer need to buy and sell the bond in order to go long and short in the credit risk. Moreover, investors can separate credit risk, liquidity risk and interest rate risk of the underlying names with credit derivatives, which also avoid further transaction costs by reversing unnecessary positions. When some bonds are not available for short selling, investors can go to credit derivative market and sell the credit risk there. Hence, the investors can trade only credit risk and there is no or limited up-front payment since the products in the credit derivative market are usually unfunded.

The credit derivative market has evolved fast in both size and complexity. According to a recent survey by ISDA [2009], the notional amount of the credit derivatives has increased to around $38.6 trillion at the end of year 2008. The development of the credit derivative market is substantial, when the fact that the notional amount was virtually nil in the 1990s is taken into account.

Another advantage of credit derivatives is from their off-balance sheet nature.

They are usually on the trading book, rather than on the balance sheet, and are more favorable than the usual debt instruments due to the capital requirements.

Market regulators have focused on the possible crisis in the fast-growing credit derivative market. On 27 September 2006, the Fed, SEC and FSA issued a joint statement on Financial Times with the title 'A safer strategy for the credit products explosion'. They pointed out that the credit derivative market has developed enormously and the market faced formidable challenges in measuring and managing financial risks. They foresaw a possible crisis and warned:

'Often it takes a crisis to generate the will and energy needed to solve a problem. Here, the industry deserves credit for acting in advance of a crisis.'

The most popular products in the credit derivative market by notional amount outstanding, are single-name credit default swap (CDS), indices and portfolio products, respectively. The single-name CDS is a contract between credit risk protection buyer and seller. The protection buyer transfers the CDS premium, usually on a quarterly basis, to the protection seller and receives the compensation if the credit event is triggered. According to the ISDA documentation, the credit event can be bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation and moratorium, and restructuring failure to pay.

When there is a credit event, the CDS contract is terminated immediately and the protection buyer will be compensated for the losses. There are two different types of settlement. When the cash settlement is chosen, the protection seller pays the difference between par value and final value of the underlying obligation. Contrarily, the protection seller buys the distressed bond at par from the protection buyer. Since the only requirement for bonds is *pari passu*, the protection buyer is implicitly granted a cheapest-to-deliver (CTD) option to give away the cheapest bond among the deliverable obligations[1]. Nowadays, most of

[1] The CTD option is only relevant when physical settlement is chosen. Under cash settlement, different deliverable obligations have the same seniority. The compensation is the difference between par value and recovered value of the obligations. The recovery rates of different deliverable obligations are identical because of identical seniority. Hence, the compensation is unique in the cash settlement, regardless of the different prices of the deliverable obligations.

the CDS contracts choose physical settlement[2].

According to the ISDA market survey, single-name CDS counts for around 50% of the notional amount outstanding of all credit derivatives and is also used in credit derivatives, such as synthetic CDOs and CDS indices. It is followed by the indices and the portfolio products. These three products count for more than 90% of all outstanding notional amount. It is worthwhile noticing that the indices, which include both CDX indices and iTraxx indices, have an enormous growth since its inception in 2004. Previously, there were several different indices traded in the market, which were not standardized and had low liquidity. The new indices are based on the most traded names in North America and Europe, and are rebalanced regularly to maintain the liquidity requirement. With the approval of the regulators, CBOT and CME have started the trading of the futures on these indices, which add further liquidity to index products.

Credit derivatives have provided investors with more liquidity and alternative ways to trade credit risk. With its specific features, the credit derivative market has become an important market for both proprietary trading desks and hedge funds.

1.2 Research Questions

Credit risk of the same name is priced in both bond and credit derivative markets. When prices in the two markets differ substantially from each other, following questions are of our interest:

Is it profitable to buy the credit risk in one market and sell it in the other?

There are various factors which affect the profit of these trading strategies. First, transaction costs in both markets play important roles. Bid-ask spreads of the

[2]Usually, the cash settlement occurs within five days after the credit event.

CDS premium are charged by dealers for their own profits. When the bid-ask spread is wide, the investor may face significant transaction cost. Even if the mid price for credit risk in the two market converges, considerable transaction costs can still drive the arbitrage profit deep under the water. Secondly, if the investor buys the bond in debt market, he has to finance the dirty price of the bond in overnight market. The cost of carry will be taken into account when he calculates the profit. Thirdly, the investor might not be able to hold his position for a considerable period of time. Due to in-house regulatory reasons, he might be forced to close his position before two prices for credit risk actually converge.

For a better understanding of different prices of credit risk, the determinants of the basis, which is defined as CDS premium minus credit spread, are closely studied. To forecast the level of the basis, investors need to identify the drivers of the basis. The movement of these state variables will determine the level of the basis, which is of vital importance for the decision on whether to buy and sell the credit risk. This leads to the second research question.

Which factors drive the basis?

Aunon-Nerin et al. [2002] have studied the influence of fundamental variables on the CDS premium. They find that a significant portion of the cross-sectional variation can be explained by fundamental factors. The determinants of the credit spread are documented by Collin-Dufresne et al. [2001]. They argue that corporate bond market is a segmented market, and there exist specific supply and demand shocks. We investigate the net effect of CDS premia and bond spread determinants on the level of basis.

After we study the basis for single-name CDS premia and the credit spread, the relationship between the investment with the indices of CDS and bonds is under investigation. This difference can be considered to have systematic credit risk only, contrasts to the basis for a single name.

Which factors drive the systematic credit risk, are they priced ac-

cordingly in credit derivative and bond markets?

The investors can buy and sell the systematic credit risk in both credit derivative and bond markets. In credit derivative market, they trade systematic component of credit risk by entering into a CDS index contract. In bond market, they are, at least in principle, able to replicate the bond index by a tracking portfolio of bonds[3]. If two markets price the systematic credit risk accordingly, there exists a stable relationship between indices of credit derivatives and bonds. Given the increasing trading volume of credit derivative indices, it is essential for investors to understand this relationship to improve the trading of the systematic credit risk.

1.3 Outline

The three research questions we consider focus on the relationship between credit risks, either single-name or systematic, and whether credit derivative and bond markets are disconnected.

In Chapter 2, for the first time in the literature the results of possible arbitrage trading with single-name CDS premia and bond-specific asset swaps are investigated. A cash-flow based arbitrage study is conducted to check whether it is profitable to buy CDS, buy bond and enter asset swap contract as fixed rate payer or vice versa. We take into account of institutional facts and transaction costs as both have an important impact on the result of an arbitrage strategy. Usually, it is more difficult to short a bond than to long a bond. Therefore, we separate the cases when the basis is positive or negative. Different opening cushions, holding period limits, and closing cushions are chosen in the analysis to determine the optimal strategies of the basis trading. In an in-sample analysis, we find that first, the ratings and industrial sectors affect mean profit per trade. Secondly, the mean profit per trade declines as the market has matured. Thirdly, the mean profit per trade of negative basis trade is higher than

[3]Usually, the bond index is not traded in the exchange. Hence, investors have to form their own bond portfolio.

that of positive basis trade. Fourthly, applying the position limit significantly raise mean profit per trade. These findings have important implications for the market participants when the disconnection between the CDS and asset swap spread exists.

Chapter 3 checks possible determinants of the basis. The basis depends on the factors that affect CDS premium and credit spread. These factors may interact with each other such that the net effect is still not clear. Using the fixed effect model, we find that individual equity return has no impact on the basis, but implied volatility, long- term interest rate and slope of the interest rate curve still significantly affect the basis. Liquidity proxy of credit derivative market behaves differently in two sub-samples. Our findings enables investors to identify whether the level of the basis is justified by state variables, or whether it gives a signal to exploit it by arbitrage trading.

Chapter 4 discusses the relationship of prices of systematic credit risks in CDS and bond markets. Using the data of the iTraxx Europe index and the iBoxx Corporate index to form two portfolios, we compare the performance of these two indices[4]. To investigate the relationship, we use a multiple time series analysis for returns of these two portfolios. The vector error correction model shows that the cointegrating relation drives the change of credit derivative and bond markets. We also find positive autocorrelation in the changes of credit derivative market and negative autocorrelations in the changes of bond market. The research on the relationship of systematic credit risks between credit derivative and bond markets is the first empirical work in this field.

[4]Directly comparison is difficult. The iTraxx index is unfunded and there is only limited up-front payment.

Chapter 2

Arbitrage between CDS and Bond Markets

2.1 Introduction

Credit risk is priced in both bond and credit derivative markets. The asset swap spread for a bond is directly comparable to the credit default swap (CDS) premium of the same name in the credit derivative market. Financial theory indicates that these two premia should be identical, otherwise the investor profits by taking long and short positions and holding this position until the premia converge. Nevertheless, such a relationship might not hold in actual markets because the investor pays the round-trip transaction costs of the CDS premium and asset swap spread to the dealers. If the discrepancy between the CDS premium and asset swap spreads is not large, the cash flow from the transactions would not be sufficient to cover the trading cost. Moreover, in our arbitrage version, the investor has to short sell the bond as counter-repo and some bonds are difficult to short sell, so an arbitrage profit becomes less likely.

The arbitrage from trading the basis, defined as the CDS premium minus the asset swap spread, is not the usual textbook arbitrage. Instead, the investor might make a loss if the spreads diverge rather than converge. Even if the basis does not change, the investor makes losses as he has to pay the financing cost.

We investigate whether CDS premia and asset swap spreads allow for profitable arbitrage strategies. The results show that the mean profits per trade from appropriate trading strategies are positive. We find that the optimal trading strategy is to enter the market when there is large discrepancy between CDS premium and asset swap spreads and to close the position when the basis is substantially tight: it pays off to be patient. We also find that strategies with longer holding periods outperform their counterparties in most cases and that the performance of negative basis trading beats that of positive basis trading. The results have important implications for the strategies of arbitrageurs in these markets.

Our research answers the question of whether it is profitable to trade the basis, and then identifies the optimal strategy. This is the first paper on arbitrage in this area. There exist an increasing number of studies on CDS premia, credit spreads and their relationships, and to put our paper into perspective we briefly discuss the relationship of our paper to these studies.

The determinants of CDS and those of the credit spread have been examined by Collin-Dufresne et al. [2001], Elton et al. [2001], Aunon-Nerin et al. [2002], who find similar factors behind changes in the CDS premium and the credit spread. Since the credit derivative and cash bond have the same underlying, the credit risk should be comparable. Longstaff et al. [2005] extend this by checking the default and nondefault components of credit spreads using the CDS information and find that liquidity has a strong impact on the non-default components. Using European data, Cossin and Lu [2005] also report that the disconnection between the credit derivative and cash bond markets is due to the price of liquidity in the cash bond.

The determinants of basis have been investigated as well. Schueler [2001] shows possibilities of basis trading and suggests various methods to calculate the asset swap spread. Buehler et al [2005] find that the volatility of the underlying entity has a strong impact on the basis. The information flow in CDS and bond markets is also discussed. The relationship between the CDS premium and credit spread is addressed and confirmed by Blanco et al. [2005]. Norden and Weber [2004] check the lead-lag relationships between equity, CDS premia and bond markets. Hull et al. [2004] consider the relationship between CDS premia, bond yields, and credit rating announcements.

Crouch and Marsh [2005] address the theoretical arbitrage relationship between CDS and asset swap spreads. Using data from the automotive sector, they find that the arbitrage relationship equating CDS premium and asset swap spread holds at low levels of credit risk but not at high levels because of the difference in liquidity and cheapest-to-deliver options. Our study sets the entrance trigger based on the level of the basis and the perceived credit risk of the underlying, for which the mid CDS premium is a proxy, the holding period limit for the position, and the exit trigger to calculate the profit of different trading strategies.

The arbitrage discussed here differs from the typical arbitrage in stock market index futures for the following reasons. The basis does not converge to zero as the different supply and demand in cash and credit derivative markets and unwinding the position could happen when a margin call forces liquidation. When the CDS premium is lower than the asset swap spread, some investors expect the long-term relationship to pull them closer to each other. If the CDS premium increases thereafter, given no change in the asset swap spread, the mark-to-market valuation of the CDS will lead to a profit. Even if one of the two spreads moves against the investor's position, he might still earn the profit when the net effect is in his favour. Nevertheless, he might be forced into interim liquidation when a certain holding time period limit is met. Furthermore, if the difference between the CDS premium and asset swap spreads widens much during the holding period, the investor might get a margin call for his collateral with the dealer and has to unwind his order immediately. A similar risk-return trade-off is analyzed in Duarte et al. [2005].

The remainder of the paper is organized as follows. Section 1 describes the credit derivative and bond markets. Section 2 presents the trading strategies and criteria for building and unwinding the position. Section 3 reports the data we use. Section 4 provides the results and analyzes the implications. Section 5 concludes.

2.2 CDS Premia and Asset Swap Spreads

2.2.1 Credit Default and Asset Swaps

A single-name credit default swap is a contract between the credit protection buyer and seller, which has a fixed leg and a floating leg as a plain-vanilla interest rate swap. The fixed leg consists of the quarterly fixed payments which the protection buyer transfers to the protection seller. The floating leg results in a transaction between the two counterparties if a credit event occurs as described in the contract. If the cash settlement is chosen, the protection seller transfers an amount of money, which equals the face value not recovered in the credit event, to the protection buyer. In the case of physical settlement, the protection seller pays the notional amount of the debt to the protection buyer while the protection buyer delivers the bond from the predetermined basket of deliverable bonds to the protection seller. The CDS contract ends immediately when the credit event triggers. According to the ISDA Agreement, the main triggers of credit events are default, bankruptcy, failure to pay or restructuring of the reference entity.

The CDS market has grown rapidly. According to recent survey data of ISDA [2009], single-name CDS has a volume of $38.6 trillion outstanding contracts at the end of 2008.

In our study we also use asset swaps. An asset swap is a contract in which the counterparties agree to exchange fixed future payments against variable future payments. Typically, an asset swap is used to translate the price risk of a fixed coupon bond into a variable coupon risk. The floating asset swap payment is calculated by using the notional amount and asset swap rate, which is composed of a benchmark rate (usually Libor or Euribor) and an asset swap spread. The buyer of an asset swap makes fixed payments and receives variable payments, and vice versa for the seller.

There is a difference between an asset swap and a plain vanilla interest rate swap. In a fair priced plain vanilla interest rate swap, there is no upfront money exchange. In an asset swap, however, the asset swap buyer, who makes fixed and receives floating payments, needs to pay the seller the amount of accrued interest from the asset swap floating leg minus the accrued interest from the bond and the difference between the par value and the bond clean price in the par-in-par-out scheme if this difference is positive. Otherwise he receives the net payment.

The payment structure also differs. In the plain vanilla interest rate swap as traded in the US market, the payment dates are every 180-days in the future. In an asset swap, both the fixed and variable payments are made at the coupon dates of the bond swapped from fixed to variable payments.

An asset swap contract does not necessarily include buying the bond; it is merely a contract for exchanging the fixed and floating payments. However, it is always used for pricing a fixed-coupon bond. The bonds are quoted with their asset swap spread and traded based on such information. Insofar this means that a bond is also included in the asset swap contract.

Usually the fixed leg payer of an asset swap also buys a bond. After he purchases the bond at the dirty price, he pays the difference between this dirty price and par, and pays the accrued interest from the floating leg of the asset swap to the counterparty to enter the asset swap contract, if the dirty price is higher than the sum of the par value and the accrued interest from the floating leg. Otherwise he receives the difference between the dirty price and the par value, plus the accrued interest from the floating leg. When the asset swap is unwound, the asset swap buyer transfers the difference of the sum of the par value and the accrued interest from the floating leg and the dirty price of the bond to the asset swap seller if the difference is positive. Otherwise he receives the difference between the par value and the clean price[5].

Table 2.1 presents the cash flows of buying CDS protection, longing the bond and entering an asset swap with and without default. These cash flow representations are the basis of our study.

The cash flow of an asset swap buyer at the settlement date of an asset swap is:

$$\begin{aligned} CF_0 = &\ Payment\ from\ the\ Seller - Payment\ to\ the\ Seller \\ &= PC_0 + AI_0(Bond)\ -\ FV - AI_0(Swap), \end{aligned} \tag{2.1}$$

where PC_0 is the clean price of the bond, $AI_0(Bond)$ is the accrued interest of the bond, FV is the face value of the bond and $AI_0(Swap)$ is the accrued interest of the floating leg of the asset swap. The accrued interest payments are determined for the period from the bond's last coupon date to the settlement date of the bond and the asset swap, respectively.

[5]Usually, a bond is traded at par when it is redeemed. This is the so called "pull-to-par" effect. Hence, no exchange of payments will be made.

Table 2.1: Cash flows of buying a bond, funding it using the overnight money market, entering into an asset swap and longing credit via credit protection through a CDS where the CDS premium is less than asset swap spread

This table presents the cash flow chart when there is no default. The upper part of the each panel describes cash flows of the asset swap package with respective bond. FV denotes the face value of the bond, P_0 is the clean price at time 0, c is the coupon of the bond, L is three-month Libor, E is EONIA rate, and ASW is the asset swap spread. The lower part of each panel presents the cash flows of a CDS contract. CDS is the quarterly payment of CDS premia.

We make the payment schedules of both asset swap and credit default swap identical to simplify the analysis, although periods in these two parts do not necessarily coincide. Additionally, payment schedules of the fixed leg and the floating leg of asset swap may also differ from each other. Usually floating legs are paid quarterly and fixed legs are paid semiannually or annually. We assume 0 is the coupon date, and there is no default between 0 and t. Variables with a tilde are not known at time 0.

	Cash Flow of Asset Swap	
	0	t
Buy the bond	-P_0	$\tilde{P}_t$+c*t
Borrow in the overnight market	FV	-FV-E_0*t
Enter asset swap, pay fixed and receive floating	P_0-FV	(L_0+ASW_0-c)*t
Unwind asset swap		FV-$\tilde{P}_t$
Sum		ASW_0*t + (E_0-L_0)*t
	Cash Flow of CDS	
	0	t
Buy CDS protection		-CDS_0*t
Unwind CDS		($\tilde{CDS}_t$-CDS_0)*DV01
	Cash flow of portfolio	
	0	t
Portfolio		(ASW_0-CDS_0)*t + (E_0-L_0)*t + ($\tilde{CDS}_t$-CDS_0)*DV01

2.3 Arbitrage Strategies

2.3.1 Negative Basis Trading Strategy

When the CDS premium is lower than the asset swap spread, we observe a negative basis. The total amount of investment when implementing a negative basis trading strategy, as we have shown above, is equal to the par value plus the accrued interest of the asset swap floating leg. Since the CDS contract is unfunded, there is no upfront cost for purchasing the protection. We assume that an investor will finance his investment on a daily basis in the overnight market, and that he rolls over his loan.

We suppose that the investor enters one standard CDS contract as protection buyer and buys one piece of cash bond. This approach with normalized notional amount fully captures the relationship between CDS and bond. One can easily raise the amount of CDS contract and bond. However, as our aim is to investigate the relationship between CDS and bond, we normalize the amount of CDS contract and cash bond without loss of generality.

We assume that the investor can trade at the price when the trading signal appears. This assumption is fair as brokers always put a certain expiration period for each quoted price, and the investor can trade at the quote in this respective time period.

The strategy consists of the following transactions. The investor purchases CDS in the credit derivatives market and the bond in the bond market. He subsequently enters the asset swap contract. Using a par asset swap contract, he matches the face value of the asset swap with that of the CDS.

If the exit trigger is met at time 1, which is assumed to be before the next coupon date, the investor unwinds his position. His cash inflow consists of four components: (1) unwinding the CDS contract; (2) closing out the asset swap; (3) selling the bond; and (4) repayment of the overnight loan.

If the CDS contract is unwound, two components have to be taken into account: the market value of the contract at the unwinding date which equals $\Sigma\beta^i_{CDS}(CDS_1 - CDS_0)$ and the accrued interest of the CDS contract $CDS_0 \cdot \Delta t/360$. The present value of the payment from the CDS premium change is calculated with a risk-adjusted discount factor $\beta^i_{CDS} = 1/(Swap_i + CDS_1)$ where $Swap_i$ is the swap rate with i year tenor. Because the cash flow could stop in the future if there is a credit event that voids the CDS contract, we add the CDS premium on the unwinding date to the 5-year interest swap rate to discount the risky cash flows.

The accrued interest of the CDS is the payment made by the investor for being protected against the credit event during the holding period.

Therefore, the net cash flow of the CDS part is the current market value of the CDS premium change minus the accrued interest or the pro-rata payment of the CDS premium. The sum is $\Sigma\beta^i(CDS_1 - CDS_0) - CDS_0 \cdot \frac{\Delta t}{365}$.

In the asset swap part, the investor's P&L when he unwinds the position is composed of par value plus the accrued interest of the asset swap floating leg, the payment due to the change in Libor rates and the payment due to the change in asset swap spreads. The accrued interest of the asset swap is calculated in the same way as the investor builds his position at time 0, which equals $ASS_0 \cdot \frac{\Delta t}{365}$. The payment due to the change in Libor rates is the net present value of the change of Libor in the next payment date:

$$\beta^1(Libor_0 - Libor_1) \cdot \frac{\Delta t}{360} \tag{2.2}$$

where $Libor_0$ and $Libor_1$ are the Libor rates when positions are built and unwound, respectively, β^1 is the risk-less discount factor of period 1, Δt is the time period between the dates when the investor builds and unwinds the position with a day count convention of actual/360[6].

[6]The $Libor_0$ and $Libor_1$ usually have irregular tenors, i.e. the period between the day

The payment due to the change in asset swap spreads is calculated in a similar way to the CDS, which equals $\Sigma\beta^i_{ASW}(ASW_0 - ASW_1)$. However, an investor uses the zero curve bootstrapped from the current swap curve as risk-less discount factor to calculate the net present value instead of using risky discount factor. The discount factor $\beta^i_{ASW} = 1/Swap_i$, where $Swap_i$ is the bootstrapped swap rate with i year tenor. The rationale behind this is that the only risk in asset swap contract is interest rate risk; the default risk of the bond issuers does not matter. Following the arguments of Duffie and Huang [1996] and Duarte et al. [2005] that counterparty risk is minimal because of the fully collateralized swap, we neglect it.

The payment schedules of asset swap rates and CDS premia are also different. Asset swap spreads are supposed to be paid with the same payment schedule as the bond, while payment schedule of the CDS has quarterly frequency and starts when the default swap contract is written.

When the investor closes the position, he sells the bond at its dirty price P_1. Meanwhile, he has to pay back the overnight loan when he unwinds the position. This payment is the amount borrowed plus the compound interest. As we have discussed, the amount borrowed equals the sum of face value and accrued interest of the asset swap when the investor opens his position, i.e. $FV + ASW_0 \cdot \frac{\Delta t_{-1}}{360}$ where Δt_{-1} denotes the time period between the date when the position is opened and the last coupon date.

Putting these parts together, profit of negative basis trading strategy can be worked out. To sum it up, if the basis meets the trigger, the investor will immediately unwind his position; if not, he will hold the position and roll it over to the next day. When the maximum holding period is met, he will unwind his position regardless of the profit.

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when the position is built and unwound, and the next coupon day of the bond, respectively.

2.3.2 Positive Basis Trading Strategy

The investor needs to reverse his position in the negative basis trading strategy when positive basis is wide enough, i.e. the entrance trigger is met. He builds his position by selling CDS as credit protection, short selling the cash bond and entering the asset swap as fixed payment receiver. He invests income from short selling the bond and the upfront payment of accrued interest from the associated asset swap in the overnight market.

The positive basis trading strategy is harder to implement than its negative counterpart. First, it is hard to borrow the cash bond and then to short sell it, particularly as some illiquid bonds are extremely difficult to obtain. Secondly, even if the investor successfully borrows the cash bond, there are potential haircut costs and possibly a margin deposit with the dealer. During the holding period, if the investor cannot satisfy the possible margin call requirement, he may be forced into interim liquidation.

We ignore the influence of haircut costs and a margin deposit requirement in our paper as it depends on the creditworthiness of individual investors. When the investor unwinds his position, he effectively terminates the CDS with the credit protection buyer, unwinds the asset swap at its market value, purchases the cash bond at its dirty price with money invested in the overnight market and sends the bond back to the lender. Profit in the positive trading strategy involves the same components as the negative basis trading strategy.

The first part is the net present value of the cash flow from the difference in CDS premia using risky discount curve and the payment of accrued interest from the CDS. The second part is from the asset swap contract, which is composed of the market value of the cash flow from the difference in asset swap spreads using the risk-less discount curve, the net present value of the change in the Libor rates and the cash outflow of accrued interest of asset swap floating leg. The third part is the dirty price the investor pays to buy back the bond and the fourth part is the interest income from the overnight market. The calculation of the profit uses the same steps as that of the negative basis trading strategy with reversed sign.

2.3.3 Setup

We assume that there is an investor who can simultaneously trade both bonds and CDS. He has no initial capital but is able to finance the investment by borrowing in the overnight market. He could also short sell the bond by borrowing from the broker. He may have position limits for both borrowing activities. The credit derivative market is not frictionless as the investor has transaction costs in buying and selling a CDS. Although the bond market is not frictionless either, we do not model the round-trip trading cost as the data are not available.

We define the basis as the difference between CDS premium and asset swap spread. A positive basis suggests, at least theoretically, that protection buying is relatively expensive. In this case, the investor possibly opens an arbitrage position by selling credit protection in the CDS market and selling the bond. A negative basis shows that buying protection is relatively cheap; the investor opens an arbitrage position by buying credit protection and buying the cash bond.

When the basis is sufficiently large relative to the mid CDS premium, and the investor expects it to tighten in the near future, he opens his position. When the basis is negative and wide, the investor will buy the CDS protection at the ask quote and enter the asset swap contract to receive the floating rate payment and pay the fixed rate payment. When the basis is positive, the investor will reverse this strategy.

Opening cushion

Independently of the type of arbitrage strategies we consider, the position would be opened when entrance trigger is met. There are many ways to determine this trigger. The traders usually have reasonable basis levels for individual bonds in mind. When the basis level is higher than what they consider is reasonable, trade orders will be placed.

In our study, we assume that the investor builds the position when a certain opening cushion is met. The opening cushion is defined as the absolute value of the basis, minus the estimated transaction cost (bid-ask spread of the CDS premium) over mid CDS premium. When the opening cushion exceeds the predetermined threshold, the position will be established. We use the relative basis rather than the absolute basis as a threshold. A basis of 10 bps might be considered tight for an entity with mid CDS of 200 bps, but not for another entity with mid CDS of 50 bps. The bid-ask spread of the CDS premium is also taken into account. Since the investor buys the CDS at the ask price and sells at the bid price, it is of vital importance for him to consider the trading cost.

If the opening cushion is high, in order for a position to be opened, the basis must obviously to be high as well, i.e. if the mispricing is large and likely to disappear shortly. Therefore, we believe that the mean profit per trade increases as the opening cushion rises.

[**Hypothesis 1: Opening Cushion**] H_0: The mean profit per trade increases monotonically with the opening cushion.

We consider only names that are rated Baa or better at the current date. However, we exclude all Baa names which have mid CDS premia higher than average mid CDS premia of Baa names in the past 90 trading days. The rationale behind this is that we assume the CDS premium is a more accurate indicator of the underlying credit quality than the rating from rating agencies.

Holding Period

As basis trading opens a short position either in the bond market in the case of a positive basis trading or in the money market in the case of negative basis trading, the investor may have a holding period limit, which restricts him from taking excessive leverage. In our design, we use and compare several exogenous holding period limits.

When the holding period limit applies, we assume that the investor can hold the short position in the bond or money market for a certain period. When the holding-period limit is met, he has to close the position regardless of whether the trade generates a profit or loss. The investor with a looser holding period limit, i.e. longer period, is likely to heap a higher mean profit at a higher risk. Hypothesis 2 is formulated:

[**Hypothesis 2: Holding Period Limit**] H_0: The mean profit increases when the holding period limit rises[7].

Every coin has two sides. It is argued that the longer the holding period limit the more likely an investor is to close the position too late. The argument is based on the fact that the basis will be more likely to diverge or maintain the status quo than to converge. However, we would expect that the basis will converge as both the CDS and bonds have comparable credit risk.

As the holding period increases, the profits can be expected to vary. If the basis does not converge, the arbitrage profit will be even worse because of the financing cost. Hypothesis 3 is formulated:

[**Hypothesis 3: Standard deviation of profit per trade**] H_0: The standard deviation of profit per trade increases when the holding period limit rises.

Closing Cushion

The investor realizes the profit or loss by closing the position. There are two possibilities for doing this: when the holding period limit is met, the position must be closed; or when the closing cushion is hit, the investor closes the position as he thinks the basis is now 'reasonable'. We assume this is the case when the current value of the basis is less than the absolute value of

[7] When holding period limit rises, the investor can hold the position longer.

the basis when the position is built multiplied by the closing cushion, i.e. if $|basis_{unwind}| < |basis_{build}| \cdot Cushion$, holds.

Market convention uses the targeted spread level instead of monetized amount of profit for basis trade. This approach is widely accepted due to the fact that tightened basis is related to the absolute level of CDS premium. Moreover, the measure in basis point will not mislead investors who have different notional amount of basis trades.

A higher closing cushion will result in lower mean profit per trade, provided the positions are closed voluntarily. On the other hand, higher cushions will cause more voluntarily closed positions, so the consequence of an increased cushion is not obvious. We believe that the first effect dominates.

[**Hypothesis 4: Closing Cushion**] H_0: The mean profit per trade increases when the closing cushion is lower.

Rating Class

In our data set, we find the basis smile phenomenon, i.e. the basis of names which belong to the best and to the worst rating classes, are higher than the basis for medium-rated names. The observation can be explained as follows: for highly rated firms the CDS premia are positive where the asset swap spread is close to zero or even negative, i.e. the credit quality of these names are higher than that of the Libor (usually Aa rating). The basis for the low rating class is high as the credit derivative market is thin and, in the case of financial turmoil, an investor might tend to buy the CDS protection at an unreasonable price just to protect against his credit exposure.

[**Hypothesis 5: Rating**] H_0: The mean profits of different rating classes are significantly different.

Maturation of the Market

The CDS market has grown rapidly in recent years. According to the ISDA survey report, the number of underlying entities, total notional amount and the number of market participants have increased sharply. As the market matures, arbitrage possibilities are expected to decline and mean profits to drop. If credit derivative and cash bond markets value the credit risk differently, investors will immediately notice the discrepancy and execute the trades. Hence, the mis-pricing in the two markets is eliminated quickly and fewer positions will be opened.

[**Hypothesis 6: Maturation**] H_0: The profit per trade of basis trading decreases over time.

2.4 Data

2.4.1 Data Description

The CDS bid and ask quotes from January 2001 through April 2006 are obtained from CreditTrade. Each record contains the created date, the name and the CreditTrade issuer identification of the underlying entity, the bid and ask quotes, the S&P and the Moody's ratings, the restructuring type, the denominated currency, the tenor, the notional amount, the industry, the credit type, the country, and the region. Because 5-year CDS is the most liquid product in the market, we choose the tenor of five years and a notional amount of either 5m or 10m.

To make the CDS premium and asset swap spread comparable, we selected senior unsecured and straight bonds for our sample, and retrieved the asset swap data for these bonds from Bloomberg service. If there is more than one bond available, we choose the one with a maturity date closest to five years. Figure 2.1 presents the mid CDS and asset swap spread of an individual entity.

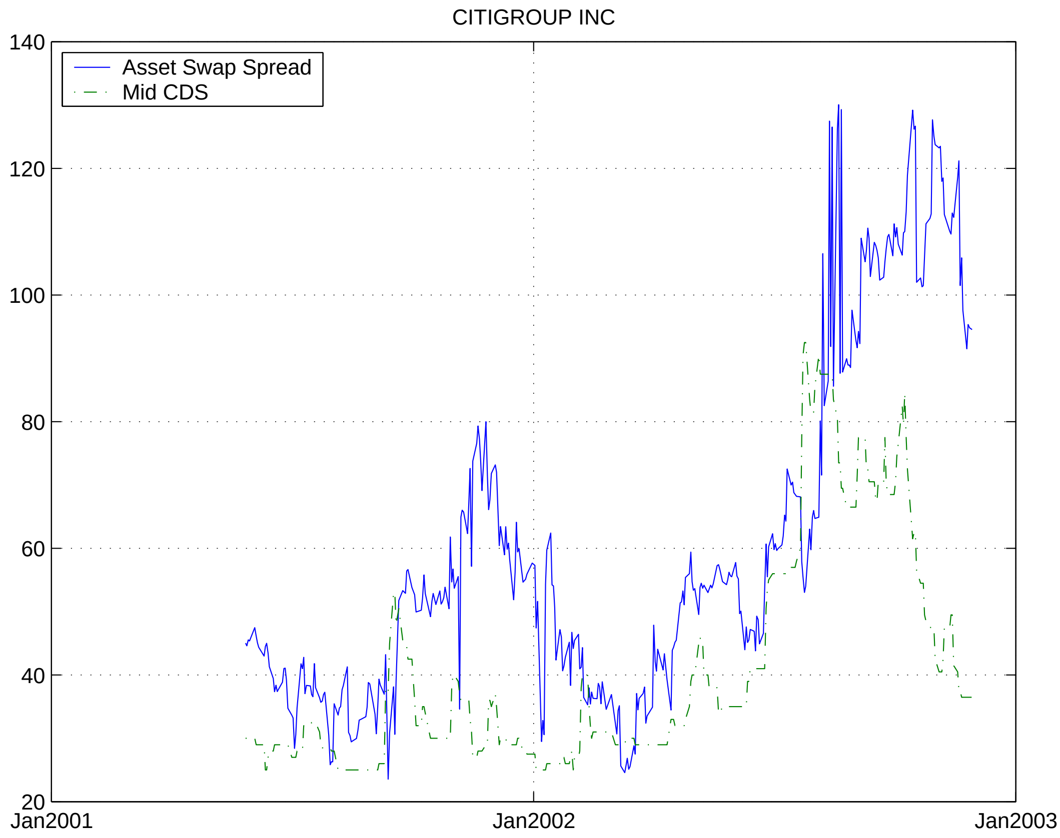
We use bid and ask quotes of CDS to capture the transaction costs of basis trade. Mid asset swap spread in our research as no bid and ask quotes for asset swap spread are available.

If CDS premium and asset swap spread do not converge or even diverge, the investor has the risk that loss may occur. This risk cannot be completely ruled out, but we can reduce the risk by trading bases which are sufficiently wide. In this case, the investor makes profit if CDS premium and asset swap spread partially converge.

There are two possible candidates for the risk-less rate in calculating the risk-less discount curve: government-bond rate and swap rate. As asset swap spread is added to Libor flat, which is the variable reference rate for plain vanilla interest rate swaps, we use, as practitioners do, the swap rate as the "risk-free" rate. If the CDS and asset swap are denominated in euro, we choose the euro-swap rate; if they are denominated in dollars, we use the dollar-swap rate.

Figure 2.1: Mid CDS and Asset Swap Spread

The dashed line and the solid line show the mid CDS and asset swap spread in bps, respectively. The underlying bond is with C 6.625% 11/15/06 which has ISIN US201615DL29.



The bid and ask quotes from CreditTrade, an internet-based broker of credit products, are essential in identifying whether the strategies are profitable or not. The asset swap spreads of the respective bonds and the swap rates are from Bloomberg service. Outlier in the database are excluded.[8]

2.4.2 Sample Statistics

Table 2.2 reports the descriptive statistics of the bid and ask quotes of CDS and the asset swap spread by rating class.

The mean value of the mid CDS premium increases with deteriorating ratings. However, due to the rigidity of the rating migration and the unbalanced nature of the data set, the order of the absolute numeric value of the mid CDS premium can vary when the number of observations is not sufficiently large. For example, we find that the mean value of the Aa3 rating class is higher than that of the Aa2 rating class. Given that the number of observations for the Aa3 rating class is just 667, around 25% of that of the Aa2 rating class and 50% of that of the Aaa rating class, the mean value can be significantly affected by one or more names. There are three reference entities with an Aa3 rating, namely Citigroup, NTT DoCoMo and Toyota Motor. The mean value is driven by the high level of Citigroup's mid CDS premium, which has a mean value of 44bps. As most of the mid CDS data are from before 2003, the period when the CDS premium was at its peak, Citigroup's high mean value comes from the unbalanced nature of the data. For a particular rating class, the standard deviation of the mid CDS premium is high when the dates of the observations vary widely. In the table, we observe that the standard deviation of the A3 rating class is comparatively higher than the others. Since the CDS market developed rapidly, the evolving nature of the mid CDS premium strongly affects the standard deviation. In the last columns, we show the maximum and the minimum values of the mid CDS premium.

We also show the descriptive statistics of the asset swap spread. Compared

[8] See Appendix for details.

with that of the mid CDS premium, the mean value of the asset swap spread does not increase monotonically with deteriorating credit quality. We observe that the mean value of the Aaa rating class is below zero, which confirms that the credit quality of Aaa is higher than that of the US$ Libor or Euribor. The standard deviation of the asset swap spread is lower than that of the mid CDS premium for rating classes lower than Aa1.

The maximum and minimum values of the asset swap spreads are shown in the next columns. We find that the maximum values of asset swap spreads. with the exception of Aa3, are lower than those of the mid CDS premium for most of the rating classes. Negative values are found in the reported minimum values for more than half of the rating classes.

The bid-ask spreads are also included in the descriptive statistics because we are interested in the development and trade flow of the credit derivative market, which can be partly inferred from the bid-ask spreads. Tight bid-ask spreads usually suggest that the liquidity in the market is adequate and two-way flows are occurring. On the other hand, wide bid-ask spreads implicitly show that there is less liquidity in the market and some of the quotes may be only be indicative.

The level of the bid-ask spreads is closely related to the mean value of the mid CDS premium; it goes up as the mean value of the mid CDS premium increases. We see that most observations are in the space between the A3 to Baa1 rating classes. According to Fitch Rating's survey, the average quality of the traded CDS names are Baa-equivalent rating classes[9]. The standard deviations of the bid-ask spread increases substantially when the credit quality falls below investment grade. The next columns report the maximum and minimum values of the bid-ask spreads. We find that certain rating classes have much higher maximum values, which can be traced back to the reference entity both Enron and Brazil.

[9]The original rating classes quoted are in the S&P domain. Here we mirror the level of the S&P rating to that of the Moody's rating.

Table 2.2: Descriptive Statistics of CDS and Asset Swap Spread

The table reports the descriptive statistics of bid and ask quotes of CDS and asset swap spreads. All numbers are reported in basis points. Moody's ratings of underlying entities are used to separate the sub-samples. The mean, standard deviation, maximum value, minimum value and number of observations are presented. Asset Swap and B-A Spread stand for asset swap spread and bid-ask spread of CDS, respectively.

	Mean			Standard deviation			Maximum			Minimum			
	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Num. Obs.
Aaa	19	-3	5	26	25	5	125	91	30	3	-63	1	1,275
Aa1	33	48	10	17	28	3	93	130	20	11	-51	3	667
Aa2	24	21	8	12	17	4	105	70	20	4	-48	2	2,487
Aa3	42	43	10	28	31	7	265	146	50	8	-30	1	3,672
A1	43	30	10	49	35	9	460	270	75	6	-38	1	4,431
A2	80	76	16	72	64	18	750	580	300	11	-28	1	4,844
A3	102	91	18	80	69	17	675	506	150	21	-24	1	3,497
Baa1	107	85	16	104	80	21	1,100	653	400	19	-47	1	5,966
Baa2	151	126	26	164	107	46	1,450	681	800	28	-5	2	3,089
Baa3	163	134	29	146	93	68	2,400	780	2,000	19	-10	1	2,918

Table 2.3: Descriptive Statistics of CDS and Asset Swap Spread Conditioned on the Sign of the Basis

The table reports the descriptive statistics of bid and ask quotes of CDS and asset swap spread conditioned on basis. All numbers are reported in basis points. Moody's ratings of underlying entities are used to separate the sub-samples. The mean, standard deviation, minimum value, maximum value and number of observations are presented. Asset Swap and B-A Spread stand for asset swap spread and bid-ask spread of CDS, respectively.

Panel A: Conditioned on Positive Basis

	Mean			Standard deviation			Max			Min			
	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Num. Obs.
Aaa	19	-3	5	26	25	5	125	91	30	3	-63	1	1,275
Aa1	33	48	10	17	28	3	93	130	20	11	-51	3	667
Aa2	24	21	8	12	17	4	105	70	20	4	-48	2	2,487
Aa3	42	43	10	28	31	7	265	146	50	8	-30	1	3,672
A1	43	30	10	49	35	9	460	270	75	6	-38	1	4,431
A2	80	76	16	72	64	18	750	580	300	11	-28	1	4,844
A3	102	91	18	80	69	17	675	506	150	21	-24	1	3,497
Baa1	107	85	16	104	80	21	1,100	653	400	19	-47	1	5,966
Baa2	151	126	26	164	107	46	1,450	681	800	28	-5	2	3,089
Baa3	163	134	29	146	93	68	2,400	780	2,000	19	-10	1	2,918

Descriptive Statistics of CDS and Asset Swap Spread Conditioned on the Sign of the Basis: Continued

Panel B: Conditioned on Negative Basis

	Mean			Standard deviation			Max			Min			
	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Mid CDS	Asset Swap	B-A Spread	Num. Obs.
Aaa	12	19	5	2	5	1	16	41	6	11	11	4	70
Aa1	32	54	10	16	25	3	88	130	20	11	13	3	538
Aa2	23	32	8	8	12	3	51	70	16	8	9	2	1,084
Aa3	39	54	9	22	29	5	120	146	40	8	8	1	2,037
A1	41	54	11	23	29	5	220	262	50	6	6	1	940
A2	69	89	15	47	55	12	400	453	200	11	12	2	2,050
A3	82	100	16	59	66	14	300	313	95	22	26	2	1,323
Baa1	86	100	15	62	66	14	570	591	100	19	21	2	1,914
Baa2	102	130	23	72	79	17	650	681	100	39	39	3	1,153
Baa3	143	167	28	79	87	25	510	552	150	29	29	2	795

Table 2.4: Decomposition of Underlying Entities

The table reports the composition of the database by currency, industry sector, domiciled country and continent, respectively. Only investment grade names are included.

Panel A

US Dollar	56%
Euro	44%

Panel B

Telco, Utility	22%
Financial	21%
Consumer goods	15%
Sovereign	11%
Automobile	4%
Other corporates	27%

Panel C

US	37%
France	12%
Netherlands	11%
UK	11%
Germany	6%

Panel D

Europe	50%
North America	37%
Asia/Non-Japan	7%
Others	6%

Next we divide the sample into two sub-samples based on the sign of the basis. Panel A of Table 2.3 reports the descriptive statistics of positive basis, while Panel B shows that of negative basis. When the rating is better than A2, the levels of CDS premia of positive basis and negative basis are similar but the asset swap spreads are lower in the case of a positive basis than for a negative basis.

As the rating deteriorates to lower than A2, the CDS premia of positive basis rise substantially while the difference between the asset swap spreads are less significant.

Table 2.4 presents a breakdown of the underlying entities in our study. In Panel A, we see that among the 32,851 pairs of CDS premia and asset swap spreads data, 56% are denominated in US dollars and 44% are denominated in euro. The underlying entities denominated in US dollars are composed of the US corporate, foreign corporate and sovereign entities. Panel B presents the breakdown for the top industries. The Telco and Utility sector counts for 22% of the data, followed by Financials (21%), Consumer goods (15%), Sovereign (11%), Automobile (4%) and other corporates (27%). Panel C shows the breakdown by country. 37% of the CDS and asset swap are issued in the USA, 12% in France, 11% in the Netherlands, 11% in the UK and 6% in Germany. The CDS and asset swaps issued in these five countries count for around 77% of all data. The breakdown by region is shown in Panel D. The Europe has a 50% share, followed by North America (37%) and Asia non-Japan (7%).

2.5 Results and Analysis

2.5.1 Sample and Trading Strategy

We use daily data to calculate the profit and loss of the negative and positive basis trading strategies and implicitly assume that the investors trade at the closing price. The closing prices of single name CDS premia, asset swap spreads and swap rates are the quoted price from CreditTrade and Bloomberg, respectively. If we do not have the closing price on that day, we skip it and roll over to the next business day that data are available.

As there are numerous combinations of entrance trigger, holding period limit and exit trigger, we investigate those that represent the important trading philosophies. We choose 50%, 30% and 10% opening cushions, or ratios of basis and mid CDS premia, for the entrance triggers in the study, which stand for the 'slow-in', 'normal', and 'quick-in' trading philosophies. When an investor chooses 50% as the opening cushion, he is more risk-averse than those who choose 10% cushion level, as he bypasses some trading opportunities.

We use 10-day, 30-day and 60-day holding period limits to check the impact if an investor cannot hold the position for as long as he chooses. For the exit trigger, we choose 90% and 70% closing cushions for the unwinding decision. The investor who has a 90% exit trigger will unwind the position when the basis has tightened 10% with respect to the basis level when the position was opened, and always closes the position earlier than those who have a 70% exit trigger. We mark these two exit triggers as 'impatient' and 'patient', respectively. If the investor is patient, he assumes that the basis will still tighten in the future and is thus willing to hold the position longer. The impatient investor, or risk-averse investor, will close the position when the basis tightens by a reasonable amount, as he does not expect the basis to contract further in the near future.

The 90% upper boundary for the exit trigger is chosen because the mean relative bid-ask spread is about 5.8%. Any exit trigger higher than 90% is likely to generate many trades where gross profits may not be sufficient to cover trading costs.

Panel A of Table 2.5 shows the descriptive statistics of the profit per trade with different opening cushions, holding period limits and closing cushions for a negative basis trading strategy. The mean profit per trade rises and the percentage of the trades that generate profit goes up along with increasing opening cushions when the holding period limit and closing cushion are unchanged. The investor has higher mean profit and more trades with profit. On average, only 22% trading strategies generate a loss; the rest have profits. The standard deviation of mean profit per trade first rises then falls as the opening cushion increases. The number of observations decreases as the opening cushion grows because the investor bypasses some trading opportunities. The results show that mean profit per trade and number of trades with a profit increase even if there are less trades. As credit risk is assumed to be priced accordingly in both markets, those which have greater difference in CDS premium and asset swap spread are more likely to present a converging basis. Therefore, those trades which have a higher opening cushion generate greater profits than those trades which have a lower opening cushion.

As we have discussed in previous section, the investor enters CDS contract and

Table 2.5: Profits of Negative Basis Trading

The table reports the mean, standard deviation, minimum value, maximum value, percentage of trades with positive profit and number of observations when negative basis trading strategy is used. All numbers are reported in basis points.

Panel A: Without Position Limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
10	Mean	-16	3	18	-15	1	11
	Standard deviation	60	62	55	58	56	48
	Maximum	319	319	319	319	319	319
	Minimum	-285	-308	-228	-285	-308	-228
	Observations	3,013	2,838	2,568	3,014	2,839	2,572
	% of trades with profit	32	55	74	37	60	73
30	Mean	-7	16	31	-6	13	22
	Standard deviation	62	58	49	59	50	42
	Maximum	319	319	319	319	319	319
	Minimum	-285	-243	-166	-285	-233	-101
	Observations	1,287	1,189	1,124	1,288	1,189	1,125
	% of trades with profit	37	64	84	45	71	84
50	Mean	4	30	42	5	25	30
	Standard deviation	59	53	47	56	47	44
	Maximum	241	241	241	236	236	236
	Minimum	-150	-117	-52	-150	-116	-47
	Observations	628	568	540	628	568	541
	% of trades with profit	45	75	92	52	82	93

Panel B: With Position Limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
	Mean	20	34	40	11	22	28
	Standard deviation	72	67	68	66	59	59
10	Maximum	319	319	319	319	319	319
	Minimum	-252	-176	-221	-252	-176	-221
	Observations	298	257	234	388	352	324
	% of trades with profit	65	78	85	61	75	83
	Mean	18	36	47	10	23	30
	Standard deviation	77	70	65	67	57	53
30	Maximum	319	319	319	319	319	319
	Minimum	-259	-137	-114	-259	-137	-101
	Observations	169	144	128	225	208	192
	% of trades with profit	60	77	88	61	76	85
	Mean	27	44	55	21	35	40
	Standard deviation	68	63	58	61	55	53
50	Maximum	241	241	241	213	213	213
	Minimum	-131	-117	-49	-131	-105	-36
	Observations	98	90	82	124	120	110
	% of trades with profit	68	86	91	69	83	91

protection buyer and buys a piece of cash bond. Without loss of generality, the investor can arbitrarily increase the notional of CDS and cash bond, given these transactions do not have impact on market prices. We use the profit per trade across all trades in our sample in order to fairly compare the results.

Banks apply credit line limits for each CDS and bond. We use mean profit per trade to compare the results from different trading strategy for the same credit line limits.

There is another measure which adds up all profits from basis trade. We do not use this approach because it does not take value at risk into account. By adding all profits together, the investor cannot directly compare two different strategies as credit lines which are used are not fully identical.

We look at the total profit with different constellations by multiplying the mean profit per trade by the number of observations, and find that the strategy with a 10% opening cushion, 60-day holding period limit and 70% closing cushion generates the highest total profit. The 10% opening cushion enables the investor to make many trades while the 60-day holding period limit and 70% closing cushion enable profits to be reaped when the basis is converging if the credit risk is priced accordingly in the cash bond and derivative markets.

We compare the results of profit per trade with 10-day, 30-day and 60-day holding period limits. The mean profit per trade and percentage of trades with positive profit rise as the holding period gets longer. With a longer holding period, the investor is less likely to be forced to liquidate the position when the closing cushion has not yet been hit. Although there is some risk that the basis may even widen through time, the economic relationship between the credit derivative and the bond markets will drive the basis tighter. There is no clear pattern for the standard deviation as the holding period limit increases, instead, some standard deviations of profit per trade take the form of an inverse U-shape. If we normalize the mean by the standard deviation, the strategies with a 60-day holding period limit clearly outperform the strategies with either a 10-day or 30-day holding period.

When analyzing details of the mean profit per trade with 70% and 90% closing cushions, we find that the mean profit per trade goes down when the closing cushion increases from 70% to 90%, except for the trading strategies with a 10-day holding period limit, albeit the difference is small. If the basis tightens to 90% of the old basis level and bounces back to the 100% level within 10 days, an investor who had stuck to a 70% closing cushion would miss the chance to unwind his position and to earn the profit. If the holding period limit was extended, the basis could have continued tightening [10]. These factors make the pattern of mean profit per trade with a 10-day holding period and 70% and 90% closing cushions different from those with 30-day and 60-day holding period, respectively.

We use the non-parametric Wilcoxon test to check whether the differences in the mean profit per trade in the sample are statistically significant. Table 2.6 shows the Wilcoxon statistic with different opening cushions, holding period limits and closing cushions.

The four columns of each panel show the test statistics for negative basis trading, with and without a position limit, and for positive basis trading with and without a position limit.

Panel A presents the test statistics across different opening cushions. The mean profit per trade of strategies with a higher opening cushion is significantly higher than that with a lower opening cushion at 5% significance level. Hence, Hypothesis 1 cannot be rejected.

Panel B reports the statistics when the holding period limit varies. The mean profit per trade with a long holding period limit is significantly higher than that with a short holding period limit. So Hypothesis 2 cannot be rejected.

[10] In Table 2.5, we see that the percentage of trades with profit increases as the holding period gets longer; otherwise the percentage drops because of additional financing costs.

Panel C documents the test statistics of the standard deviation in strategies with different holding period limits. The result shows that null hypothesis, i.e. the standard deviation of trading strategies with a 10-day holding period limit equals that of the strategies with a 30-day holding period limit, can be rejected. The same result is found for the null hypothesis that the standard deviation of trading strategies with a 10-day holding period limit equals that of the strategies with a 60-day holding period limit. However, we cannot reject the null hypothesis that the standard deviation of trading strategies with a 30-day holding period limit equals that of the strategies with a 60-day holding period limit in negative basis strategy with position limit. Hypothesis 3 can thus be rejected.

Panel D shows the test statistic for two closing cushions. The mean profit per trade with a 70% closing cushion is significantly higher than that of the strategy with a 90% closing cushion. So Hypothesis 4 cannot be rejected.

Table 2.6: Hypothesis Testing

The table reports the test statistics of non-parametric Wilcoxon test with different opening cushions, holding period limits and closing cushions.

Panel A: Opening cushion

	Negative basis without position limit	Negative basis with position limit	Positive basis without position limit	Positive basis with position limit
H_0: p(OC=30) = p(OC=10) vs H_a: p(OC=30) > p(OC=10)	-13.39*	-0.336	-37.90*	-21.14*
H_0: p(OC=50) = p(OC=30) vs H_a: p(OC=50) > p(OC=30)	-9.44**	-2.77**	-17.87**	-9.78*
H_0: p(OC=50) = p(OC=10) vs H_a: p(OC=50) > p(OC=10)	-20.18*	-3.31**	-49.60**	-27.11**

Panel B: Holding period

	Negative basis without position limit	Negative basis with position limit	Positive basis without position limit	Positive basis with position limit
H_0: p(HP=30) = p(HP=10) vs H_a: p(HP=30) > p(HP=10)	-30.99**	-6.44**	-29.44**	-11.26**
H_0: p(HP=60) = p(HP=30) vs H_a: p(HP=60) > p(HP=30)	-18.18**	-3.27**	-16.22**	-5.58**
H_0: p(HP=60) = p(HP=10) vs H_a: p(HP=60) > p(HP=10)	-48.29**	-9.54**	-44.85**	-16.50**

Panel C: Standard deviation

	Negative basis without position limit	Negative basis with position limit	Positive basis without position limit	Positive basis with position limit
H_0: σ(HP=10) = σ(HP=30) vs H_a: σ(HP=10) $\neq$ σ(HP=30)	1.08*	1.24*	0.67*	0.94*
H_0: σ(HP=30) = σ(HP=60) vs H_a: σ(HP=30) $\neq$ σ(HP=60)	1.33*	1.04	1.33*	1.55*
H_0: σ(HP=10) = σ(HP=60) vs H_a: σ(HP=10) $\neq$ σ(HP=60)	1.43*	1.29*	0.90*	1.45*

Panel D: Closing cushion

	Negative basis without position limit	Negative basis with position limit	Positive basis without position limit	Positive basis with position limit
H_0: p(CC=70) = p(CC=90) vs H_a: p(CC=70) > p(CC=90)	4.45**	7.42**	35.18**	20.29**

* significant at 5% level
** significant at 1% level

2.5.2 Impact of Position Limit

We also analyze the position limit feature. With the above strategy, the investor will continue building his positions if the basis is still significantly wide after the first position is opened. Since the arbitrage position is self-funded[11], some will argue that it makes sense just to increase the position at the first day to two-fold or more. In practice, hedge funds may take the double down strategy, i.e. they double bets on the risky arbitrages because they regard it as an even better chance than before. However, risk managers are likely to reject the taking of excessive positions. Hence, we assume that the investor can open only one long position and one short position for each name. He is allowed to build other positions for the same entity if, and only if, the previous position is closed. Therefore, the risk is better controlled than if many positions are built with the direct consequence that the frequency of trading has decreases notably. When the position limit is reached, the investor has to bypass trading opportunities even though the entrance trigger is met. We assume that the investor can have only one long or short position in each underlying entity.

In credit markets, there are certain bases which do not converge due to the specialness of either CDS or bond. Since our strategy is based on the expectation that credit risks are priced accordingly, we shun the cases where CDS and bond include specialness, and concentrate on the bases where credit risk is the main driving factor[12].

Using this approach, the investor can avoid building excessive positions in those special CDS and bonds whose credit risks do not converge. We expect a higher mean profit per trade here than for a strategy without a position limit.

Panel B of Table 2.5 and the second column of Table 2.6 describes the arbitrage profits for single names with position limits and tests the statistical significance

[11] No upfront payment from the investor in the CDS contract.

[12] A concrete example is Deutsche Telekom bond 7.5% 2033. This bond has a step-up clause in the prospectus. If Deutsche Telekom's issuer ratings, both from S&P and Moody's, are downgraded to the grade below BBB+ and Baa1, the coupon will increase by 50 basis points. Therefore, the DT 7.5% 2033 has a special component, and its CDS and asset swap spread do not necessarily converge.

using the Wilcoxon approach, respectively.

When the opening cushions for the strategies rise, we observe that mean profits increase, which implies that the wider basis is more likely to converge than the others. The proportion of trades with positive profits also goes up along with increasing opening cushions. Hypothesis 1 cannot be rejected when the position limit for each individual name is imposed.

The mean profits and the proportion of positive profits increase as the holding period limit increases. Again, the investor reaps higher profits with a longer holding period limit to avoid interim liquidation. The second column of Table 2.6 Panel B shows that Hypothesis 2 cannot be rejected.

However, the standard deviations of the profits no longer have a hump shape. On the contrary, the standard deviation drops with an increasing holding period limit, except for the trading strategy with 50% opening cushion, 60-day holding period and 90% closing cushion. With the position limit, the investor will not take further positions if the basis does not tighten. Hence, he avoids trading bases which do not converge. Hypothesis 3 is thus rejected.

The mean profits and proportion of positive profits go down when the closing cushions expands. When the closing cushion is 90%, the mean profits and proportion of positive profits are lower than those with 70% closing cushion. So Hypothesis 4 cannot be rejected.

By placing the position limit, the investor could avoid taking excessive risk when the basis does not tighten in a considerable period of time. Although the number of trades is only around 16% of those without a position limit, the investor can be much better off as the mean profit is higher. Since the position is self-funded, i.e. he could raise the notional amount invested in every trade if he has access to the capital market, the investor prefers the strategies with a position limit because of the higher mean profits.

2.5.3 Impact of Rating, Sub-periods, Sector and Currency

The basis smile effect is well documented in previous researches. The basis at the high and low ends of the rating spectrum is higher than for those in the middle of the spectrum. The underlying names with a high rating, such as Aaa or Aa, usually have very low or even negative asset swap spreads as their credit quality is higher than that of Libor. Given that the CDS premium is greater than zero by definition, we observe a positive basis for the higher rating classes. The basis of lower rating classes, Baa or below, is also expected to be positive due to the thin supply of the CDS protection. Hence, a high CDS premium drives the basis wider. The stylized facts of the basis smile suggest that the discrepancy between the CDS premium and asset swap spread is rating dependent, and affects profits and losses in basis trading. We incorporate rating dummy variables into our calculations to check whether the impact of the rating class is substantial.

We also add the industry and currency dummy variables to check if the different industries or the currency of the underlying have any influence on the profits from the basis trading.

As the market is maturing, more investors will exploit the mis-pricing between two markets, which could substantially remove possible arbitrage opportunities. We also incorporate a time trend variable into the model to capture the impact of market maturity on profits from basis trading.

The regression equation is thus formed:

$$
\begin{aligned}
\pi_i = c + \beta_{Time} T_i + \beta_{Aaa} D_{Aaa,i} + \beta_{Baa} D_{Baa,i} \\
+\beta_{Cur} D_{Cur,i} + \beta_{Automobile} D_{Automobile,i} + \beta_{Financial} D_{Financial,i} \\
+\beta_{Consumer} D_{Consumer,i} + \beta_{Telco-Utility} D_{Telco-Utility,i} + \epsilon_i,
\end{aligned}
\tag{2.3}
$$

where c is the constant, D_{Aaa}, D_{Baa} are dummy variables for the rating class Aaa/Aa and Baa[13], D_{Cur} is dummy variable for the denominated currency, $D_{Automobile}$, $D_{Financial}$, $D_{Consumer}$ and $D_{Telco-Utility}$ are dummy variables for the sectors of automobile, financial and insurance, consumer goods and telecommunications and utilities sectors, respectively. T captures the time trend, which is calculated as the year when the position is built minus 2001.

Table 2.7: Linear regression using profits from negative and positive basis trading

The table reports the results of various regressions for negative and positive basis trading strategies with different combination of exogenous variables. The t-statistics, R-squared and number of observation are also shown.

	Negative basis without position limit	Negative basis with position limit	Positive basis without position limit	Positive basis with position limit
Currency	13.9	1.5	44.6	17.8
	(12.79)**	(0.56)	(16.42)**	(4.11)**
Automobile	9.3	-18.1	-7.2	0.3
	(5.22)**	(3.34)**	(1.11)	(0.03)
Financials	-1.0	-7.7	-28.4	-19.7
	(0.86)	(2.26)*	(8.66)**	(3.84)**
Consumer goods	-25.6	-8.4	-10.2	-6.6
	(17.07)**	(11.31)**	(2.65)**	(0.95)
Telco/Utility	-5.3	26.4	-55.8	-19.3
	(3.79)**	(7.46)**	(19.22)**	(3.81)**
Aaa/Aa	-9.7	-12.5	55.0	19.1
	(8.89)**	(4.14)**	(21.17)**	(4.21)**
Baa	-10.8	-25.6	-68.6	-74.6
	(8.75)**	(6.80)**	(24.65)**	(15.32)**
Time trend	-9.9	-8.3	16.7	5.1
	(23.64)**	(7.64)**	(23.59)**	(3.92)**
Constant	20.9	44.7	-85.6	-27.2
	(21.23)**	(20.6)**	(30.26)**	(3.31)**
Observations	27,519	3,537	103,278	19,961
R-squared	3%	8%	3%	2%

* significant at 5% level
** significant at 1% level

The results are reported in Table 2.7. The first two columns of Table 2.7 show the parameter estimates and t-statistics of negative basis trading strategies with and without a position limit, respectively. We run a least-square regression with several groups of exogenous variables, such as time trend, rating class, currency and industrial sector.

[13]As we have grouped ratings Aaa, Aa, A and Baa, the rest of the names have an A rating.

In the first column, we show the parameter estimates of the negative basis trading strategy without a position limit. The coefficient on the currency dummy variable is -34 bps and is statistically significant, which suggests that basis trading with US$-denominated names generates higher profits than that with euro-denominated names. The significance and sign of the coefficients on industry sector dummy variables are mixed. The coefficient for the automobile sector is negative and significant, while for consumer goods it is positive and significant. The coefficients on financials and telco and utilities are not statistically significant. Basis trading in the consumer goods sector generates on average 59.1 bps profits higher than the others, while the automobile sector gives on average 12.5 bps profits lower profits. Both Aaa/Aa and Baa rating dummies are statistically significant and negative. The profits per trade of basis trading with Aaa/Aa and Baa ratings are 8.1 bps and 6.2 bps lower than the profits per trade with A rating, respectively. The coefficients for the time trend is 1.8 bps, which suggests that on average the profit per trade increases along the time axis.

The estimates for the negative basis trading strategy with a position limit are reported in the second column. The coefficient on the currency dummy variable is significant and negative at -11.9 bps. This is in line with the results of the trading strategy without a position limit. Additionally, the coefficients on industry sector dummy variables, such as automobile, financial, and consumer goods have the same sign and statistical significance as those of the trading strategy without position limit. The only exception is that the coefficient for the telco and utility sector dummy variable is now positive and statistically significant. In contrast, the coefficient is negative and insignificant when there is no position limit. The coefficients for rating dummy variables have the same sign and statistical significance as those of the trading strategy without a position limit.

From the regression results, we find that the coefficients on rating dummy variables are negative and statistically significant for trading strategies both with and without position limits. Therefore, we cannot reject Hypothesis 5. However, the tests on the null hypothesis that profit per trade decreases as the market gets more mature give mixed results. When the investor has no position limit, the profit per trade on average can even increase along the time axis. The profit per trade decreases when the investor has a position limit. Hence, we can reject Hypothesis 6 when there is no position limit, but cannot reject it when there is.

2.5.4 Analysis of Positive Basis

Table 2.8 presents the mean and standard deviation of profits from positive basis trading. Comparing the mean profit per trade with that of negative basis trading, we find that the mean values of positive basis trading are substantially lower than those of negative basis trading.

The changes in mean profit per trade due to the changes in opening cushion, holding period limit and closing cushion are similar to those of a negative basis trade: the mean profit per trade increases as the opening cushion goes up, the holding period limit is longer and the closing cushion is lower. The inverse U-shape standard deviation is observed when the holding period limit is 30-days. We find the standard deviation declines with 10-day and 60-day holding period limits. Table 2.6 shows the statistical test of the hypothesis. From these results, Hypothesis 1, 2 and 4 cannot be rejected but Hypothesis 3 is rejected.

The strategies with a position limit perform better. When the opening cushion is greater than or equal to 30%, the holding period limit is longer than or equal to 30-days and the closing cushion is 70%, the mean profits are between 18 bps and 47 bps. The investor has avoided taking excessive positions that are less likely to converge by implementing the position limit. Nevertheless, the results of mean profit per trade are falling like a stone when the investor switches from the negative basis trading with a position limit to the positive basis trading with a position limit. The mean profit per trade of strategies with negative basis is higher than that of strategies with positive basis; while the standard deviation of strategies with negative basis is lower than that of strategies with positive basis.

The third and fourth columns of Table 2.7 reports the parameter estimates and

Table 2.8: Profits of Positive Basis Trading

The table reports the mean profit, standard deviation, different quantiles, minimum value, maximum value, percentage of trades with positive profit and number of observations when positive basis trading strategy is used. All numbers are reported in basis point.

Panel A: Without Position Limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
10	Mean	-48	-28	-6	-45	-34	-24
	Standard deviation	263	273	200	208	187	153
	Maximum	1,402	1,520	1,657	1,354	902	902
	Minimum	-5,991	- 6,551	-5,722	-5,750	-6,355	-5,750
	Observations	10,454	9,654	8,448	10,451	9,650	8,443
	% of trades with profit	29	43	52	22	26	29
30	Mean	-15	8	22	-13	-4	0
	Standard deviation	212	179	170	144	121	129
	Maximum	1,402	1,520	1,657	1,354	902	902
	Minimum	-5,529	-5,006	-5,006	-5,750	-5,750	-5,750
	Observations	5,105	4,637	4,048	5,101	4,633	4,044
	% of trades with profit	35	52	62	31	37	41
50	Mean	1	9	16	-1	3	6
	Standard deviation	63	66	64	50	49	48
	Maximum	857	857	857	613	613	613
	Minimum	-524	-402	-121	-524	-402	-210
	Observations	2,684	2,490	2,201	2,683	2,489	2,200
	% of trades with profit	38	54	66	41	49	55

Panel B: With Position Limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
10	Mean	-23	-10	1	-42	-31	-25
	Standard deviation	146	158	145	205	210	181
	Maximum	694	747	747	747	902	902
	Minimum	-1,640	-2,784	-2,778	-5,722	-6,551	-5,722
	Observations	1,082	1,001	875	2,957	2,756	2,427
	% of trades with profit	34	41	46	21	25	28
30	Mean	-1	23	36	-15	-2	2
	Standard deviation	163	155	131	187	183	193
	Maximum	876	1,080	876	876	902	902
	Minimum	-1,995	-1,002	-756	-5,750	-5,750	-5,750
	Observations	555	497	439	1,439	1,318	1,158
	% of trades with profit	45	59	65	30	37	41
50	Mean	14	32	38	2	7	10
	Standard deviation	106	113	116	65	66	67
	Maximum	850	850	850	613	613	613
	Minimum	-167	-266	-121	-219	-266	-146
	Observations	297	265	239	785	737	660
	% of trades with profit	47	66	72	39	48	53

t-statistics of the time trend, the rating class, the currency and the industrial sector dummy variables. The parameter estimates on currency dummy variables are significant. Basis trading with euro-denominated cash bonds and CDS gives a higher profit on average. The coefficients with the industry sector dummy variables gives a mixed pictures. The coefficients on the dummy variable of the automobile sector are not statistically significant. Contrarily, the coefficient on consumer goods sector from positive basis without a position limit is significant and negative; the coefficients on financials and telco and utility sectors are negative and significant.

The coefficients on Aaa/Aa rating dummy variables are positive and significant, which differs from those of negative basis trading with negative and significant parameter estimates. The coefficients on Baa rating dummy variables are negative and significant, and have the same sign and significance as those of negative basis trading. So Hypothesis 5 cannot be rejected. The coefficient estimates on time trend is positive and significant for the positive basis trading strategy without position limit, but insignificant for the positive basis trading strategy with position limit. Hence, Hypothesis 6 is rejected.

The mean profits of positive basis trading are substantially lower than those of negative basis trading. There are several factors driving the bad performance of positive basis trading.

First, bid-ask spreads of CDS premia in positive basis trading have higher mean values than those in negative basis trading. The bid-ask spread, a proxy for the liquidity of the CDS contract, is an exogenous variable which does not depend on the sign of the basis. A high bid-ask spread implies low liquidity in the market. Table 2.9 shows that the mean bid-ask spreads of positive basis trading are substantially higher than those of negative basis trading when the holding period limit is 10-days. The difference declines with increasing holding period limits. Since the difference between CDS premia is discounted for five years from the date of building, one basis point of trading costs lowers the profit by about 4 bps.

Table 2.9: Decomposition of Profit and Loss

The table reports the mean CDS premia, mean bid-ask spreads of CDS premia, mean profit per trade, mean profits given profit and mean profits given loss for both positive and negative basis trading strategies. Different trading strategies are used. All numbers are reported in basis point.

Panel A: Negative basis trading without position limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
10	Mean CDS premia	45	44	43	45	44	43
	Mean bid-ask spreads	9	9	9	9	9	9
	Mean profit per trade, overall	-16	3	18	-15	1	11
	Mean profit per trade given positive profits	43	42	40	34	30	29
	Mean profit per trade given negative profits	-44	-46	-46	-44	-44	-38
30	Mean CDS premia	35	34	34	35	34	34
	Mean bid-ask spreads	8	8	7	8	8	7
	Mean profit per trade, overall	-7	16	31	-6	13	22
	Mean profit per trade given positive profits	47	45	43	36	31	30
	Mean profit per trade given negative profits	-40	-34	-31	-41	-33	-23
50	Mean CDS premia	30	28	28	30	28	28
	Mean bid-ask spreads	7	7	6	7	7	7
	Mean profit per trade, overall	4	30	42	5	25	30
	Mean profit per trade given positive profits	49	48	46	40	35	33
	Mean profit per trade given negative profits	-33	-24	-16	-34	-21	-10

Panel B: Negative basis trading with position limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
10	Mean CDS premia	51	50	51	48	47	48
	Mean bid-ask spreads	10	9	9	9	8	9
	Mean profit per trade, overall	20	34	40	11	22	28
	Mean profit per trade given positive profits	55	55	56	45	41	42
	Mean profit per trade given negative profits	-45	-44	-53	-42	-36	-38
30	Mean CDS premia	38	37	37	36	35	35
	Mean bid-ask spreads	9	8	8	8	7	7
	Mean profit per trade, overall	18	36	47	10	23	30
	Mean profit per trade given positive profits	60	60	59	44	40	39
	Mean profit per trade given negative profits	-47	-45	-48	-44	-32	-25
50	Mean CDS premia	33	32	32	30	30	30
	Mean bid-ask spreads	8	7	7	7	7	6
	Mean profit per trade, overall	27	44	55	21	35	40
	Mean profit per trade given positive profits	58	58	62	47	46	45
	Mean profit per trade given negative profits	-39	-37	-21	-36	-21	-13

Decomposition of Profit and Loss: continued

Panel C: Positive basis trading without position limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
10	Mean CDS premia	184	178	168	184	178	168
	Mean bid-ask spreads	20	19	17	20	19	17
	Mean profit per trade, overall	-68	-57	-41	-64	-57	-46
	Mean profit per trade given positive profits	58	62	64	47	44	43
	Mean profit per trade given negative profits	-118	-146	-150	-94	-92	-82
30	Mean CDS premia	107	100	94	107	100	93
	Mean bid-ask spreads	12	11	10	12	11	10
	Mean profit per trade, overall	-35	-25	-10	-31	-24	-14
	Mean profit per trade given positive profits	61	64	65	48	43	43
	Mean profit per trade given negative profits	-86	-120	-128	-65	-64	-52
50	Mean CDS premia	34	33	28	34	33	28
	Mean bid-ask spreads	5	5	4	5	5	4
	Mean profit per trade, overall	-6	6	14	-7	2	5
	Mean profit per trade given positive profits	43	41	36	27	25	23
	Mean profit per trade given negative profits	-36	-34	-29	-31	-19	-17

Panel D: Positive basis trading with position limit

	Closing cushion	70			90		
	Holding period	10	30	60	10	30	60
Opening cushion							
10	Mean CDS premia	120	118	116	133	128	125
	Mean bid-ask spreads	16	15	14	15	14	13
	Mean profit per trade, overall	-34	-15	0	-54	-44	-35
	Mean profit per trade given positive profits	55	56	62	45	45	44
	Mean profit per trade given negative profits	-78	-64	-53	-79	-74	-65
30	Mean CDS premia	108	96	89	86	81	76
	Mean bid-ask spreads	13	11	10	10	9	8
	Mean profit per trade, overall	-17	20	32	-30	-19	-6
	Mean profit per trade given positive profits	68	73	72	50	49	51
	Mean profit per trade given negative profits	-83	-55	-41	-63	-58	-46
50	Mean CDS premia	47	44	39	35	33	29
	Mean bid-ask spreads	7	7	6	5	5	5
	Mean profit per trade, overall	1	9	40	-9	6	10
	Mean profit per trade given positive profits	67	64	63	38	35	33
	Mean profit per trade given negative profits	-57	-98	-24	-39	-21	-17

Secondly, We observe more positive basis in our sample. Let us look at the involved transaction of positive basis trade. To trade positive basis, the investor sells a bond and enters a CDS contract as protection seller. In this strategy, the investor needs to borrow the bond, which is usually difficult in bond market. Therefore, the number of positive bases is higher than that of negative bases as positive bases trade is difficult to implement. We also observe that the mean profit per trade of positive basis is lower than that of negative basis. The main reason is that positive bases do not converge as positive basis trade is difficult to implement. If the strategy were easy to implement, investors would have sold bonds and entered CDS contract as protection seller. These transactions would have driven CDS premia higher and asset swap spreads of bonds lower, and bases would have converged.

Thirdly, we find the mean profits are conditional on the profit or loss. If trades generate profit, mean profits are close for positive and negative basis trading, while if trades generate losses, they are substantially different in the two trading strategies. In Table 2.9, we observe lower mean profits for positive basis if the trades generate losses. When the creditworthiness of the underlying deteriorates, an investors will buy CDS protection regardless of the price[14]. Unfortunately, in this case, the investor who executes his trading strategy according to the opening cushion, holding period limit and closing cushion, writes the CDS protection. And as the basis widens again, the trading strategy backfires and the investor suffers substantial losses.

Lastly, the higher CDS premium incorporates the cheapest-to-deliver option. Such an additional character in the CDS contract may justify the discrepancy between the CDS premium and asset swap spread, especially a higher CDS premium, as both credit risk and the CTD-option are priced into the CDS premium.

[14]As stylized facts, we see many investors were better buyers of CDS contracts when there was massive unwinding of synthetic CDOs and covering positions of Lehman Brothers and Icelandic banks in the second half of 2008. The CDS quotes, especially ask quotes, were very high and sometimes did not even exist.

2.6 Conclusion

Our study checks the relationship between CDS premia and asset swap spreads by implementing basis trading strategies. We replicate the strategies used by traders using asset swap for the perceived interest rate risk. This paper provides essential analysis for evaluating these various strategies. We find that there are positive mean profits per trade when appropriate basis trading strategies are implemented to exploit the different prices for credit risk in credit derivative and bond markets. Mean profits depend on the rating class and industrial sector, while the time trend is of mixed statistical significance and affects the profits from the basis trading. In general, mean profits from negative basis trading are higher than those from positive basis trading due to trading costs and the credit risk exposure.

To earn higher profits, the investor needs to open a position when the basis is wide and close it when the basis has tightened substantially. A less strict holding period limit raises the mean profit per trade. If there is a position limit for each individual name, mean profits are also higher. These findings have important implications for market participants when there is a disconnection between CDS and asset swap spreads.

An out-of-sample approach would be helpful to determine and compare the results of different trading strategies.

2.7 Appendix

2.7.1 A Concrete Example

We now look at a concrete example with US$10m notional amount. Citigroup's five-year CDS with quarterly payment is quoted at 28/36 on 25 April 2002. The 28/36 is a pair of bid and ask quotes, which means the dealer is to ask for 36bps for the CDS protection and to give away the CDS protection for 28bps. The asset swap spread of Citigroup's cash bond (ISIN: US201615DL29) is quoted at

51.10 bps. The bond has semiannual coupon payment and the redemption date is 15 November 2006. The day count conventions are 30/360 and actual/360 for the bond and CDS, respectively.

Table 2.10: A Concrete Example

Panel A: CDS Quotes (bps)

Date	Bid	Ask
25 April 2002	28	36
6 May 2002	40	50

Panel B: Asset Swap Spreads (bps)

Date	Spread
25 April 2002	51.1
6 May 2002	49.54

Panel C: 3-mo Libor (in %)

Date	Rate
25 April 2002	1.93%
6 May 2002	1.92%

Panel D: Accrued Interest of Asset Swap Floating Leg (in %)

Accrued interest of asset swap when opening the position	Accrued interest of asset swap when closing the position	Profit of Libor
0.4676%	0.5368%	0.0002%

Table 2.10(a) - (c) shows the quotes of the CDS premia, asset swap spreads, and Libor. The basis spread is -19.1 bps. Suppose this the basis spread level meets the entrance trigger for the trading strategy, the investor executes the trading strategy by entering the five-year CDS contract as protection buyer. In the meantime, he longs the bond with the same face value at the dirty price, i.e. he pays both clean price and accrued interest of the bond. The investor immediately enters the asset swap contract at the asset swap spread, i.e., he agrees to transfer the semiannual payments to the counterparty, which is the same as the coupon payment of the bond. The counterparty agrees to pay the investor Libor rate plus asset swap spread on a quarterly basis. The Libor rate is 1.93% and the asset swap spread is 51.1 bps on that day. The day count conventions are 30/360 and actual/360 for the fixed leg and floating leg, respectively.

If the bond is traded below (above) par, the investor pays (receives from) the dealer the difference between par value and the bond's clean price. Furthermore, the investor pays the accrued interest from asset swap floating leg and receives the accrued interest from the bond coupon payment. There are 69 days between the last floating leg payment and now (from 15 February 2002 to 25 April 2002, see the second column in Panel E). The payment of the accrued interest on the bond coupon cancels out the amount received from the accrued interest from the fixed leg of the asset swap. Therefore, the investor's total cash outflow at 25 April 2002 is US$10,046,760 [15].

The investor borrows this cash outflow in the overnight market at the Fed fund rate of 1.88% that day. If he is going to roll over his loan to the next day, the Fed fund rate will change. Fed fund rates are reported in Panel H.

On 6 May 2002, the CDS is quoted at 40/50, and the asset swap spread is 49.54bps. If we assume the exit trigger of the trading strategy is not met but the holding period limit is, the investor unwinds his position that day. He terminates the CDS contract with the counterparty and pays the accrued interest on the CDS. The day count convention of CDS is actual/360 and the holding

[15] It equals the face value plus the accrued interest for the floating leg of the asset swap.

A Concrete Example: Continued

Panel E: Discount Factor for Cash Flows of Asset Swap

Payment structure of asset swap	Actual days from the day when position is opened	Actual days from the day when position is closed	Discount factor	Actual days	Profit of asset swap
2/17/1997	-1893	-1904			
5/15/1997	-1806	-1817			
8/15/1997	-1714	-1725			
11/17/1997	-1620	-1631			
2/16/1998	-1529	-1540			
5/15/1998	-1441	-1452			
8/17/1998	-1347	-1358			
11/16/1998	-1256	-1267			
2/15/1999	-1165	-1176			
5/17/1999	-1074	-1085			
8/16/1999	-983	-994			
11/15/1999	-892	-903			
2/15/2000	-800	-811			
5/15/2000	-710	-721			
8/15/2000	-618	-629			
11/15/2000	-526	-537			
2/15/2001	-434	-445			
5/15/2001	-345	-356			
8/15/2001	-253	-264			
11/15/2001	-161	-172			
2/15/2002	-69	-80			
5/15/2002	20	9	0.99881	9	0.000004
8/15/2002	112	101	0.98668	92	0.000039
11/15/2002	204	193	0.97469	92	0.000039
2/17/2003	298	287	0.9626	94	0.000039
5/15/2003	385	374	0.95154	87	0.000036
8/15/2003	477	466	0.93998	92	0.000037
11/17/2003	571	560	0.92832	94	0.000038
2/16/2004	662	651	0.91717	91	0.000036
5/17/2004	753	742	0.90615	91	0.000036
8/16/2004	844	833	0.89527	91	0.000035
11/15/2004	935	924	0.88451	91	0.000035
2/15/2005	1027	1016	0.87377	92	0.000035
5/16/2005	1117	1106	0.86339	90	0.000034
8/15/2005	1208	1197	0.85301	91	0.000034
11/15/2005	1300	1289	0.84265	92	0.000034
2/15/2006	1392	1381	0.83242	92	0.000033
5/15/2006	1481	1470	0.82264	89	0.000032
8/15/2006	1573	1562	0.81265	92	0.000032
11/15/2006	1665	1654	0.80278	92	0.000032
					0.000640

Table 2.10 A Concrete Example: Continued

Panel F: Risky Discount Factor for Cash Flows of CDS

Payment structure of CDS	Actual days from the day when position is closed	Risky discount factors	Actual days	DF01
7/25/2002	80	0.98859	80	0.219687
10/25/2002	172	0.97564	92	0.249330
1/27/2003	266	0.96258	94	0.251340
4/25/2003	354	0.95051	88	0.232347
7/25/2003	445	0.93819	91	0.237154
10/27/2003	539	0.92563	94	0.241692
1/26/2004	630	0.91363	91	0.230945
4/26/2004	721	0.90178	91	0.227950
7/26/2004	812	0.89009	91	0.224995
10/25/2004	903	0.87855	91	0.222078
1/25/2005	995	0.86704	92	0.221577
4/25/2005	1085	0.85592	90	0.213980
7/25/2005	1176	0.84483	91	0.213554
10/25/2005	1268	0.83376	92	0.213072
1/25/2006	1360	0.82283	92	0.210279
4/25/2006	1450	0.81228	90	0.203070
7/25/2006	1541	0.80175	91	0.202665
10/25/2006	1633	0.79124	92	0.202206
1/25/2007	1725	0.78087	92	0.199556
4/25/2007	1815	0.77086	90	0.192715
				4.410191

Panel G: Accrued Interest and Profit of CDS Premia (in %)

Accrued Interest of CDS	Profit from change of CDS
-0.0110%	0.1764%

Table 2.10 A Concrete Example: Continued

Panel H: Funding Cost

Fed Fund Rate	1/360	Factor	Compounded Interest
0.0188	0.0001	1.0001	
0.0181	0.0001	1.0001	1.000102
0.0181	0.0001	1.0001	1.000153
0.0181	0.0001	1.0001	1.000203
0.0181	0.0001	1.0001	1.000253
0.0188	0.0001	1.0001	1.000304
0.0188	0.0001	1.0001	1.000356
0.0181	0.0001	1.0001	1.000408
0.0175	0.0000	1.0000	1.000458
0.0175	0.0000	1.0000	1.000507
0.0175	0.0000	1.0000	1.000556

period is 10 days. Given the CDS premium of 50bps on 6 May 2002, we calculate that the accrued interest on the CDS is US$1,100 (see Panel G). The net present value of the change in the CDS premium is calculated using the risky discounting curve. Since the ask quote on 25 April 2002 is 4bps lower than the bid quote on 6 May, the profit due to the change of CDS premium is US$17,640. The total profit from the CDS part is US$16,540[16].

The cash flow from the asset swap part is composed of the profit from the change in asset swap spreads, the change in Libor, and the accrued interest from the asset swap floating leg (see Panels D and E). The cash flow from the change in the asset swap spread is calculated using the risk-less discounting curve. As the difference is now 1.56bps, the net present value is US$6,400. The Libor rate on 25 April 2002 is 1.93%, so the cash flow from the Libor's change is $\Delta Libor \cdot 20/360 \cdot DF01 \cdot 10$ million, which is US$20. There are 20 days between 25 April 2002 and 15 May 2002. $DF01$ is the discount factor at the first payment of the floating leg. The Libor for other future payment dates are not relevant since they cancel each other out. These two cash flows from the asset swap part total US$6,420.

The investor pays back the loan from the overnight market. The Fed fund rates of the following days are shown in Panel H. The accrued interest from the asset swap floating leg is US$53,680. We aggregate the accrued interest from the asset swap floating leg and calculate a net payment of US$1,334[17].

If the bond is priced below (above) par, the investor receives (pays) the difference between the par value and the bond's clean price from (to) the dealer. Afterwards, he sells the bond in the market at the dirty price. Hence, the effect of the dirty price is netted out and he receives the par value for certain.

The profit of this round-trip trading is the sum of the cash flow of CDS, asset swap and the overnight market loan. The investor earns US$24,294 profit here[18].

[16] By subtracting US$1,100 from US$17,640.

[17] The principal and interest are US$10,046,760 and US$5,586. By subtracting them from US$10,053,680, we calculate a change of US$1,334.

[18] We add the US$16,540, US$6,420 and US$1,334.

2.7.2 The Profit per Trade of Selected Trading Strategies

Fig 2.2 to Fig 2.13 show the distribution of the profits of all trades with negative and positive trading strategies throughout the time. Fig 2.2 to Fig 2.4 report the profit per trade of negative trading strategies without position limit, while Fig 2.5 to Fig 2.7 present that with position limit. Fig 2.8 to Fig 2.10 show the profit per trade of negative trading strategies without position limit and Fig 2.11 to Fig 2.13 report that with position limit.

Most of the trades take place in the earlier period of the whole sample. The trades are less observed after year 2004. Moreover, we find extreme losses in the positive basis trading part. In the left part of Fig 2.8, we find that one trade even generates more than 100% losses. One can easily recall the credit event happened in the autumn of 2001: the collapse of Enron. Furthermore, some losses between 20% and 80% are also found in the same figure, which are generated by the trades with Alcatel, sovereign debt of Brazil, and Enron, respectively. To sell the CDS at normal rate and buy them back in an inflated price shortly is the main reason for these deep under water losses.

Figure 2.2: The Profit per Trade of Negative Trading Strategies: Comparison of Opening Cushions

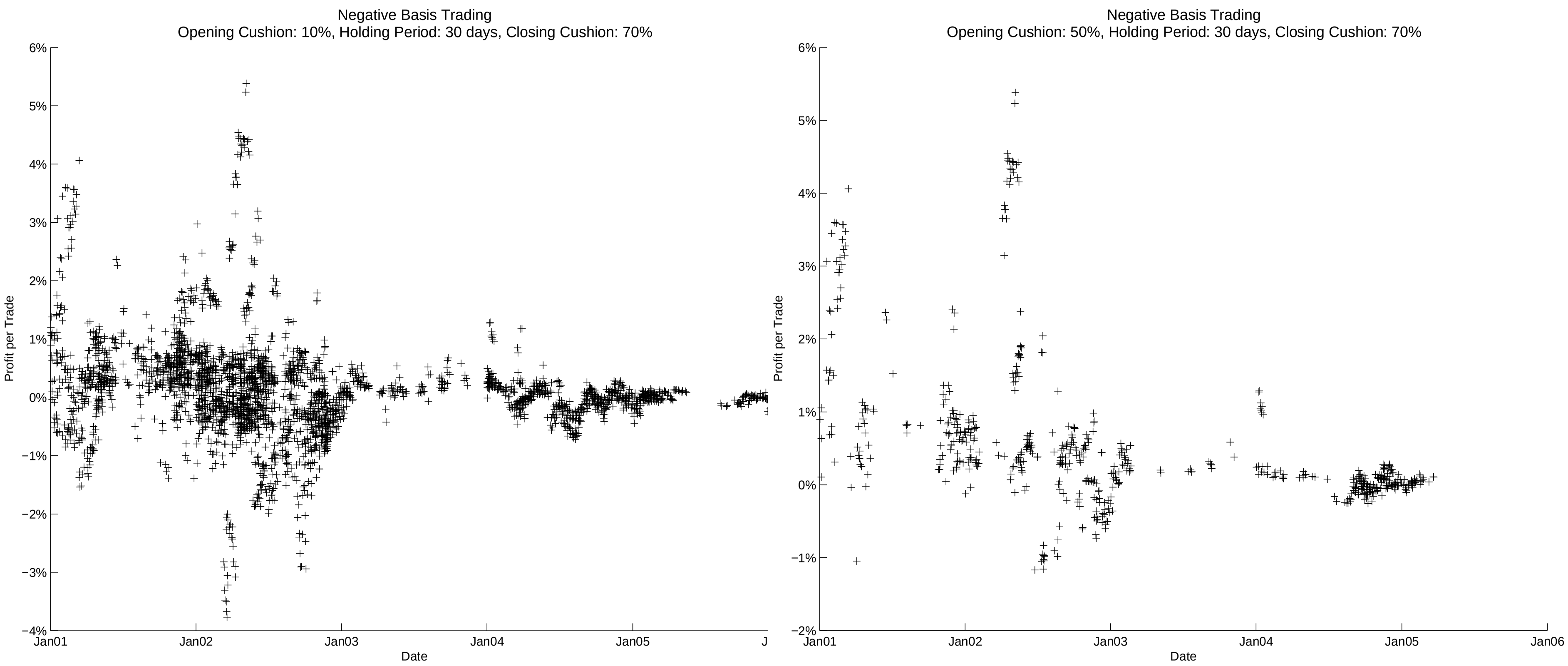


Figure 2.3: The Profit per Trade of Negative Trading Strategies: Comparison of Holding Periods

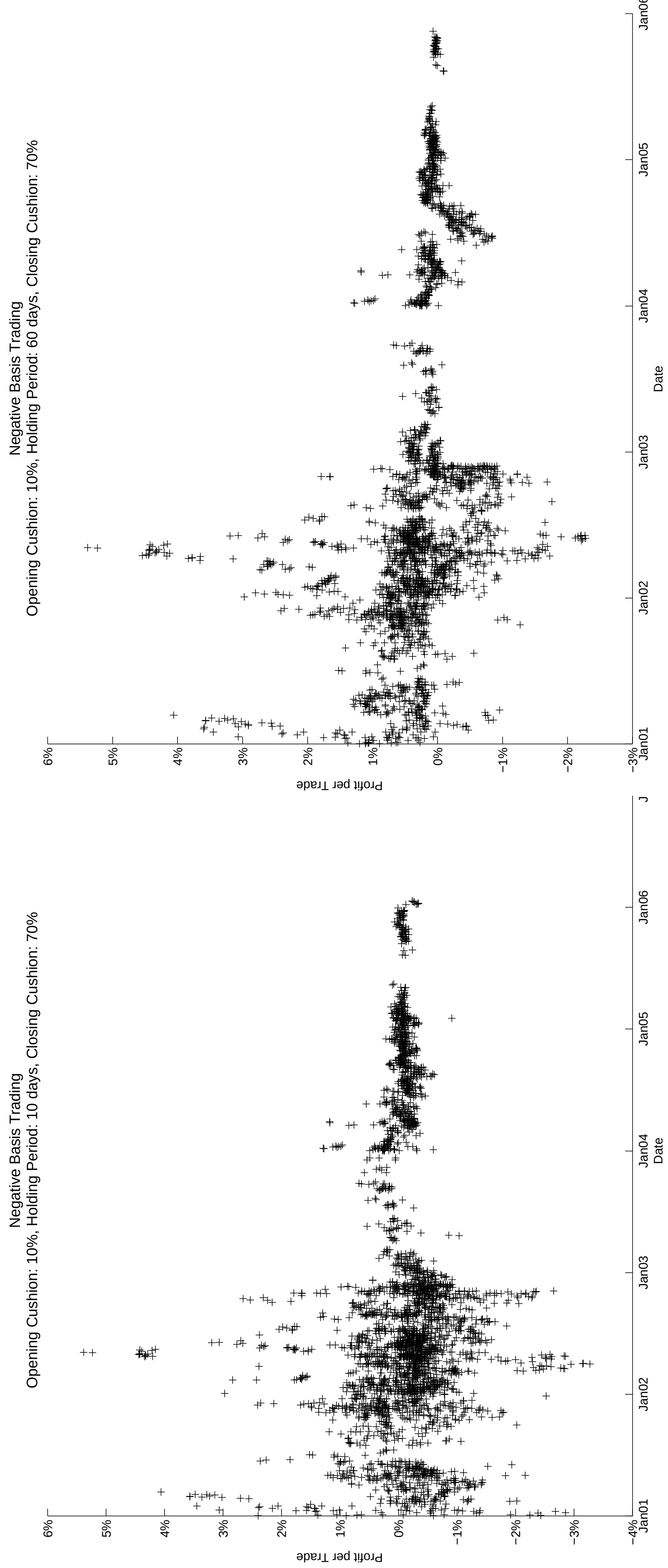


Figure 2.4: The Profit per Trade of Negative Trading Strategies: Comparison of Closing Cushions

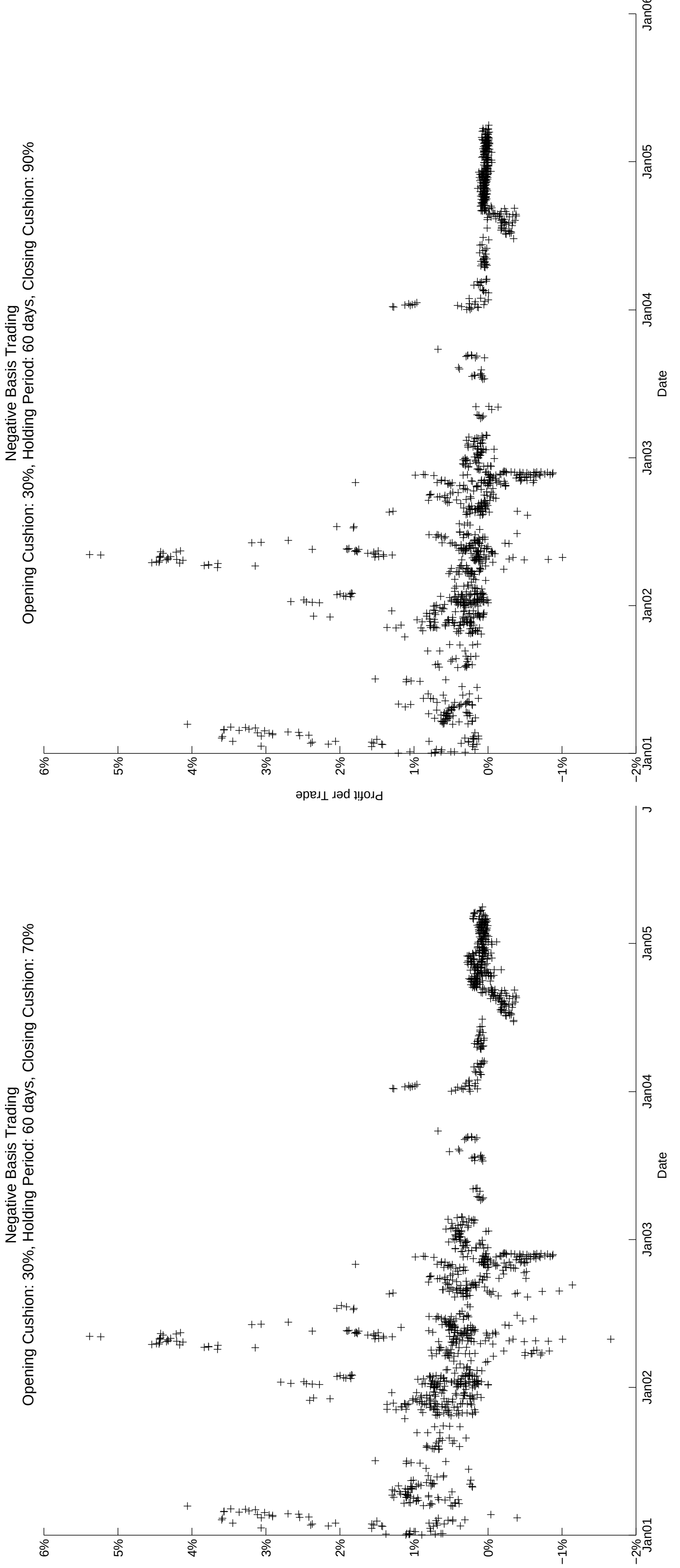
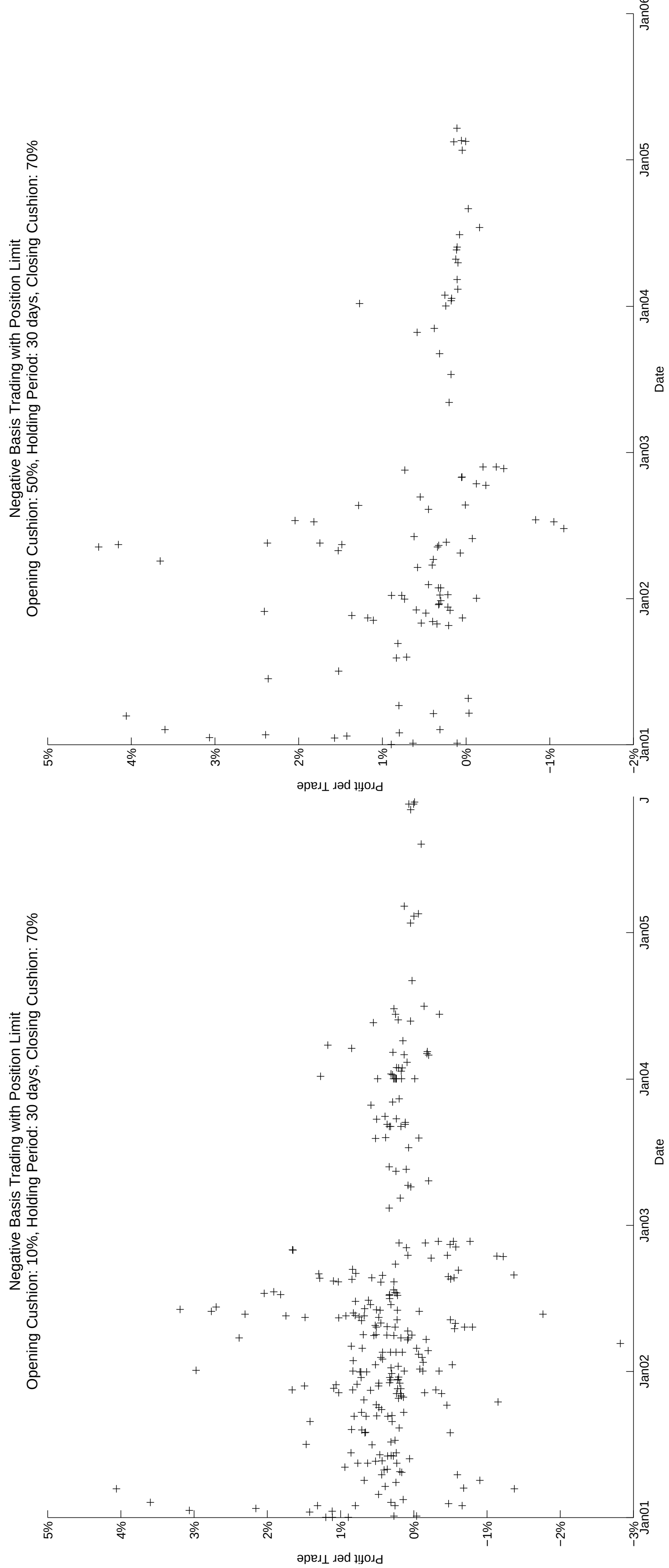


Figure 2.5: The Profit per Trade of Negative Trading Strategies with Position Limit: Comparison of Opening Cushions



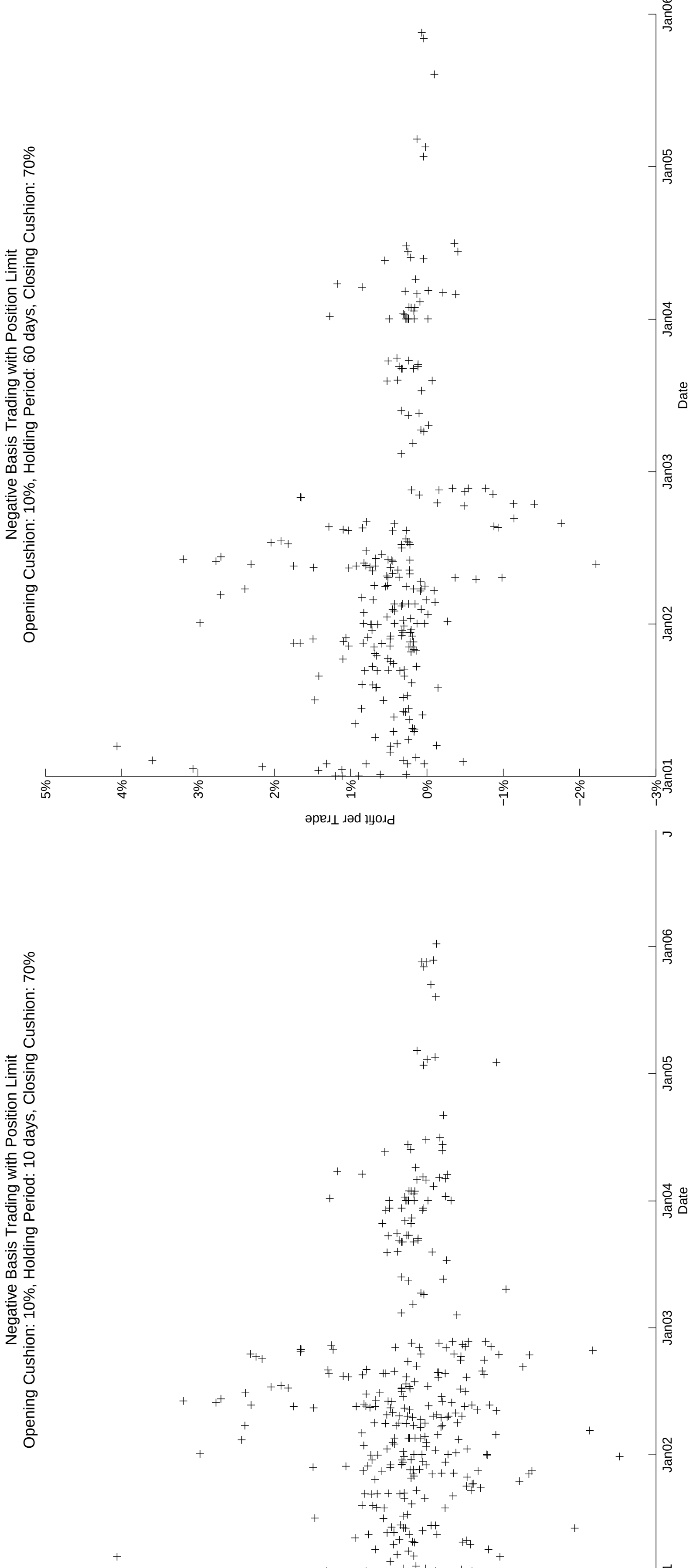


Figure 2.6: The Profit per Trade of Negative Trading Strategies with Position Limit: Comparison of Holding Periods

Figure 2.7: The Profit per Trade of Negative Trading Strategies with Position Limit: Comparison of Closing Cushions

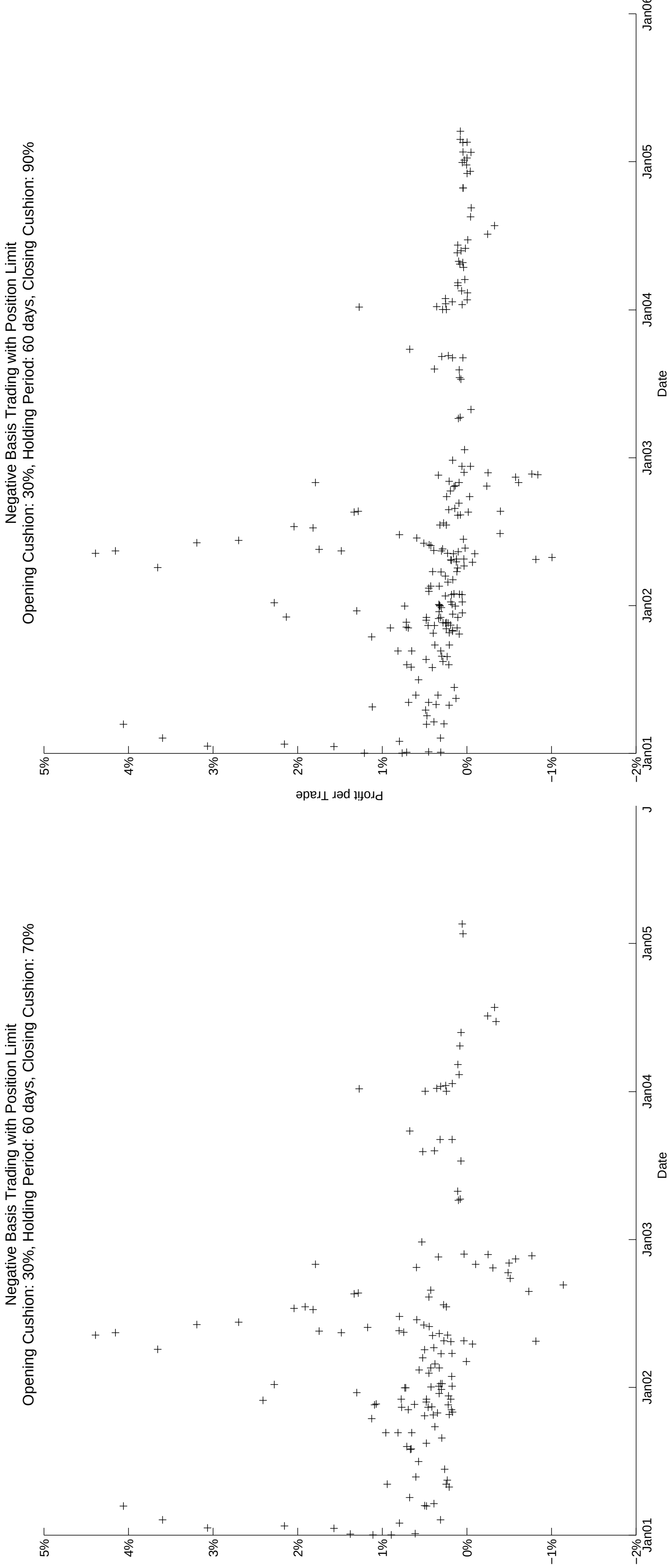


Figure 2.8: The Profit per Trade of Positive Trading Strategies: Comparison of Opening Cushions

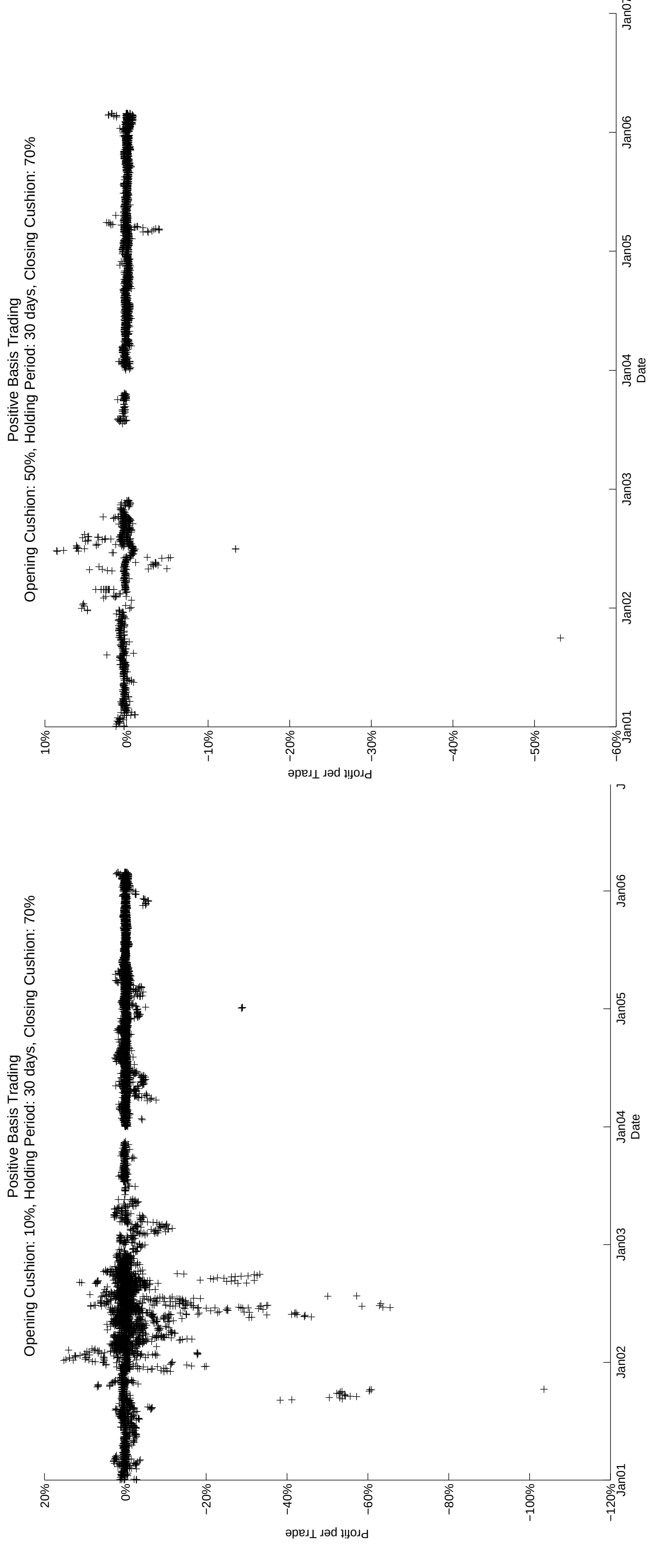


Figure 2.9: The Profit per Trade of Positive Trading Strategies: Comparison of Holding Periods

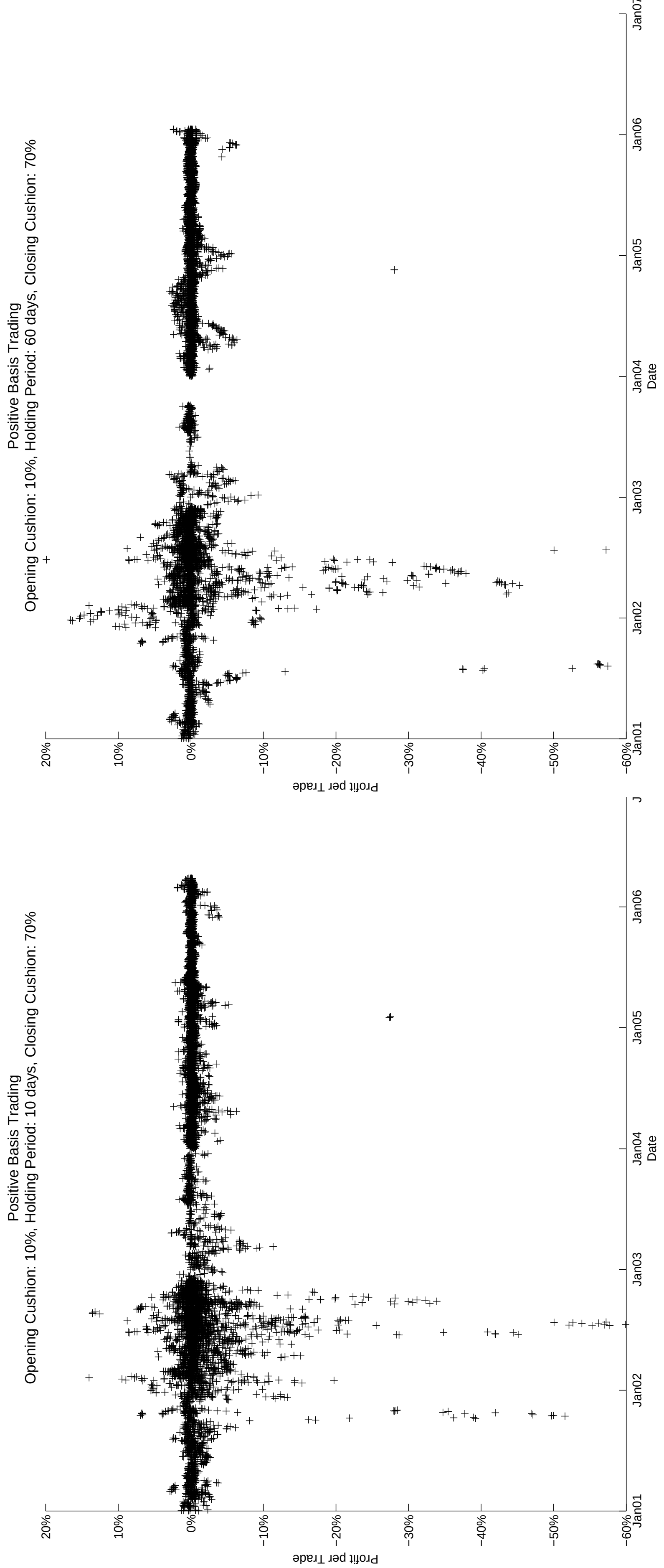


Figure 2.10: The Profit per Trade of Positive Trading Strategies: Comparison of Closing Cushions

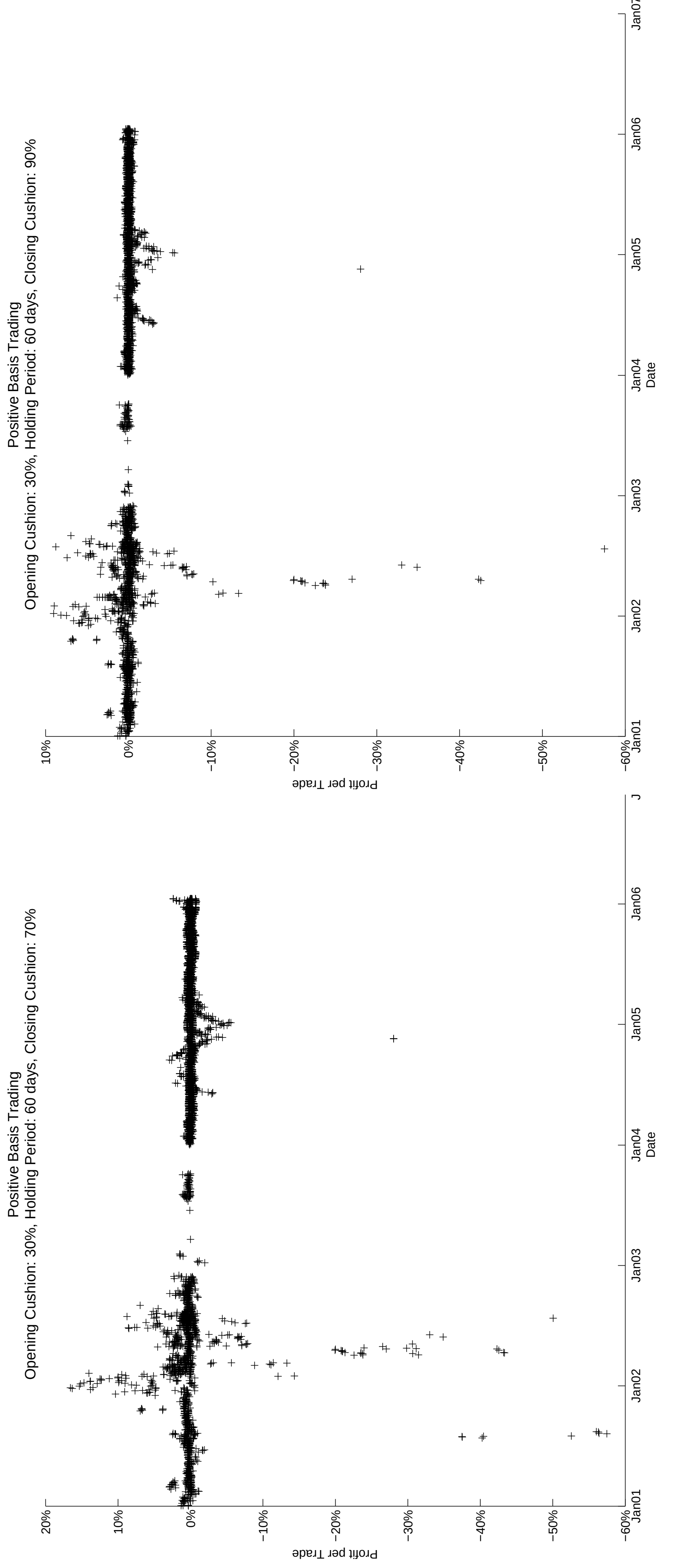


Figure 2.11: The Profit per Trade of Positive Trading Strategies with Position Limit: Comparison of Opening Cushions

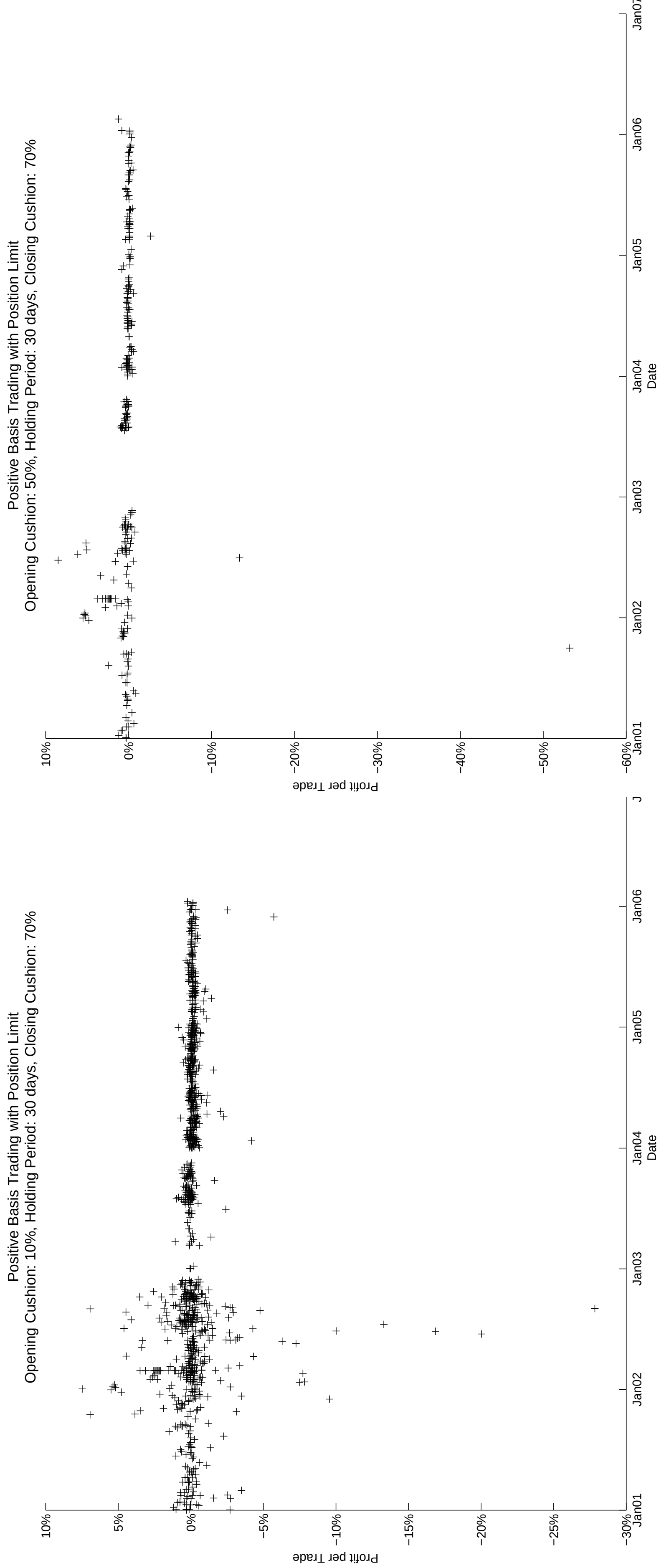


Figure 2.12: The Profit per Trade of Negative Trading Strategies with Position Limit: Comparison of Holding Periods

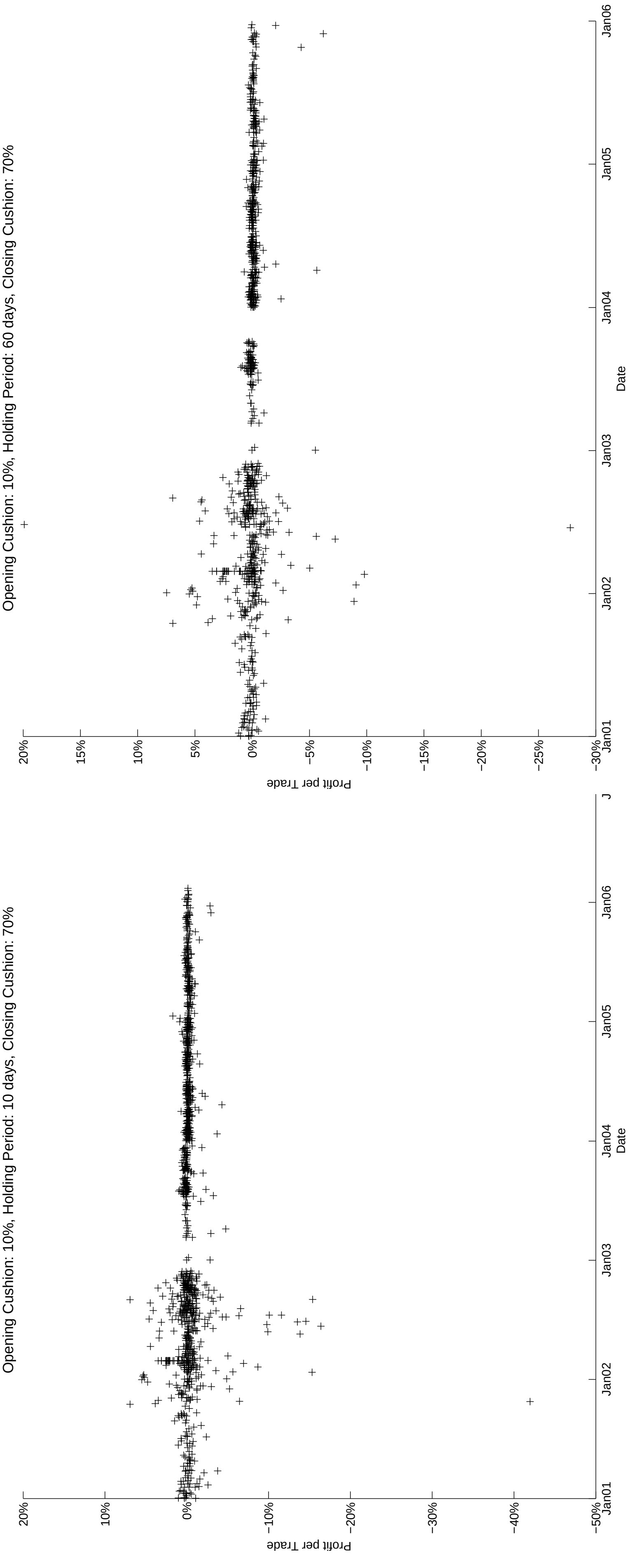
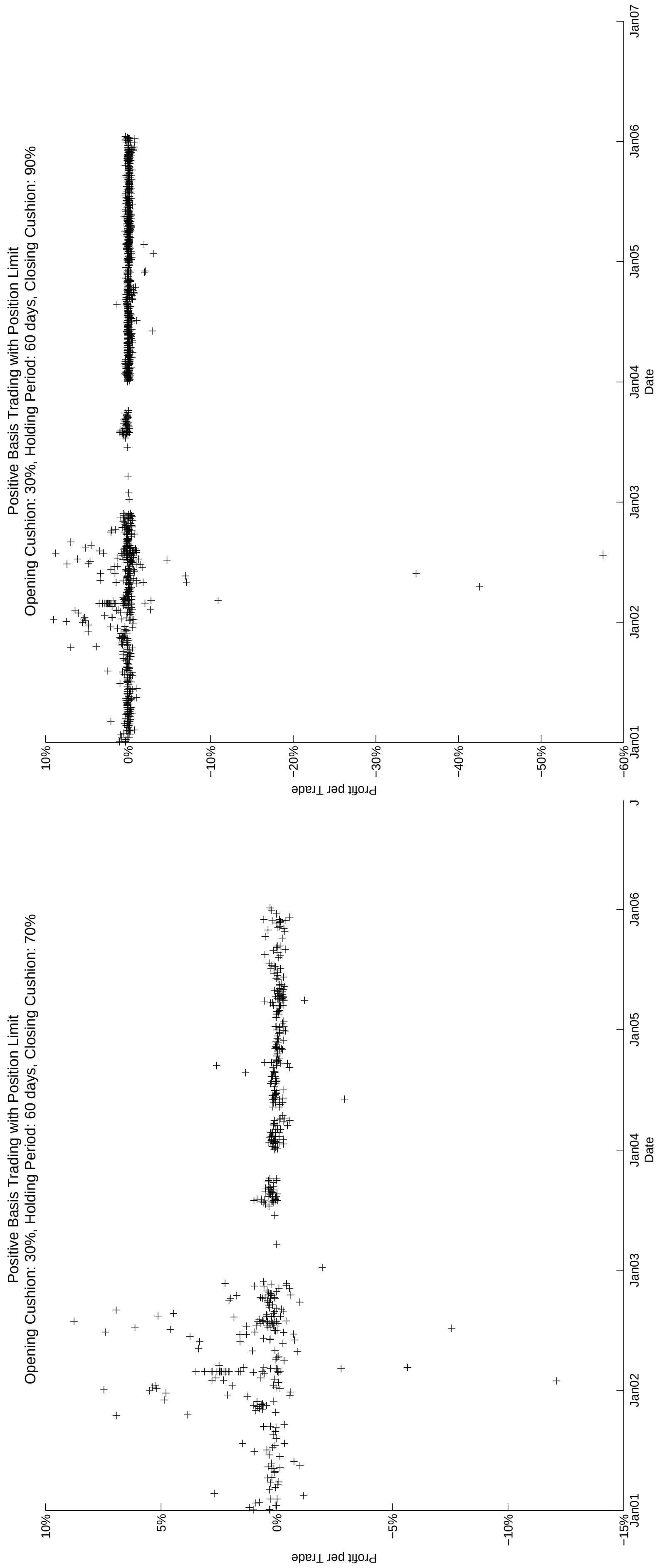


Figure 2.13: The Profit per Trade of Positive Trading Strategies with Position Limit: Comparison of Closing Cushions



2.7.3 Data quality

We have checked outliers in CDS premia and asset swap spreads of both negative and positive basis strategies.

Positive basis strategy

Basis trades with significant losses (greater than 5% per trade) are not due to data error. Here is a list of entity and respective basis trades with significant losses.

Table 2.11: List of possible outliers

Entity name	Trades
Alcatel	332
AT&T	14
Bayerische Hypo-Vereinsbank	4
Brazil	301
Colombia	124
Commerzbank	6
Deutsche Telekom	5
ENRON	194
France Telecom	31
Philippines	11
Qwest	27
Turkey	182
TYCO	600
Venezuela	236
Verizon	40
VNU	27
Grand Total	2,134

The number of trades in the second column consists of the trades in all eighteen strategies (opening trigger, holding period limit, and closing trigger).

The main reason for these negative results is the fast deteriorating credit quality. In this case, the CDS premium usually deteriorates more than asset swap spread. Additionally, the bid and ask spreads have substantially widened in this circumstance; and investors paid higher round-trip trading costs.

In this list, Enron, Alcatel, and Tyco all had bumpy times in 2001. Enron went bust, and the other two were restructured. They comprised 1,126 trades, which was more than 50% of total trades. AT&T, France Telecom, Deutsche Telekom, Quest, Verizon, and VNU have shown hikes in CDS and asset swap spreads in 2002 due to systemic risks in Telco sector, driven by WorldCom event. These Telco companies comprised only 144 trades, less than 5% of total trades.

Brazil, Philippines, Columbia, Turkey, and Venezuela comprised 854 trades when investors were burdened by emerging markets when Argentina defaulted in 2001.

The negative results are very often when we have a longer holding period limit. As the investor opens his position, and in a certain time period there was an credit event, such as Enron or Alcatel, which force him to close the position when holding period limit is met.

If we had excluded these trades out of our sample, the results would be biased as investors did not know a priori these idiosyncratic or sector risks.

Negative basis strategy

The problem we find is the data point of Carnival Corp as at May 8, 2002. This one will be deleted.

Chapter 3

The Determinants of the Basis

3.1 Introduction

One of the main risks when investing in a debt security is credit risk, i.e. the risk due to uncertainty about a counterparty's ability to meet payment obligations. Credit derivatives can help investors and corporations manage the credit risk of their investments by providing insurance against adverse movements in the counterparty's creditworthiness. If the borrower defaults, the losses on the investment will be at least partly offset by the insurance payments. Thus, credit derivatives can provide a way to decrease in total credit risk exposure.

In spite of the downturn in most other markets, the market for credit derivatives has dramatically expanded within the last ten years. According to a recent survey by ISDA [2009], the global credit derivatives market grew from virtually zero in 1993 to $40 billion in 1996. In 2008, it reached an outstanding notional value of $38.6 trillion. Credit default swaps (CDS) make up by far the largest share of the market for credit derivatives and are traded for two main reasons: to manage credit risk and to earn income.[19] First, pure credit risk can be transferred directly from one party to another without actually transferring ownership of

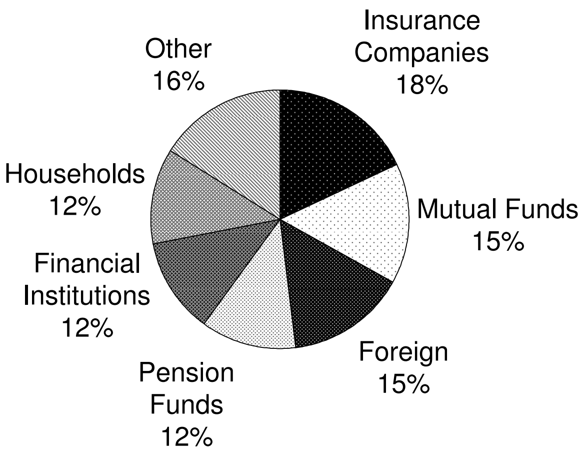
[19] Tax and balance sheet considerations also induce investments in CDS.

the debt instruments themselves. Secondly, CDS may be used speculatively to take a view on the deterioration or the improvement in the credit quality of a reference credit exposure. These strategies aimed at exploiting the differences between cash bond markets and credit default swap markets have become known as 'trading the basis', where the basis is defined as the CDS spread minus the bond spread.

In this paper, we focus on the panel structure and the determinants of the CDS premia, credit spreads and the basis. Since the credit derivatives market and the bond market should be strongly interdependent as both are a medium for trading default risk, we first try to identify the relationship between single issues through unit root tests and Johansen cointegration tests. The latter allow us to determine whether a similar behavior exists in the long run. To extend this approach, we apply a vector autoregressive model and thus probe whether price movements in one market spread instantaneously into the other. A further analysis through a vector error correction model is used to investigate the direction, strength and rapidity with which these changes occur. After establishing the relationship of the two markets, we turn to a direct analysis of the basis, of its sensitivity both to specific issues and to general factors like equity returns, volatility and liquidity. As an alternative to the fairly standard use of first differences, we propose the use of a fixed-effects estimation that allows us to simultaneously capture the effect of the previous period on the subsequent period, and the additional effect of the regression variables.

The remainder of the paper is structured as follows. In section 3.2, we describe the markets in which bonds and CDS are traded. Section 3.3 summarizes theoretical and empirical studies on bond yield spreads, CDS and the basis. A descriptive analysis of our raw data and the sampling process applied is followed by a description of the time series in section 3.4 and 3.5. Basic econometric properties are explored in section 3.5.4. An empirical analysis of the determinants of CDS premia, credit spreads and the basis is conducted within the fixed effects model in section 3.6. Section 3.7 summarizes and concludes.

Figure 3.1: Bond Holders



3.2 Bond and CDS Markets

3.2.1 The bond market

Bond markets match government agencies and companies intending to borrow capital at a predictable cost over a fixed period of time with investors who have funds to lend.

The major issuers of bonds are central governments, government agencies, municipals and corporates. The Bank for International Settlements (BIS) has estimated a growth from an aggregate value of \$28 trillion in 1995 to \$38 trillion in 2001. Generally, a central government is the largest single issuer of bonds, but the aggregate corporate sector has a higher amount of outstanding debt (approximately 60% since 2000.)

Once issued, bonds are bought by numerous institutions, including mutual funds, pension funds, insurance companies, banks and private households.

Overall, the secondary market is strongly dominated by well-informed institutional investors who seek to buy long-standing credit obligations that can be easily sold in the market. Since bonds represent a contractual obligation of the issuer to investors, interest is paid in regular intervals and provides the bondholder with a regular and predictable cash flow. Although bond prices may fluctuate considerably, an investor can rely on each coupon payment and the eventual repayment of face value. In addition, bonds offer the chance to match the duration of assets and liabilities, and allow diversification of an investment portfolio to reduce the overall risk profile. Their interest rate sensitivity makes bonds a common instrument for interest rate hedging and speculation.

The secondary market is mainly organized as an OTC market, with the exception of a few organized secondary bond markets such as the New York Stock Exchange Automated Bond System (NYSE ABS), but these do not usually provide a liquid market without arbitrage opportunities.

3.2.2 The CDS Market

A credit default swap constitutes the exchange of a fee, paid by the default protection buyer, for a payment by the default protection seller if a credit default event on a given reference asset occurs. The default protection can be purchased on almost every debt instrument, including loans, bonds, sovereign and derivative contracts. The default payment usually equals the difference between the original value of the reference asset and its recovery value. In this respect, the payments associated with the CDS are very similar to those for an insurance contract: in return for regular premium payments, any shortfall due to adverse credit events is borne by the protection seller. But in contrast to insurance, the buyer need not have an insurable interest in the debt instrument but may merely speculate that a credit event will occur.

CDS contracts can differ with regard to the maturity, the notional amount, the definition of the credit event, the protection buyer's and seller's payments, and so forth. Naturally, buyers would want to interpret the scope of protection as widely as possible, while sellers would want to interpret it narrowly. The International Swaps and Derivatives Association (ISDA) Guidelines has therefore

Table 3.1: CD Market Participants

The table gives the percentage market share of the market participants. The percentages for 2004 are estimates. Source: BBA Credit Derivatives Report.

	Buyers			Sellers		
Year	2001	2003	2004 (pred.)	2001	2003	2004 (pred.)
Commercial Banks	52	51	47	39	38	32
Securities Houses	21	16	17	16	16	15
Hedge Funds	12	16	19	10	13	16
Insurers	6	7	8	33	20	33
Corporates	4	5	7	2	4	4
Governments	2	2	2	–	–	–

published standard guidelines for these properties in its 2002 Master Agreement and in the new 2003 credit derivatives definition.

Most key CDS market participants act as buyers and sellers simultaneously.

Commercial banks have historically been the largest players in the CDS market. On the buyers' side, they account for approximately 50% of all transactions, but insurers are predicted to catch up with them on the sellers' side in 2004. Overall, commercial banks, securities houses and insurance companies still constitute the majority of market participants. Hedge funds which emerged as protection buyers in 2001, are expected to overtake securities houses as sellers in 2004.

Most activity in the CDS market is handled through intermediary dealers in the OTC trade who provide liquidity to CDS buyers and sellers, trade for their own accounts and put together and manage structured portfolio products. Current price ranges for CDS can be obtained either from internet platforms, the largest of which are Creditex and CreditTrade, or via telephone from another broker. These provide reference prices for marking-to-market existing transactions based on average prices supplied by dealers and on trade prices in the inter-dealer market. A number of large intermediaries also publish indicative bid and offer CDS price quotes for the most frequently traded sovereigns on their websites.

Although the CDS market is significantly smaller than the bond market, the ISDA definitions have led to a higher degree of standardization. Trading is concentrated at certain maturities, mainly five years, whereas bonds have different maturities and coupon payments. This may simplify CDS hedging for intermediaries and result in tighter bid-offer spreads.

In addition, CDS markets have the potential to become more liquid than bond markets for the following reasons: If companies issue debt infrequently or if long-term investors hold most of the debt, liquidity will be constrained in the bond market but not in the CDS market.[20] Taking a short position in a particular credit through the bond market involves selling the bond short and borrowing it in the repo market. Especially in Europe, liquidity in the repo market is unpredictable because a significant proportion of bond holders are restricted in their lending of securities. In cases where a company's creditworthiness quickly deteriorates, such as Xerox and Pacific Gas and Electric in 2000 and 2001, Rule [2001] has documented that the CDS market is more liquid than the bond market. An increasing number of market participants agree with these observations. While only 10 market participants provided five–year CDS prices on roughly 100 names in 2000, more than 30 banks and brokers now act as market makers on over 300 global credits. The top ten counterparties at times cover as many as 700 credits each.

Although liquidity for CDS can be low at times, it seems that the CDS market has turned into a highly accurate measure of credit quality. Credit Magazine [2004] claims that some market participants refer to the market as an additional rating agency. CDS prices for the Swiss employment agency Adecco, e. g., were rising for months before S&P downgraded the company to speculative grade in April 2004. The Bank for International Settlements [2004] explores the relationship between ratings downgrades and CDS spreads in a special analysis. The results appear to confirm that CDS spreads increasingly indicate future ratings actions and tend to widen well in advance of the announcement of a downgrade. In addition, Credit Magazine [2004] argue that the introduction of a CDS index

[20] Still, the reference securities are necessary for physical settlement following a credit event.

and the widespread use of automated trading platforms has increased liquidity almost to the level of treasury bonds.

In spite of the numerous advantages of investing in a CDS, there are a number of risk factors that may affect protection buyers or sellers. While CDS with a 5-year maturity are quite liquid, there is no active market for off-the-run maturities. In particular, instruments with a remaining time to maturity of between 4 and 5 years trade at a significant premium. Even though protection sellers mostly enjoy a very high rating, this does not mean that they cannot default. Tavakoli [2001] reports that central banks at times issue CDS on bonds issued by their central government, which implies a perfect default correlation of the bond and the CDS. Nevertheless, the CDS trades at a positive premium. Contagion is a vital element of almost all CDS because of the high degree of market concentration. It is therefore nearly impossible to obtain protection with the optimal default correlation of -1. And in spite of the higher degree of standardization since the 2003 ISDA definitions, there is still a considerable risk of legal disputes when the quality of the reference entity deteriorates.

To conclude this section, we give a short introduction to the relationship between CDS and bonds.

In theory, bond CDS spreads or premium payments should be closely related to bond yield spreads in excess of risk-free rates. To see this, consider a portfolio A composed of a short position in the CDS on a corporate bond with notional \$100 and a long position in a risk-free bond with the same notional and a portfolio B with a long position in the corporate bond on which the CDS is written. If no credit event occurs, the payoff at maturity of portfolio A and B equals \$100. In the event of a credit event, portfolio B has a payoff equal to the recovery rate R times \$100. Portfolio A, on the other hand, pays \$100 minus the protection payment (1-R) times \$100, which also adds up to R times \$100. Since the two portfolios have the same risk profile and identical payoff structures, they should also have the same initial price. Accordingly, the CDS and corporate bond should trade at the same spread level.

If the spread differential between the CDS and the bond, the basis, is not zero, it enables investors to use a common strategy termed basis arbitrage. A spread on the CDS which is higher than in the bond market is known as a positive basis. The reverse market situation, with the CDS spread below the cash price of the reference position, is known as negative basis, but is less common. Investors who believe that the basis has widened or narrowed by too much can express that view through the CDS market. Nevertheless, there are a number of highly plausible reasons why market prices for CDS can be different from credit spreads on corporate bonds. As already mentioned, a lack of liquidity in the term repo market for corporate bonds can mean that CDS premia move higher relative to credit spreads on bonds if demand for protection increases, reflecting the cost of taking a short position in the bond to arbitrage between the two markets. The cheapest-to-deliver option described above could also require CDS premia to be higher. Protection sellers for CDS may require an additional premium since they have no contractual rights such as information requirements. Some market participants may prefer to take credit risk through an unfunded instrument such as a CDS instead of purchasing a bond. This may increase the supply of default protection and thus reduce CDS premia relative to bond spreads. Different tax rates may also have a discriminating impact on CDS and bond spreads.

3.3 Literature Review

The growth in literature on credit derivatives and CDS in particular has kept up with the development of the market. In this section, we provide an overview of selected theoretical and empirical studies of bond yield spreads, CDS prices and the basis.

Theoretical work in the area commences with Longstaff and Schwartz [1995] who present a model for pricing credit spread options based on credit spreads that follow an exogenous mean-reverting process. Das [1995] prices credit derivatives within a structural-form compound option model framework with stochastic interest rates. Reduced-form models are developed by Duffee [1999], who gives a simple argumentation for the replication of CDS, Hull and White [2000] and Hull and White [2001] who allow for correlated defaults and Houweling and Vorst [2003] who implement a Duffie-Singleton type of model for CDS quotes. They show that the equality between CDS premia and bond spreads only holds approximately in the market and that this approximation results in a large deviation between theoretical and market CDS premia. For the empirical part of their study the authors estimate risk-neutral processes for default-free interest rates, hazard rates, and recovery rates, and find that using the government curve as a proxy for the risk-free interest rate systematically overestimates credit risk, using the swap curve results in a small but statistically significant bias, and that only the repo curve yields unbiased estimates. To extract both hazard and recovery rates from bond prices, they keep the recovery rate fixed and scale the hazard function accordingly. Overall, Houweling and Vorst [2003] find that the reduced-form model outperforms the direct comparison of CDS premia and bond spreads, but that the premia generated by the model still deviate by 20% to 50% from the observed market premia in an out-of-sample test.

In a similar model framework, Longstaff et al. [2005] develop closed-form expressions for corporate bond prices and CDS premia in order to study the components of bond yield spreads using information extracted from CDS. For this purpose, they discount bond cash flows at an adjusted rate incorporating a liquidity process, and thus attempt to capture the liquidity component in bond prices. The risk-free interest rate and the hazard rate are computed from CDS premia. To test robustness, the authors alternately take government rates, repo rates and swap curves as specifications of the riskless rate, and find a significant non-default component in corporate spreads for each of them. This non-default component is strongly related to measures of bond-specific illiquidity, measures of Treasury richness and measures of overall liquidity in the fixed-income markets.

Empirical studies on the properties of bond spreads, CDS premia and the basis are scarce. Collin-Dufresne et al. [2001] use a time-series of bond price quotes to analyze the impact of financial variables suggested by traditional default-risk models such as the spot rate, the slope of the yield curve, leverage, volatility and the business climate on bond yield spreads. They find that these factors only explain one quarter of the variation and that the residuals are highly correlated. This is attributed to the presence of a large systematic component which the authors are unable to determine from a variety of structural-form variables such as liquidity, firm value and economic state variables. Firm specific factors in particular seem to affect bond yield spreads more than the aggregate measures common to all corporate bonds.

Aunon-Nerin et al. [2002] explore the explanatory power of factors implied by structural-form models such as ratings, market value leverage, local interest rates, the variance of stock prices etc. for CDS premia. In contrast to the results of Collin-Dufresne et al. [2001] for bonds, they find that all these variables have a significant impact on CDS premia while liquidity measured as market capitalization does not seem to matter. By fitting a reduced-form model and subsequently analyzing the model errors, the authors claim that equity market information such as stock price change and volatility can explain up to 50% of these errors.

Extending the work of Houweling and Vorst [2003], Blanco et al. [2005] investigate the validity of the theoretical relationship between CDS premia and bond credit spreads and determinants of changes of these measures of credit risk. For their sample of CDS quotes and bond yields, they find that the approximate equality holds only when the risk-free rate is proxied by the swap rate and argue that the credit spread and the CDS premium form a lower and upper boundary for the true price of credit risk, respectively. The results for the factors affecting credit spreads and CDS premia are in line with earlier studies. Variables suggested by structural-form models explain a quarter of the variation in CDS premia and are worse for credit spreads. The impact of stock returns and implied volatilities is larger and more significant for CDS premia. On the other hand, price discovery seems to take place primarily in the CDS market, resulting in the same price for credit risk in both markets in the long run.

This aspect is further explored by Norden and Weber [2004]. Their analysis of a time-series of stock, bond and CDS market data indicates that stock returns are negatively associated with CDS and bond spread changes for the same company, and that the stock market leads both of the other markets. In a pairwise comparison, the authors document a more pronounced relationship between CDS and stock markets than between bond and stock markets. CDS spread changes, in turn, lead bond spread changes in most cases and significantly contribute to price discovery. The strength of these lead-lag relationships seems to be affected by the average credit rating of the firm but not by its size.

Schueler and Galletto [2003] explore the time-series behavior and determinants of the basis. For the time interval from September 2001 to March 2003, they are able to demonstrate a clear co-movement of the average basis with the performance of the credit markets measured as the JPMorgan's aggregate index euro. Plotting the average basis across the ratings spectrum, they obtain a basis smile which agrees with the intuition that high-quality bonds often trade sub-Libor whereas CDS premia must be positive, while speculative grade debt trades at a large positive basis because of repo market restrictions and because the CTD option is more valuable for CDS on low-rated reference entities. In addition, they argue that differences in the investor base for bonds and CDS, demand and supply conditions, and bond characteristics such as convertibility and coupon step-up or step-down features, have an impact on the basis.

Summarizing the results of these studies, there is broad agreement that structural-form models can only capture a fraction of actual credit risk through variables such as leverage, the firm value and interest rates. Equity-specific factors such as changes in the stock price, the stock return and implied volatility have additional explanatory power for both bond spreads and CDS. On the other hand, results for the impact of liquidity are mixed. Liquidity seems to be a central issue at least for the bond market, and thus for the basis, while CDS are less affected, a result that is in line with the intuition that CDS positions can either be neutralized through resale in the secondary market or through taking the reverse position in an otherwise identical contract.

3.4 Data

In this section, we describe our data set for the CDS, the bonds and the variables that are used in our analyses.

3.4.1 CDS Data

The data source for the credit default swaps is the CreditTrade database. CreditTrade, a London-based company, is one of the largest providers of online information on credit derivatives. For the period from January 2001 to April 2004, we obtain daily bid and ask quotes for 333 issuers. Since we have no transaction prices available, we compute the mid quote as a proxy. At the issuer level, the database contains the issuer name, industry, country and region according to CreditTrade classification, as well as the issuer rating for senior debt. At the issue level, it includes the rank of the debt deliverable under the CDS contract, the time to maturity, the currency and notional amount of the default protection, the credit type and information on the restructuring option. Some 59% of all observations are for issuers from the corporate sector, 21% for banks and 20% for sovereigns. We see that the fraction of CDS on corporate debt including banks relative to the sovereign sector is higher than the proportion of corporate to sovereign debt. This illustrates that debt issues which are nearly default-free, such as U.S. Treasury notes, are less popular as reference entities in the CDS market. Investors have little incentive to hold them as default insurance, and the stable credit quality makes them less attractive for speculative purposes.

Among the 23 industry groups contained in the database, the financial industry makes up for 23% of all observations. The next groups, telecommunications and manufacturing, only make up about 11% and 9%, respectively. The remaining sectors all lie between 0.4% and 5%. The high number of CDS for the telecommunications sector may partly be due to higher risk perception caused by the spectacular WorldCom default.

At the issue level, we find that the time to maturity ranges from 1 year to 10 years, but at 77%, 5 years to maturity is most common by far, followed by 10 and 3 years at 7% each. This agrees with most earlier studies. The currency of the underlying issue is either U.S.$ (55%), Euro (39%) or Yen (6%). It is interesting to note that $-denominated issues are most prevalent, even though North America accounts for only a quarter of all reference entities. We see this as an indication that most reference entities from the emerging markets and about half of the Japanese reference entities are destined for the international market, and therefore denominated in U.S.$.

The notional amount of the CDS equals 5 million for 34% of all observations, 10 million for 60% and 1 billion for 6%. The higher notional of 1 billion may be less in demand because few protection buyers need to insure an equivalent exposure. The amount is also too large for speculators, who may have to physically deliver the bond in the case of default through constrictions in the repo market. In addition, only few protection sellers may be willing to take on such a large amount of credit risk and the price will thus be disproportionately high.

For 94% of all observations, only senior debt is deliverable under the CDS contract, the other observations allow for delivery of subordinate debt. This reflects the preference of most market participants for standardized contracts. About 54% of the observations concern CDS that incorporate the pre-1999 definition of restructuring, see section 3.2.2. Some 36% already use the modified restructuring option, and 10% allow for modified modified restructuring. It is remarkable that even for a time-series running from 2001 to 2004, such a high proportion of contracts contain current ISDA specifications. We believe that this illustrates how necessary consistent treatment of restructuring is for the future development of the CDS market.

From the entire CDS data sample, we first exclude all time series for which there are not enough changes. Our selection criterion is a minimum of 15 changes on a weekly basis per half year. In addition, we only choose CDS with 5 years to maturity since we have no consistent way to treat CDS with different times to maturity. These two criteria decrease our sample by approximately 25%.

3.4.2 Bond Data

We collect data for the bond market from the Bloomberg online system. For each of the remaining CDS, we first determine the ticker of the issuer as denoted in the CreditTrade database. All bonds listed under this ticker are then chosen as potential reference bonds.[21] First, all bonds with embedded options such as convertibility, step-up or step-down coupon features and put/call features are excluded from the sample since we have no consistent way to price these options for different issuers and times to maturity. As bonds paying floating rate coupons are subject to interest rate risk while CDS specify a regular fixed payment, we only choose bonds with fixed coupon rates. In order to avoid exchange rate issues, we also discard bonds denominated in currencies other than U.S.$ and Euro. Except for these criteria, a priori we accept all senior unsecured bonds and debentures with maturity between 2001 and 2015, including those that were classified as non-outstanding during the time of our analysis. Since this sample does not necessarily include a bond that exactly matches the five years of maturity of the corresponding CDS, we choose one bond with less and one bond with more than five years to maturity during the life of the CDS. We then use linear interpolation to obtain an appropriate synthetic five-year bond. In order to keep the error as small as possible, we also limit the difference between the maturities of the two bonds to five years.

We calculate two proxies for the bond yield spread. First, we determine the difference between the synthetic five-year bond yield and the five-year treasury rate. For European entities, the yield to maturity of the Bundesobligation[22]

[21] At times, this ticker applies to more than one company. In this case, we include all bonds identified by this ticker in our search. Altria Group, Inc., e. g., is a subsidiary of Philip Morris Cos., Inc. and all Altria bonds are listed under the "MO" ticker.

[22] The Bundesobligation is a debt security issued by the federal government of Germany with fixed coupon payments and a five-year term to maturity. It is deemed to be the default

is used while we choose the five-year U.S. Treasury rate for American issues. Secondly, we compute the difference between the synthetic bond yield and the interest swap rate. This allows us to compare whether, as Houweling and Vorst [2003] find, the interest rate swap rate is a better proxy for the risk-free interest rate than the treasury rate because of a liquidity premium the latter may contain. Hence, we also use an interest rate swap of five-year tenor.

Subtracting our proxies for the risk-free rate from the corporate bond yield, we obtain credit spreads with respect to both the government rate and the swap rate. Therefore, we also are able to compare the behavior of the basis with regard to the two proxies of the risk-free rate.

3.4.3 Equity Data

Equity market data is in two parts: equity market index data and individual equity data, all acquired from the Bloomberg service. For the European reference entities, the benchmark market index is the Dow Jones Stoxx 50. This index provides a blue-chip representation of sector leaders in 17 European countries. It captures approximately 60% of the free-float market capitalization of the Dow Jones Stoxx Total Market Index, which in turn covers approximately 95% of the free-float market capitalization of the countries represented. For the American reference entities, we use the S&P 500 index as the benchmark market index. The returns from the two market indices are used as the proxies of the state variables of the whole economy. The individual equity returns are taken as proxies of the health of the individual companies.

Changes in the volatility directly affect the future expected default probabilities of the individual reference companies. To model this effect, we use the implied volatilities from traded call options. We also incorporate the call-option implied volatilities of the benchmark market indices, to capture changes in the average expected default probabilities for the whole economy.

risk-free and eligible for use as a collateral.

3.5 Descriptive Data Analysis

Before we determine the impact of the explanatory on CDS prices, bond spreads and the basis, we give a basic overview over the time–series that remain from our initial sample.

3.5.1 CDS Time Series

Most empirical studies find that the rating of the issuer of the underlying debt has a significant impact on the CDS premium. We therefore present the properties of our reference set in Table 3.2 by rating.

Table 3.2: Descriptive Statistics of CDS by Rating

Mean, median, standard deviation, skewness and kurtosis of the mean of CDS bid and offer quotes, grouped by the S&P rating. The first–to–last column gives the number of observations that obtained the rating, the last column the number of reference entities with the rating class.

S&P RATING	Mean	Std. Dev.	Obs.	Ref. Ent.
AAA	50.42	20.54	204	2
AA	39.75	27.78	1240	22
A	69.20	54.12	3407	63
BBB	152.22	116.71	1490	38
BB	544.02	293.80	425	10
B	1155.43	843.28	205	5

For the AAA rating level, we have two reference entities for which both mean and median CDS are higher than the for the AA rated issues. We believe that this is partly due to the fact that the time series for both AAA rated issues only begin in late 2001, when CDS prices were generally lower than in the following years. For all other rating levels, the mean and median increase as the credit rating deteriorates. The standard deviation relative to the mean value is lowest at 41% for the AAA rating class and highest at 78% for the A rating class. This implies that there is a high variation in CDS that is not explained by default risk alone, especially for the classes which contain a high number of observations. A t-test reveals that the top four ratings classes from AAA to BBB do not have significantly different means at the 90% significance level. The same is true for the lower two rating classes and those for which no rating was available. This supports the notion that CDS are significantly lower for investment grade debt than for non-investment grade. We also find that most CDS are written on securities that have a rating between AA and BBB, an indication that investors may combine less highly rated investment grade debt with a CDS contract as default insurance. In addition, the high relative volatility of the CDS in these classes may indicate that either the risk perception or the risk aversion of the investors have changed over time.

Overall, we find that there is substantial volatility in mid CDS quotes on the ratings level. As expected, we find that the mean CDS is increasing as the credit rating deteriorates.

3.5.2 Credit Spread Time Series

For the CDS time series, we first present the properties of the credit spreads of the risky bond that was used to compute the credit spread, by rating.

From Table 3.3, we observe that the credit spread widens as the rating deteriorates. As expected, the total spread levels with respect to swap rates are about 30 basis points lower than those with respect to the government rate since swap rates are determined on Libor, which in turn supposedly contains a credit risk premium. However, the mean value of the credit spreads with respect to the government rate of the AAA class is greater than that of the AA class. At first sight, this contradicts the fact that an AAA rating signifies better credit quality. However, we note that all of the 204 observations within the AAA class take place between November 2001 and December 2003, while the 1240 observations for the AA class are spread over the entire period from January 2001 to December 2004. Such an unbalanced panel may well shift the mean credit spread of the higher ratings class upwards.

Table 3.3: Descriptive Statistics of Credit Spread by Rating

Mean, standard deviation, number of observations and reference entities of credit spread, grouped by the S&P rating.

Panel A: Descriptive Statistics Using the Swap Rate

S&P RATING	Mean	Std. Dev.	Obs.	Ref. Ent.
AAA	25.81	6.24	204	2
AA	27.04	16.87	1240	22
A	60.84	35.09	3407	63
BBB	127.34	73.65	1490	38
BB	397.81	42.52	425	10
B	828.81	10.87	205	5

Panel B: Descriptive Statistics Using the Government Rate

S&P RATING	Mean	Std. Dev.	Obs.	Ref. Ent.
AAA	70.52	6.24	204	2
AA	61.61	22.58	1240	22
A	99.80	38.35	3407	63
BBB	160.52	76.89	1490	38
BB	442.92	42.4	425	10
B	877.91	10.87	205	5

3.5.3 Basis Time Series

We then compute the basis as the difference between the CDS price and the credit spread using both swap and government rates. The descriptive statistics are reported in Table 3.4.

We see that the mean value of the basis with respect to the swap rate is higher than that with respect to the government rate for every ratings class. The spreads between the two different measures of the basis range between 35 and 50 basis points. In addition, an effect known as the basis smile can be inferred from Table 3.4: the basis decreases while the rating deteriorates from AAA to A and subsequently increases. In their study on basis behavior, Schueler and Galletto [2003] also observe a basis smile. They argue that the higher basis for AAA and AA rated reference entities is caused by the necessity for a positive CDS premium, while credit spreads for such issues can also be negative for the swap rate. For sub-investment grade debt, the basis may widen because of repo

Table 3.4: Descriptive Statistics of Basis by Rating

Mean, standard deviation, number of observations and reference entities of the basis, grouped by the S&P rating.

Panel A: Descriptive Statistics Using the Swap Rate

S&P RATING	Mean	Std. Dev.	Obs.	Ref. Ent.
AAA	24.61	10.94	204	2
AA	12.71	13.19	1240	22
A	8.36	22.14	3407	63
BBB	24.88	37.76	1490	38
BB	146.22	19.47	425	10
B	326.61	2.07	205	5

Panel B: Descriptive Statistics Using the Government Rate

S&P RATING	Mean	Std. Dev.	Obs.	Ref. Ent.
AAA	-20.10	10.94	204	2
AA	-21.86	17.28	1240	22
A	-30.60	25.24	3407	63
BBB	-8.30	39.09	1490	38
BB	101.11	20.02	425	10
B	277.52	2.07	205	5

market constraints increasing CDS prices, or through the higher value of the cheapest-to-deliver option for CDS when the underlying bond has a higher default probability.

3.5.4 Econometric Time–Series Properties

Any regression using non-stationary exogenous and endogenous variables will only give spurious results. Before we progress further, we check the time-series properties for both the level and the first difference of the CDS, the credit spread and the basis with regard to stationarity.

Unit Root Test

To determine whether the underlying data generating processes of the time series we observe have a unit root, we apply an augmented Dickey-Fuller test. The analysis is based on a weekly basis, which suggests that it should be sufficient to include one lag in order to capture any higher order autocorrelation. In the first step, we discard all time series with fewer than 25 observations on the weekly level, which reduces our data set to 73 time series.

Table 3.5: Unit Root Test for CDS, Credit Spread and Basis

Panel A and Panel B report the results of the augmented Dickey–Fuller tests. The test is based on weekly data. The null hypothesis is that the underlying data generating process has a unit root. The column headings 1%, 5% and 10% suggest we can reject the null hypothesis at these levels, respectively. 'Above' suggests that the null hypothesis cannot be rejected at 10% level.

Panel A: Unit Root Test with Swap Rate as Risk-free Rate

	1%	5%	10%	Above
CDS	2	3	2	66
Credit Spread	4	1	4	64
Basis	16	9	6	42

Panel B: Unit Root Test with Government Rate as Risk-free Rate

	1%	5%	10%	Above
CDS	2	3	2	66
Credit Spread	3	1	2	65
Basis	10	4	7	34

Table 3.5 shows the results of the augmented Dickey-Fuller tests. Taking 5% as the threshold, we cannot reject the null hypothesis that the underlying data generating process contains a unit root for 68 out 73 time series for the CDS data. When using the swap rate as the risk-free rate with the same threshold value, 69 out of 73 time series of credit spreads are non-stationary, and 67 out of 73 time series of credit spreads are non-stationary when the series of government rates is used. Overall, more than 90% of the individual credit default swap price and credit spread time series seem to be non-stationary. Before discussing the results for the basis, as defined as the difference between the credit default swap price and the credit spread, we note that its stationarity would imply that the credit default swap price and the credit spread are cointegrated

with a cointegrating vector of $[1, -1]$. From the last rows of panel A and B, however, the null hypothesis of unit root can be rejected in only 25 and 14 basis time series at the 5% level with respect to the swap rate and the government rate; the majority are non-stationary. To determine whether this suggests a restricted cointegration, we conduct an explicit cointegration test of the credit default swap price and credit spread in the next section.

To determine the order of integration of the time series, we repeat the stationarity test on the first differences of the time series. As before, we use one-lag for possible higher order autocorrelation.

Table 3.6: Unit Root Test for First Difference of CDS, Credit Spread and Basis

Panel A and Panel B report the results of the augmented Dickey–Fuller tests on the first differences of the time series. The test is based on weekly data. The null hypothesis is that the underlying data generating process has a unit root. The column headings 1%, 5% and 10% suggest we can reject the null hypothesis at these levels, respectively. 'Above' suggests that the null hypothesis cannot be rejected at 10% level.

Panel A: Unit Root Test with Swap Rate as Risk-free Rate

	1%	5%	10%	Above
CDS	73	0	0	0
Credit Spread	73	0	0	0
Basis	72	0	1	0

Panel B: Unit Root Test with Government Rate as Risk-free Rate

	1%	5%	10%	Above
CDS	73	0	0	0
Credit Spread	73	0	0	0
Basis	71	2	0	0

Table 3.6 presents our results. Almost all time series are stationary at the 1% level on the first differences, with only two basis time series stationary at the 5% level and one at the 10% level. This allows us to conclude that the credit default swap price and credit spread are integrated of order one. Recall from Table 3.5 that 34% and 19% of the basis time series were already stationary at

this level; the rest are integrated of order one. In the next section, we try to determine further characteristics of the cointegration relationship between the CDS and the credit spread time series.

Cointegration Test

To explore the relationship between the CDS and the credit spread time series, we employ the Johansen cointegration test. The trace statistics are used to judge whether the two time series are cointegrated. Both two-lags and the constant term are included in the test.

Table 3.7: Johansen Cointegration Test

The table reports the results of the Johansen cointegration test with the CDS premium and the credit spread. The number of the cointegrating vectors are reported. Panel A shows the results using the swap rate as the risk-free rate and Panel B presents the results using the government rate as the risk-free rate.

Panel A: Johansen Cointegration Test with Swap Rate as Risk-free Rate

Cointegrating Vectors	Number
0	40
1	26
2	7

Panel B: Johansen Cointegration Test with Government Rate as Risk-free Rate

Cointegrating Vectors	Number
0	45
1	21
2	7

Table 3.7 summarizes our results. 40 and 45 tests reject the hypothesis that the CDS prices and the credit spreads are cointegrated with respect to the swap rate (the government rate). 26 and 21 tests suggest that there is one cointegrating vector for the two time series. Two cointegrating vectors are suggested by 7 tests for both rates. Comparing these results with the unit root tests in

the previous section, 25 and 14 tests reject the null hypothesis of having a unit root. Thus, an additional 8 and 14 series are stationary when the restriction of the [1, -1] cointegrating vector is not imposed.

These results indicate that 33 and 28 pairs of CDS and credit spread time series have a long-run relationship. Hence, to use the vector error correction model to analyze the relationship between the CDS premia and the credit spread is not applicable to all the single names.

3.6 Fixed Effects Estimation

3.6.1 The Effect of Individual Firm Properties

As an alternative to the vector error correction model, we analyze the relationship between the exogenous variables and the basis using fixed effects models. The intuition of using the fixed effect model is that the mean of the basis varies significantly with respect to different rating classes. Table 3.8 shows that the mean of the rating class AA is around the mean of the whole sample, while those of the A and BBB rating classes are nearly 50% and 200% that of the whole sample, respectively. As we expected, the standard deviation increases fast when the credit quality deteriorates. All these suggest there is an unobserved factor in the level of the basis which is related to the credit quality.

Table 3.8: Descriptive Statistics of Basis by Combined Rating Class

The table shows the mean, the standard deviation, the minimum, the maximum and the number of the observations of the basis by rating class. The numbers are reported in basis point.

	Mean	Std. Dev.	Min	Max	Obs.
Whole Sample	15.40	41.36	-154.68	481.24	5072
AA	12.57	17.66	-34.23	144.60	904
A	8.55	25.05	-148.57	249.87	2706
BBB	21.00	49.73	-154.68	286.94	1145

Fixed effect models are often used to explore the impact of a time-invariant, unobserved effect on the dependent variable that is itself unobservable but correlated with the regressors. As we have already seen that basis levels vary strongly within different ratings classes, we believe that the correlation assumption will hold. Because of the correlation between basis and credit quality, we adopt the fixed effect model rather than the random effect model[23].

We therefore estimate the following model:

$$basis_{i,t} = \beta_1 R^I_{i,t} + \beta_2 vol^I_{i,t} + \beta_3 liq^I_{i,t} + c_i + \epsilon_{i,t} \tag{3.1}$$

where $basis_{i,t}$ denotes the difference between the CDS premium and the credit spread on underlying i at time t. We maintain the assumption that the unobserved effect c_i is time-invariant within the sub-sample and correlated with the exogenous variables.

$R^I_{i,t}$ and $vol^I_{i,t}$ are the weekly return of the individual equity, the call-option implied volatility of the individual equity which proxies the business climate and the business risk of the underlying entity, respectively. liq is the proxy for the liquidity of the credit derivative market, which is defined as the relative bid-ask spread. In order to avoid the endogeneity problem, we take the spread on Tuesdays.[24] c_i denotes the unobserved effect that is time-invariant for each individual underlying entity i.

Since we find that both credit derivatives and bond markets exhibit significantly different behavior before and after mid 2002, we subdivide our sample into two time intervals from January 2001 to September 2002 and from October 2002 to December 2003 in order to ensure time-invariance. The specific date of Septem-

[23]The random effect model is more efficient than the fixed effect model. However, the random effect model generates inconsistent estimators when the unobserved, time-invariant factor is correlated with any of the exogenous variables. In our case, credit quality is likely to be correlated with the individual equity return, call-option implied volatility and the liquidity proxy. Therefore, we prefer the fixed effect model to the random effect model.

[24]The basis is the difference between the CDS premium and the credit spread. Therefore, using the relative spread on Thursdays is not appropriate for the estimation, so we use the relative bid-ask spread, (ask-bid)/mid CDS, on Tuesdays as the instrument variable for liquidity.

ber 30th is picked for a number of reasons. First, any attempt to separate the total sample at an earlier date would still result in an unbalanced number of observations before (1866 observations) and after (3206 observations) this date. Secondly, separating at a later point in time, on the other hand, would make the results of any estimation which uses time-sensitive data, such as equity, less indicative of the actual dependencies. We therefore chose a date when speculation about the possibility of the second Gulf war reaching a crescendo and large investor groups from the Gulf region started transferring property from the US to other countries. Meanwhile, the market had started to be concerned about on the case of WorldCom. Both left the credit derivative and bond markets more volatile. To avoid the impact of outliers, we also delete all time series for which we have less than 26 observations. The remaining number of entities is then 57.

The stock return is stationary process. The volatility and liquidity proxy are not stationary, but they are mean reverting processes, which implies that the second moment cannot be infinite.

Before estimating the model, we check the correlation between the exogenous variables. Table 3.9 presents the correlation coefficients of the endogenous and exogenous variables. We find that it is low, as the highest correlation is less than 35%.

Table 3.9: Correlation of Endogenous and Exogenous Variables

The table reports the correlation between the basis, the individual equity return, the call-option implied volatility, the liquidity proxy, the long-term interest rate and the slope of the interest rate curve.

	Basis(Swap)	Equity Return	Individual Volatility	Liquidity Proxy	Long-term Interest Rate	Slope of Interest Rate
Basis(Swap)	1					
Individual Equity Return	-0.044	1				
Individual Volatility	0.175	-0.183	1			
Liquidity Proxy	-0.168	0.032	-0.260	1		
Long-term Interest Rate	0.010	-0.077	-0.230	0.086	1	
Slope of Interest Rate	-0.046	0.122	-0.347	0.303	-0.227	1

From economic theory, since the CDS and the bond have the same reference entity, the individual equity return, which proxies for the total value and business climate, should have the same impact on these two instruments, and the basis, defined as the CDS premium minus the credit spread, should be indifferent to change in individual equity return. We form the first hypothesis:

H1: The basis does not change when the firm value and the business climate change.

Although CDS and bond have the same reference entity and thus have the same proxy for the business risk, call-option implied volatility, we would expect that they react differently when the call-option implied volatility changes. Since the credit derivative market has higher liquidity than the bond market and the capital needed to change the risk exposure in the credit derivative market is lower than that in the bond market, investors will prefer to adjust risk exposure in the derivative market, which makes the CDS premium more sensitive to a change in the business risk. Hence, the second hypothesis is formed:

H2: Investors prefer to adjust credit risk exposure in the credit derivative market, i.e., the basis is positively correlated to call-option implied volatility.

The liquidity also plays an important role in determining the level of the basis. When the liquidity of credit derivative market improves, the CDS premium will drop. Therefore, we form the third hypothesis:

H3: If the liquidity of the credit derivative market worsens, the basis will increase because of the positive liquidity premium in the credit derivative market.

The estimation results are presented in Table 3.10. We find that the coefficients on the individual equity return of all three samples are insignificant, while those on the individual volatility of all three samples are positive and significant. The numeric values do not differ substantially. We infer that the impact of the in-

Table 3.10: Fixed Effects Estimation of Basis (Swap)

The table presents the coefficient estimates for the whole sample and the two sub–samples. The first column reports the result of the whole sample; the next two columns report the results of the two sub–samples. The last three rows give the the number of observations, number of reference entities and the goodness-of-fit in each sample.

	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.143	-0.275	0.181
	-0.132	-0.16	-0.182
Individual Volatility	0.724	0.725	0.78
	(0.053)**	(0.076)**	(0.066)**
Liquidity Proxy	-19.995	-111.407	12.102
	(6.083)**	(10.003)**	-7.944
Observations	5072	1866	3206
Number of Ref. Entities	57	48	57
R-squared	0.05	0.12	0.04

Standard errors in parentheses
* significant at 5%; ** significant at 1%

dividual volatility does not vary much in the two sub-samples. The coefficients on the liquidity proxy of the whole sample and the earlier period sample are negative and significant, but that of the latter period sample is not significant. The numeric value of the coefficient with the earlier period sample is more than five times that of the whole sample, which is due to the insignificant coefficient in the latter period sample. Hence, we conclude that the Hypothesis 1 and 2 cannot be rejected, whilst Hypothesis 3 is rejected.

The possible reason for the rejection of Hypothesis 3 comes from the fact that the market behaves differently in the two sub-periods. In the earlier period, when the liquidity worsens, the bond market is more affected than the credit derivative market. Hence we observe negative and significant coefficients. In the later period, the influence of the liquidity on the credit derivative market and the bond market is virtually identical and they offset each other, and the liquidity no longer plays a significant role in determining the level of the basis. In January 2005, Simon Boughey pointed out in Riskwater.com:"In fact, the structure and pattern of the CDS market in those days militated against the successful development of an online platform. Liquidity, though growing rapidly, was much less than it is today. Moreover, liquidity tended to be spasmodic and concentrated in specific sectors ...". According to this, we would argue, liquidity in both markets had improved in the later period.

To check the robustness of the above findings, we repeat the fixed effect estimation in Equation 3.1 for individual rating classes. We combine AA+, AA and AA- S&P rating into an AA rating class in our regression. Using the same procedure, we form the A and BBB rating class. These three rating classes have 904, 2,706 and 1,145 observations in the whole sample, respectively, which counts for 94% of all observations.

Table 3.11 reports the output from the fixed effect estimation by rating class. In the table, Panel A summarizes the result of fixed effect estimation of rating class AA, Panel B illustrates that of rating class A, and Panel C illustrates rating class BBB.

All the three panels again confirm the results in Table 3.10, except for the minor difference that the individual equity return of rating class A is significant in the earlier period sample and the liquidity proxy of rating class BBB is insignificant in the whole sample. This comes from the fact that the number of observations in the BBB rating class in the latter period sample outnumbers that in the earlier period sample markedly. We also see that the coefficients on call-option implied volatilities increase as the rating deteriorates. In the whole sample, when the call-option implied volatility rises 1%, the basis climbs 0.298, 0.469 and 0.886 basis point for the AA, A and BBB rating classes, respectively. The basis of BBB rating class is almost three times more sensitive than that of AA rating class, which is reasonable. The coefficients on the liquidity proxy do not have such pattern by rating classes. The R^2 in the latter period are lower than those in the earlier period, which is affected by the no-longer significant liquidity proxy in the model. The results are inline with our expectation and confirm the finding that call-option implied volatility is the only significant factor in the latter period. As the market matures, the liquidity proxy, which is significant in the early period, no longer plays an important role in pricing the basis.

These findings suggest that the past strategies of pricing basis should be adjusted due to the different behavior of the market in recent period.

3.6.2 The Effect of Individual Firm and Interest Rate Properties

The interest rate also has significant influence on the CDS premium and the credit spread. In early works, Aunon-Nerin et al. [2002] and Blanco et al. [2005] document that the long-term interest rate, proxied by the ten-year interest rate, and the slope of the interest rate curve, which is defined as the difference between the ten-year and two-year interest rate, have significant impact on the change of the CDS premium and the credit spread. The interest rate swap of euro and US Dollar are used for European and American reference entities, respectively. Here we use fixed effect models to investigate whether these effects have a significant impact on the basis. Before we run the regression, we assume that if both the credit derivative market and the bond market have the same sensitivity to the change of the interest rate, then the coefficients of these two factors will not be statistically significant. However, if they react differently to the change in the interest rate, we will be able to find significant, either positive or negative, coefficients. The fourth hypothesis is thus formed:

H4: The basis does not change when the long-term interest rate and the slope of yield curve changes.

We therefore estimate the following model:

$$basis_{i,t} = \gamma_1 R^I_{i,t} + \gamma_2 vol^I_{i,t} + \gamma_3 liq^I_{i,t} + +\gamma_4 r^l_{i,t} + \gamma_5 r^s_{i,t} + c_i + \epsilon_{i,t} \tag{3.2}$$

$R^I_{i,t}$ and $vol^I_{i,t}$ are the weekly return of the individual equity and the call-option implied volatility of the individual equity, which proxy the business climate and the business risk of the underlying entity, respectively. liq is the proxy for the liquidity of the credit derivative market, which is defined as the relative bid-ask spread. $r^l_{i,t}$ is the ten-year long-term interest rate. For European and American entities, we use the interest rate swap of Euro and U.S. Dollar, respectively. $r^s_{i,t}$ is the slope of the interest rate curve, which is defined as the ten-year interest

Table 3.11: Rating Class Break Down of Basis (Swap)

The table presents the fixed effect estimation of the basis by different rating classes. The first column reports the estimation with the whole sample, the next two columns show the estimation with the earlier period sample and the latter period sample, respectively. The individual equity return, the call-option implied volatility and the liquidity proxy are included as exogenous variables. The last three rows present the number of observations, the number of reference entities and the goodness-of-fit of each sample.

Panel A: Rating Class AA

Rating Class: AA	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.273	-0.159	0.026
	-0.167	-0.225	-0.164
Individual Volatility	0.298	0.227	0.44
	(0.068)**	(0.104)*	(0.061)**
Liquidity Proxy	-39.532	-128.42	6.463
	(7.058)**	(11.434)**	-6.75
Observations	904	436	468
Number of Reference Entities	12	10	12
R-squared	0.08	0.26	0.1

Panel B: Rating Class A

Rating Class: A	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.11	-0.311	-0.052
	-0.136	(0.129)*	-0.213
Individual Volatility	0.469	0.438	0.519
	(0.058)**	(0.066)**	(0.080)**
Liquidity Proxy	-21.683	-76.481	2.642
	(6.522)**	(8.938)**	-9.447
Observations	2706	1121	1585
Number of Reference Entities	36	28	33
R-squared	0.03	0.11	0.03

Panel C: Rating Class BBB

Rating Class: BBB	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.476	-1.34	0.73
	-0.41	-0.863	-0.397
Individual Volatility	0.886	1.344	0.692
	(0.150)**	(0.334)**	(0.144)**
Liquidity Proxy	-31.889	-149.398	-34.915
	-21.177	(73.998)*	-19.18
Observations	1145	241	904
Number of Reference Entities	19	10	19
R-squared	0.04	0.11	0.04

Standard errors in parentheses
* significant at 5%; ** significant at 1%

rate minus the two-year interest rate. We use the interest rate swap again to be consistent with the calculation of the long-term interest rate. c_i denotes the unobserved effect that is time-invariant for each individual underlying entity i.

Table 3.12: Fixed Effect Estimation of Basis (Swap) with Interest Rate Variables

The table presents the coefficient estimates for the whole sample and the two sub–samples. The first column reports the result of the whole sample; the next two columns report the results of the two sub–samples. The last three rows give the the number of observations, number of reference entities and the goodness-of-fit in each sample.

	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.169	-0.27	0.153
	-0.13	-0.157	-0.178
Individual Volatility	0.909	1.066	1.018
	(0.053)**	(0.102)**	(0.071)**
Liquidity Proxy	-20.08	-98.249	1.755
	(5.934)**	(9.963)**	-7.773
Long-term Interest Rate	12.415	12.509	9.219
	(0.849)**	(1.918)**	(1.568)**
Slope of Interest Rate Curve	19.859	16.704	34.069
	(1.347)**	(1.558)**	(3.554)**
Observations	5072	1866	3206
Number of Ref. Entities	57	48	57
R-squared	0.09	0.18	0.10

Standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 3.12 presents the fixed effect estimation with both firm-specific and interest rate factors. The first column shows the coefficients for the whole sample, and the next two columns report the coefficients for the two sub-samples. We find that the coefficients on firm-specific factors have the same sign and significance as those in Table 3.10. The coefficients on individual equity return are not significant in all three samples. Contrarily, the coefficients on call-option implied volatility are positive and significant in all three samples. The coefficient on liquidity proxy is again significant in the earlier period but insignificant in the latter period. The coefficients on the interest rate factors are significant and positive, which implies that the credit derivative market is more sensitive to the change of the interest rate factors than the bond market.

CDS is a derivative product, which is often traded higher when credit investors are driven by volatile equity markets. Cash bond is relatively resilient due to its thin liquidity. As CDS is much more driven by the volatility, the coefficient on volatility is positive and significant.

The sign of liquidity proxy is negative in the earlier period. If liquidity proxy, (Ask CDS - Bid CDS)/Mid CDS, increases, liquidity condition in credit market deteriorates, and the regression suggests that basis decreases. I.e., CDS increases less than credit spread; or CDS decreases more than credit spread.

When economy and funding environment are in good shape, credit spread decreases more than CDS. The reason is that credit spread contains a liquidity component, or liquidity plays a more important role in cash bond than it does in CDS. If economy and funding environment improve, liquidity increases and liquidity component in basis point also drops. So credit spread moves faster. When economy and funding environment are in distress, credit spread increases more than CDS does due to the liquidity component.

The results of interest rate related factors show that the Hypothesis 4 can be rejected.

Although CDS and credit spread have the same reference entity, the basis is still sensitive to the changes in the long-term interest rate and the slope of yield curve. The R^2 increases sharply when these two additional factors are added. For the whole sample, it changes from 5% to 9%, and for the two sub-samples, it changes from 12% and 4% to 18% and 10%, respectively.

It is obvious that the interest rate factors captures the additional variation of the basis and this model performs better than the previous one. By inserting interest rate factors, we are able to explain more about the basis than simply by using the firm-specific factors. The results also reveal the fact that the two markets react differently to the change in interest rate factors, which is consistent in both the whole sample and the two sub-samples.

In basis trade, an investor will borrow and lend in overnight market. In a negative basis trade, an investor borrows money from the overnight market to buy the bond. The change in basis thus depends on the liquidity in overnight money market. The slope of interest rates is widely used as the signal of money market liquidity. A steep curve shows there is sufficient liquidity so that long-term liabilities can be funded by short-term borrowing. Market participants will, in this circumstance, be able to borrow in overnight market and trade basis, which will in turn have impact on changes in basis. In this case, including interest rate variables will increase the explanatory power.

Again, we check the robustness of the findings by repeating the fixed effect estimation for individual rating classes. As in the previous subsection, we form AA, A and BBB rating classes by combining the original S&P ratings, which accounts for 94% of all observations.

The results are shown in Table 3.13. Panel A shows the results of rating class AA. The coefficients on the individual equity return are all insignificant and negative. These properties are the same as those without interest rate variables of rating class AA and with interest rate variables of pooled rating classes. The coefficients on the individual volatility are all positive and significant. The coefficient of the sample before Sept 30, 2002 is 0.354, which is lower than those of the whole sample and latter sample at 0.433 and 0.45, respectively. The coefficient on the individual volatility of the earlier sample is significant at the 1% level, while those of the whole sample and latter sample are significant at the 5% level. The higher impact of individual volatility in the latter sample is also due to the higher CDS premia in the latter period. The numeric values of the coefficients of all three samples are higher than those of the estimation of rating class AA without interest rate variables but lower than those with interest rate variables of pooled rating classes.

The coefficients on the liquidity proxy are significant and negative in the whole period and in the earlier period. However, it becomes insignificant in the latter period. When the liquidity of the credit derivative market increases, the basis decreases in both the whole sample and the earlier period sample. Nevertheless,

Table 3.13: Rating Class Break Down of Basis (Swap) with Interest Rate Variables

The table presents the fixed effect estimation of the basis by different rating classes. The first column reports the estimation with the whole sample, the next two columns show the estimation with the earlier period sample and the latter period sample, respectively. The individual equity return, the call-option implied volatility, the liquidity proxy, the long-term interest rate and the slope of the interest rate curve are included as exogenous variables. The last three rows present the number of observations, the number of reference entities and the goodness-of-fit of each sample.

Panel A: Rating Class: AA

Rating Class: AA	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.294	-0.172	-0.112
	-0.162	-0.224	-0.159
Individual Volatility	0.433	0.354	0.45
	(0.068)**	(0.140)*	(0.065)**
Liquidity Proxy	-43.629	-121.557	-2.139
	(6.954)**	(12.501)**	-6.594
Long-term Interest Rate	10.508	4.813	10.193
	(1.318)**	-2.794	(1.723)**
Slope of Interest Rate Curve	12.701	7.332	15.643
	(1.841)**	(2.125)**	(4.455)**
Observations	904	436	468
Number of Ref. Entities	12	10	12
R-squared	0.14	0.28	0.18

Panel B: Rating Class: A

Rating Class: A	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.167	-0.343	-0.094
	-0.132	(0.123)**	-0.204
Individual Volatility	0.639	0.573	0.724
	(0.058)**	(0.087)**	(0.084)**
Liquidity Proxy	-20.313	-58.44	-4.773
	(6.314)**	(8.561)**	-9.031
Long-term Interest Rate	10.148	7.053	11.769
	(0.881)**	(1.573)**	(1.804)**
Slope of Interest Rate Curve	19.096	14.164	28.197
	(1.306)**	(1.212)**	(4.021)**
Observations	2706	1121	1585
Number of Ref. Entities	36	28	33
R-squared	0.11	0.22	0.12

Standard errors in parentheses
* significant at 5%; ** significant at 1%

the liquidity proxy has no impact on the basis in the latter period sample. The numeric value of the coefficient of the earlier sample is almost three times of that of the whole sample. The results are similar to those of the estimation both without interest rate variables of rating class AA and with interest rate variables of pooled rating classes.

Panel C: Rating Class: BBB

Rating Class: BBB	The Whole Period	Before Sept 30 2002	After Sept 30 2002
Individual Equity Return	-0.274	-1.312	0.716
	-0.402	-0.852	-0.392
Individual Volatility	0.963	2.319	0.916
	(0.150)**	(0.503)**	(0.157)**
Liquidity Proxy	-24.01	-220.343	-43.654
	-20.808	(73.539)**	(19.073)*
Long-term Interest Rate	17.565	37.568	6.751
	(2.492)**	(10.109)**	(3.359)*
Slope of Interest Rate Curve	-2.808	52.458	34.4
	-5.815	(23.982)*	(7.522)**
Observations	1145	241	904
Number of Ref. Entities	19	10	19
R-squared	0.09	0.18	0.08

The coefficients on the long-term interest rate are positive. The coefficients in the whole sample and the latter period sample are significant, but that for the earlier period sample is not. The numeric values of the coefficients of the whole sample and the latter sample are 10.508 and 10.193, respectively. Compared with the coefficients of the estimation with pooled rating classes, we find that the coefficient of the earlier period sample is positive and significant when the sample has pooled rating classes. The coefficients on the slope of interest rate curve are all positive and significant. The numerical value of the whole sample, the earlier sample and the latter sample are 12.701, 7.332, and 15.643, respectively. The impact is greater in the latter period, which is similar to the result of the estimation with pooled rating classes.

Panel B presents the results of the estimation with rating class A. The coefficients on the individual equity return of the whole sample and the latter period sample are insignificant, but that of the earlier sample is negative and significant. Contrarily, all coefficients in the estimation with pooled rating classes are not significant. When compared with those without interest rate variables of rating class A, we find that the coefficients of both with and without interest rate variables in the earlier sample are significant and negative. The numeric values are also close to each other.

The coefficients on the individual volatility of all three samples are positive and significant, which are similar to those of the samples both without interest rate variables of rating class A and with interest rate variables of pooled rating classes. The numeric values are 0.639, 0.573 and 0.724, respectively. We find that the basis changes more in the latter period sample when the individual volatility increases by 1%. This pattern is found in the results of the estimation without interest rate variables of rating class A, but not in those with interest rate variables of pooled rating classes.

The coefficients on the liquidity proxy have comparable properties to those without interest rate variables of rating class A and those with interest rate variables of pooled rating classes. They are negative and significant in the whole period and in the earlier period. However, they become insignificant in the latter period. The coefficients on the long-term interest rate of all three samples are positive and significant, and comparable to those with interest rate variables of pooled rating classes. The numeric value of the latter sample is greater than that of the earlier sample. However, the relation is reversed when we look at the results of the estimation with pooled rating classes. The coefficients on the slope of the interest rate curve of all three samples are positive and significant also. These findings and the numerical values of the coefficients have a similar pattern to those of the estimations both with both interest rate variables of rating class A and without interest rate variables of pooled rating classes.

Panel C shows the results of the estimation with rating class BBB. The coefficients on the individual equity return of all three samples are not significant, and identical to the results of the estimation both with interest rate variables of pooled rating classes and without interest rate variables of rating class BBB.

The coefficients on the individual volatility of all three samples are positive and significant. Again, they are identical to the results of the estimations both with interest rate variables of pooled rating classes and without interest rate variables of rating class BBB. Moreover, we find that the numeric value of the estimation in the earlier period sample is more than twice the size of that in the latter period sample, at 2.319 and 0.916, respectively. This is consistent with the results of the estimation without interest rate variables of rating class BBB. Compared with the coefficients of 1.066 and 1.018 from the estimation with interest rate variables of pooled rating classes, the difference here is much more substantial.

The coefficients on the liquidity proxy are negative and significant for the estimations with two sub-samples but not with the whole sample, which is likely to be due to the fact that the impact of the liquidity proxy is significantly different in the two sub-samples, and thus leads to the high variance of the estimated coefficient with the whole sample. The numeric value of the coefficient in the earlier period sample is around five times that in the latter period sample. When we compare them with the results of the estimation with interest rate variables of pooled rating classes, we find that the liquidity proxy is significant in the whole sample with pooled rating classes but insignificant in the latter period sample with pooled rating classes. When looking at the number of the observations, we notice that in the latter period sample it is about four times that in the earlier period. This property of the sub-samples differs substantially from those of estimations with interest rate variables of pooled rating classes. The difference comes from the very unbalanced sub-samples in rating class BBB. Similar results are found in those of estimations without interest rate variables of rating class BBB.

The coefficients on the long-term interest rate of all three samples are positive and significant. When we crosscheck them with those of estimations with interest rate variables of pooled rating classes, we find that the difference between the earlier and the latter period samples is more significant than that of the estimation with interest rate variables of pooled rating classes. For the names with BBB rating, the impact of the long-term interest rate in the earlier period sample is about five times greater than that in the latter period sample. The coefficients on the slope of the interest rate curve are positive and significant in the estimations of two sub-samples. Compared with the results of the estimation with interest rate variables of pooled rating classes, where we find positive and significant coefficients in the whole sample, the coefficient here is insignificant for the estimation in the whole sample. This is also due to the unbalanced number of observations of the rating class BBB, which are clustered in the latter period sample. The numeric value of the estimation in the earlier period sample is greater than that of the estimation in the latter period sample, which is contrary to those of the estimation with interest rate variables of pooled rating classes.

All in all, the fixed effect estimation of the basis with samples of different rating classes show that the liquidity proxy and the slope of the interest rate curve have various impact on the basis, especially for the rating class BBB. These phenomena are due to the unbalanced observations of the names with rating class BBB. In the latter period sample, there are much greater observations. On the other hand, the CDS premia and the basis of BBB rating class are relatively high because of the worse credit quality and the thin market in the CDS products. When the investor is determined to exploit the difference between CDS and credit spread of the same underlying entity, he has to seriously take the rating class of the name he trades into account. The factors also have different impacts on the basis along with the maturation of the market. It is clear that they behave substantially differently in the earlier and the latter period samples, especially the liquidity proxy. Hypothesis 4 can be rejected.

3.7 Conclusion

The discrepancy between the credit derivative and bond markets, which usually reflects either positive or negative basis, is determined by many factors. In this paper, we examine the determinants of the basis using fixed effect models to capture the time-variant mean of the basis and find the properties of the basis. The fixed effect estimation allows us to capture the difference in the constant terms, which is apparently driven by the rating classes. The findings of the determinants of the basis are mixed. First, the CDS premium and the credit spread are integrated of order 1 for most of the reference entities. The non-stationarity property suggests that the usual regression cannot provide meaningful results. Secondly, business climate and business risk are checked. We find that the business climate, proxied by the individual equity return, does not have a significant impact on the basis. The business risk with the call-option implied volatility as the proxy, however, is positive and significant. The basis will rise when the level of the business risk goes up, which hints that the credit derivative and the bond markets behave differently towards business risk. Thirdly, the liquidity of the credit derivative market affects the change of the basis in the earlier period sample but not the latter period sample. The liquidity of the credit derivative market improved in the latter period sample and the effect of the liquidity proxy is cancelled. Fourthly, the long-term interest rate and the slope of the interest rate curve also drive the basis. When the long-term interest rate and the slope of the interest rate curve increase, the basis rises.

After identifying the drivers of the basis, investors can analyze and compare the credit risk of the same underlying in the credit derivative and bond markets. Moreover, the prediction of the basis using the drivers enables investors to benefit from the difference in the price of the credit risk in the credit derivative and bond markets by buying the credit risk in one market and selling it in the other.

Chapter 4

The Relationship of Systematic Credit Risks

4.1 Introduction

"The credit derivatives market has changed more than ever in the last six months, in terms of the variables traded, and that is because of the merging of the two indices."

Around a year after the inception of iTraxx indices, Andrew Palmer, global head of credit derivatives market at JPMorgan in London, made the comments above on the impact of the launch of iTraxx indices.

Since the inauguration of iTraxx indices, the transparency and liquidity in credit markets have substantially improved. Many market participants have deemed the iTraxx platform as representing market consensus on overall credit quality and trade the iTraxx indices to express their view on credit markets. Thus, it is of great interest to examine the relationship between the iTraxx index and the iBoxx index, which is the benchmark index for the bond market.

Though it is already shown that the credit derivative market leads the bond market for individual names, the relationship between the indices of credit market and bond market has not yet been investigated. Since credit investors have been increasingly trading the iTraxx indices for improved liquidity, clarifying the relation between the iTraxx and iBoxx indices will assist them to make decisions.

Literatures on the relationship between credit derivative and other markets are now much more prevalent for individual names. Blanco et al. [2005] find that the credit derivative market leads the bond market for individual entities in the price discovery process from 2001 to 2002. Norden and Weber [2004] show that the CDS market plays a more important role for price discovery for individual names than the corporate bond market from 2000 to 2002. Although it is new and the regulation is less matured, the fast developing credit default swap market has strongly affected the investor behavior and has led the information flow relatively to the bond market[25].

Based on the transaction data from January 2002 to July 2003, Cossin and Lu [2005] find that on average the differences between the default premium implied by the bond and the CDS premium are very small after stripping out the liquidity layer and adjusting for the accrued interest. Byström [2006] looks at the relationship between the iTraxx index and the stock prices by forming a synthetic stock index made up of the names in the iTraxx index. He finds that iTraxx CDS spreads tend to widen when stock price goes down and vice versa, which underpins the existing relationship between the iTraxx index and stock prices. As a stock can be deemed as the most subordinated debt of the underlying, a very natural question arises: What is the relationship between the iTraxx index and the underlying's outstanding debt?

The composite members of the iTraxx and iBoxx indices, and the form an investment takes, are different, so the conclusions drawn from the single-name data are not directly applicable. Therefore two different trading strategies are used to ease the comparison of the returns.

[25] The credit derivative market is less strictly regulated than the equity and bond markets. In the US, the Commodity Futures Modernization Act of 2000 excluded derivatives not traded on any exchange from the jurisdiction of the Commodity Futures Trading Commission. And while regulators from the Fed, SEC and FSA have addressed the importance of the regulating of the credit derivative market, no effective regulation yet seems to have emerged.

The structure of the paper is as following: Section 1 discusses the CDS and cash bond markets, Section 2 introduces the cointegration model, Section 3 describes the data set, Section 4 presents the results of the empirical analysis and Section 5 concludes.

4.2 The CDS and Bond Indices

4.2.1 Credit Default Swap

Credit default swaps (CDS) are used to transfer the credit risk of the underlying entity from one party to another and are also the main building block for other credit derivatives. When two counterparties enter a CDS contract, the protection buyer pays the CDS premium (usually quarterly) to the protection seller and the protection seller covers the loss of the face value when a credit event occurs. In physical settlement, the protection buyer delivers the notional amount of the deliverable obligations to the protection seller and receives the notional amount paid in cash. Contrarily, the protection seller pays the protection buyer the par minus recovery rate of the underlying in cash settlement.

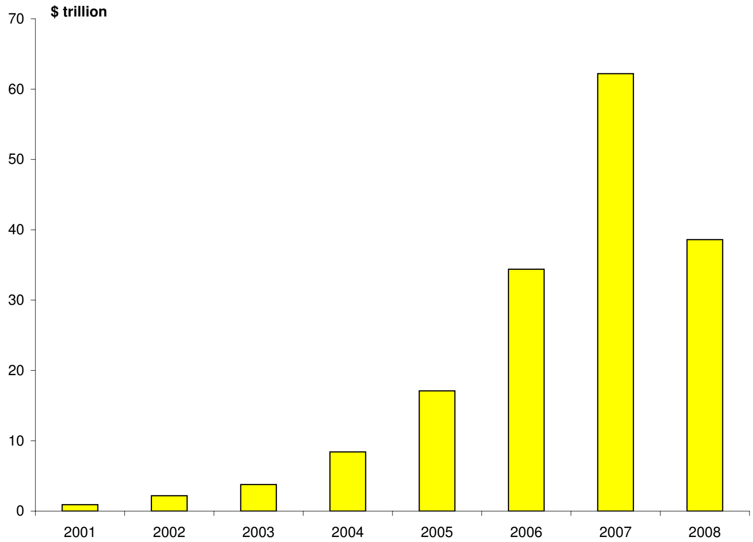
In the end of 2008, CDS market had increased to $38.6 trillion notional outstanding from virtually nil in the 1990s. Figure 4.1 reports the notional outstanding amounts of the CDS from surveys conducted by ISDA [2009].

By the nature of OTC products, the trading cost of CDS is also significant. The average relative CDS bid-ask spreads, defined as the bid-ask spread over the mid CDS premium, was over 5% between 2001 and 2006[26]. Hence, a more liquid instrument would benefit credit investors.

[26]The relative spreads are calculated using the CDS data from 2001 to 2006.

Figure 4.1: The Amount of CDS Outstanding

The figure shows the amount of CDS outstanding using the ISDA survey data. The x-axis shows the date point when the survey is conducted and the amount outstanding is reported by the y-axis, in trillion U.S. Dollars.



4.2.2 iTraxx CDS Index

iTraxx indices were launched by the International Index Company (IIC) on July 21st, 2004. The iTraxx family covers different regions, currencies, yields, volatilities and various industrial sectors. The benchmark indices are composed of iTraxx Europe, iTraxx Europe HiVol and iTraxx Europe Crossover[27].

All indices are updated every six months (March and September). The iTraxx CDS Europe index (hereafter iTraxx index) includes top 125 names, equally weighted, in terms of CDS volume traded in the six months prior to the poll. Top 30 highest spread names from iTraxx Europe make up the iTraxx Europe

[27]See Appendix for the full structure of the iTraxx family.

HiVol index while the iTraxx Europe Crossover index contains 45 European sub-investment grade reference entities. The iTraxx family covers a wide variety of the credit markets for different investors.

Table 4.1 describes the cash flow of a transaction involving an iTraxx index. When there is no credit event until the maturity, the buyer of the protection pays the CDS premia to the seller, usually the market maker, on a quarterly basis. Where a credit event occurs, the protection seller delivers the nominal face value of the deliverable obligations tied to the reference entity, and receives the defaulted obligation with the same face value. The amount of the nominal face value, $w \cdot N$, is determined by the weighting of the reference entity w and the notional amount of the iTraxx contract N. After the credit event, the notional amount is reduced by the nominal face value paid by the seller to $(1-w) \cdot N$ and the seller still receives the CDS premia until maturity subject to other possible credit events.

Table 4.1: The Cash Flow of iTraxx Index

Panel A shows the cash flow of a contract of iTraxx index for protection buyers when there is no default during the whole period. The CDS denotes the spread of iTraxx index, the N denotes the notional amount, the UP denotes the upfront payment when the contract is signed and T denotes the last period of the contract. Panel B presents the cash flow of a contract of iTraxx index when one of the underlying entities defaults at time t. w denotes the weighting of the defaulted underlying in the iTraxx index and DORE denotes the delivered obligation of the reference entity.

Panel A: No Default

Date	0	1	2	...	...	...	...	T
Spread Payment	-	-CDS·N	-CDS·N	...	...	...	...	-CDS·N
Other Payment	UP	-	-	...	...	...	...	-

Panel B: Default at Time t

Date	0	1	2	...	t	t+1	...	T
Spread Payment	-	-CDS·N	-CDS·N		-CDS·N	-CDS·N(1-w)	...	-CDS·N(1-w)
Other Payment	UP	-	-	-	N·w	-	-	-
Delivery					-DORE			

Since its inception, credit market investors have been actively trading iTraxx and its related products. They now make it easier to take large trades on a standard basket to speculate or hedge credit risk. It is also recognized that bid-ask spreads are tighter and liquidity for investors is improved. Unlike other credit products, the iTraxx family has standardized maturity dates, which adds the transparency and liquidity for all credit investors.

Hedge funds and trading desks, credit arbitrage desks and structured credit desks within banks trade iTraxx indices intensively, including trading index tranche and index options. However, real money investors, such as insurance companies and pension funds, face legal and regulatory restrictions on trading the iTraxx indices or products tied to them. In 2005, a survey report from Merrill Lynch shows that over 90% of hedge funds use the indices whilst only 40% of real money investors use them.

Nowadays, many trading strategies are based on the iTraxx indices, which integrates them well into the credit market. For example, credit investors use the iTraxx indices to modify the credit duration of the portfolio with lower transaction costs. Other popular trading strategies consist of convergence/dislocation trades tied to iTraxx HiVol against iTraxx Europe, steepeners/flatteners on the 5-year and 10-year part of the curve (curve trade), trading single names with their sectors (relative-value trade) and the pure alpha strategy based on security selection tied to the benchmark.

Products tied to the indices are also traded. The options on indices, especially those on the iTraxx Crossover index, are more popular than those on single names. As the trade of options on single names are based on the credit news and thus often in one direction, it is less attractive for dealers to enter these contracts.

4.2.3 iBoxx Bond Market Index

iBoxx indices, also published by International Index Company, are rule-based indices. The bonds to form the indices are selected from bonds which are tradable and available to investors and asset managers. The iBoxx indices have a hierarchical structure and are composed of sub-indices based on currency, type of issuer, maturity, credit rating and sector, and are used by investors as the benchmark indices for the bond market. They are rebalanced either monthly or quarterly, depending on index type, according to the selection criteria of each index. The face value of the amount outstanding on each bond decides its weighting.

We use the iBoxx EUR Corporates Overall index (hereafter called the iBoxx index) in our research as it represents the important benchmark for the non-sovereign bond market and is composed of the most liquid names. Hence, we are able to detach the price of liquidity risk from the price of credit risk and interest rate risk. The iBoxx index contains fixed coupon, step-ups and event-driven bonds. Callable dated and undated subordinated corporate debt and soft bullets are also included. The selected bonds have minimum time to maturity of one year, minimum rating of BBB- (S&P or Fitch) or Baa3 (Moody's)[28], minimum amount outstanding of 500 million euro.

The index is rebalanced monthly on the last business day. If an included bond is leaving the broad iBoxx EUR Overall index[29], the bond will be substituted.

4.3 Model

4.3.1 Motivation

As Blanco et al. [2005] have already shown that CDS premia tied to individual names and individual bond yields are highly correlated, and there is the price discovery process, this paper investigates whether the returns from index trading strategies are comparable. It is still unclear whether the relationship between indices is similar because the names included in the indices are different. Nevertheless, the returns are determined by the most liquid names, i.e., most traded names, in the markets. Since both markets are driven by the credit risk, we expect certain relationship between the returns.

[28] The lowest rating applies when the ratings from the agencies differ.
[29] The iBoxx EUR Overall index is also rebalanced monthly.

Since the liquidity and efficiency of the iTraxx index and iBoxx index have made them one of the most attractive tools in the market, clarifying relationships between the iTraxx index and iBoxx index should enhance credit investors' understanding of the market and improve their decision making. We first test whether the iTraxx, iBoxx and five-year Euro swap rates are stationary processes. We then use the cointegration test and VEC model to check both long-run steady state and short-run dynamics among these series if they are non-stationary. The construction of the iBoxx index means we cannot easily detach the price of interest rate risk from that of the credit risk, which makes it hard to compare it with the iTraxx index. Therefore, five-year swap rate is included to measure the impact of the variations in the interest rate. The price of liquid risk is minimized in the analysis since only the most liquid instruments are used.

The research on the individual names motivates the error-correction type model:

iTraxx CDS Europe Index

$$\Delta c_t = f_c(\Delta X) + \gamma_c(ecm)_{t-1} + \epsilon_{c,t}. \tag{4.1}$$

iBoxx EUR Corporates Overall Index

$$\Delta b_t = f_b(\Delta X) + \gamma_b(ecm)_{t-1} + \epsilon_{b,t}. \tag{4.2}$$

Swap Rate

$$\Delta i_t = f_i(\Delta X) + \gamma_i(ecm)_{t-1} + \epsilon_{i,t}. \tag{4.3}$$

Here c and i are the level data of iTraxx index and swap rate, respectively. b is the logarithm of iBoxx index. $f(\Delta X)$ is a linear function of first-difference of X, where $\Delta X = [\Delta c\, \Delta b\, \Delta i]$, Δc, Δb and Δi are respective lagged first-differenced c, b and i and the error-correction term $(ecm)_{t-1}$ is a linear combination of c_{t-1}, b_{t-1} and i_{t-1}. The three ϵ are the error terms. The error correction term is to capture the short-run dynamics when the series are substantially away from the steady state. No special functional form is assigned to the error correction term at this stage.

The error correction system clearly specifies that if the underlying economic relationship between iTraxx index, iBoxx index and swap rate holds, there are both the long-run steady states and short-run dynamics. Credit investors should take both the steady states and dynamics into account in their decision making where the model is valid.

In the section on empirical results, we first check the stationarity properties of the time series and test the cointegration hypothesis. Then the error correction system is estimated. We drop the other exogenous explanatory variables for brevity.

4.3.2 Specification

The reduced form of the model is specified with Gaussian errors:

$$Y_t = A_1 Y_{t-1} + ... + A_k Y_{t-k} + E_t, t = 1, ...T, \tag{4.4}$$

where $Y_t = [c_t, b_t, i_t]$, $Y_{-k+1}, ..., Y_0$ are known variables, $Y_1, ..., Y_{t-1}$ are predetermined variables and E_t are i.i.d. Gaussian errors. By differencing, the error correction form of the model is:

$$\Delta Y_t = \Gamma_1 Y_{t-1} + ... + \Gamma_{k-1} Y_{t-k+1} + \Pi Y_{t-k} + E_t, \qquad t = 1, ...T, \tag{4.5}$$

where $\Gamma_i = -(I - A_1 - ... - A_i)$ for $i = 1, ..., k-1$, $\Pi = -(I - A_1 - ... - A_k)$ and $\Pi = \alpha\beta'$, with factor loading α and cointegrating vector β. If the series are cointegrated, the cointegrating vector describes the underlying long-run equilibrium relation among the iTraxx index, iBoxx index and swap rate.

4.4 Data

4.4.1 Description

The daily data of the iTraxx index, iBoxx index and 5-year Euro interest swap rates are used in the empirical analysis. All variables are in levels and the sample period is June 21st, 2004 to Jan 29th, 2007, which covers the downgrading of GM and Ford's debt to non-investment grade. Figure 4.2 shows the time series of the whole period in levels.

The iTraxx index series is updated every 6 months with the various coupon rates, which is used to determine the upfront payment when the new index is inaugurated. The iTraxx CDS Europe indices are numbered from 1 to 6, with 6 as the latest issuance. Table 4.2 shows the issuance date, coupon rate, maturity date and the number of series.

The daily iTraxx index and iBoxx index are retrieved from the web site of the International Index Company, and the five-year Euro swap rates are those provided by Bloomberg. We use the most recently issued iTraxx CDS Europe indices, i.e. on-the-run index, to form the time series in our research[30].

[30] The coupon rates of the iTraxx indices are different, and are related to the calculation of upfront payment.

Figure 4.2: The iTraxx, iBoxx Indices and the Swap Rate

The figures show the daily level data of iTraxx index, iBoxx index and swap rate. The iTraxx index is in bps, the iBoxx is the price index and the swap rate is in %.

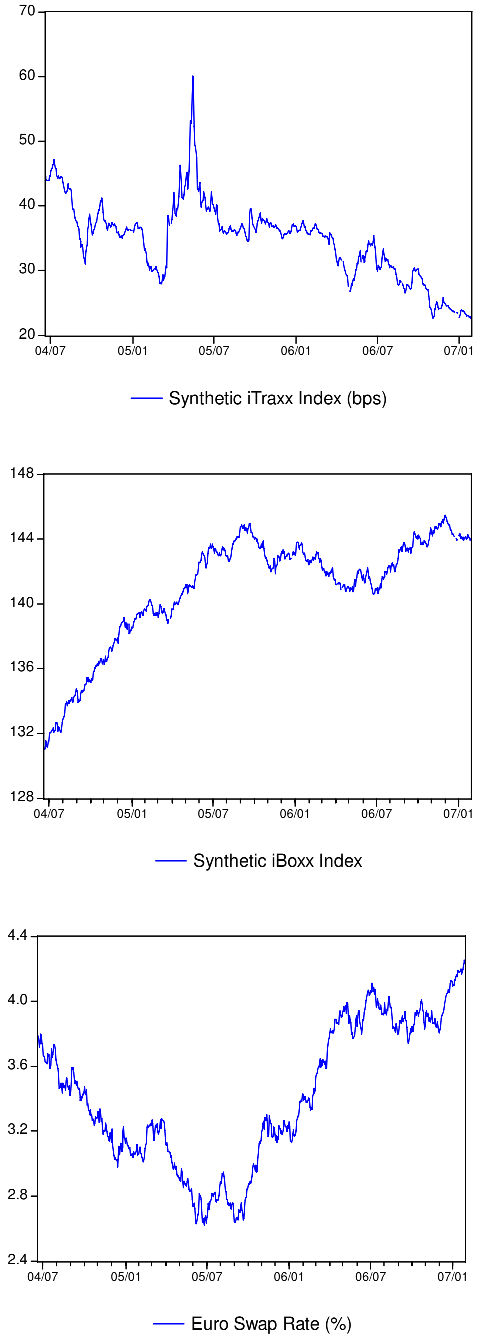


Table 4.2: Properties of iTraxx CDS Europe Index

The table shows the properties of the iTraxx CDS Europe Index with descending issuance date. The fixed rate of iTraxx index are presented in percentage. The closing date of each series is also reported.

Name	Fixed Rate(%)	Series	Maturity	Close
DJ iTraxx Europe 5Y	0.45	1	Sep 20th, 2009	Sep 17th, 2004
DJ iTraxx Europe 5Y	0.35	2	Mar 20th, 2010	Mar 18th, 2005
iTraxx Europe 5Y	0.35	3	Jun 20th, 2010	Sep 23rd, 2005
iTraxx Europe 5Y	0.35	4	Dec 20th, 2010	Mar 31st, 2006
iTraxx Europe 5Y	0.40	5	Jun 20th, 2011	Oct 3rd, 2006
iTraxx Europe 5Y	0.30	6	Dec 20th, 2011	Feb 15th, 2007

The dimension of the iTraxx index and the iBoxx index are also worthwhile discussing. The iTraxx index is quoted in basis points, while the iBoxx index is a price index that depends on the price of individual bonds included in the index with respect to the price index level after rebalancing from the end of the last month.

Since the iTraxx index is unfunded and the iBoxx is funded, a direct comparison of these series cannot generate meaningful results. Hence, two portfolios are formed. The trading strategy of Portfolio A is to buy the iTraxx index and sell it at a later stage. The total investment is zero and the amount due to the change of the iTraxx index is $\Delta C_{iTraxx} \cdot DV01 \cdot N_{iTraxx}$, where ΔC_{iTraxx} is the change of the iTraxx CDS Europe spread, $DV01$ is the Euro value of the change of one basis point of CDS, and N_{iTraxx} is the notional amount.

The trading strategy for Portfolio B is to replicate the iBoxx index by buying the bonds in the market and selling them later. The amount invested is financed using the swap rate. All in all, the net investment is also zero. The return from this portfolio is $log\frac{\sum_{i=1}^{n} P_{i,t}N_{i,t-s}}{\sum_{i=1}^{n} P_{i,t-1}N_{i,t-s}}$, where $P_{i,t}$ and $P_{i,t-1}$ are the price of bond i at date t and $t-1$, respectively. $N_{i,t-s}$ is the notional amount of bond i at date $t-s$. The payment of the swap rate is also added.

The iTraxx index data retrieved from IIC have both bid and ask prices. We manually form the mid price by taking the average of these two series for a synthetic iTraxx index. The iBoxx EUR Corporates Overall indices are composed of sub-indices with different time to maturity. The iBoxx EUR Corporates Overall 3-5 year and iBoxx EUR Corporates Overall 5-7 year indices are selected and the average of these two indices are used to construct a synthetic iBoxx EUR Corporates Overall 5 year index.

We elect to use the 5-year swap rate, collected from Bloomberg, rather than the government bond rate to avoid the liquidity premium in the government bonds[31].

4.4.2 Descriptive Statistics

Table 4.3 shows the descriptive statistics of the synthetic iTraxx index, synthetic iBoxx index and the swap rate[32]. Altogether there are 688 observations from June 2004 to January 2007. The iTraxx index and the swap rate are reported in basis points and the iBoxx index is shown in relative ratio.

Table 4.3: Descriptive Statistics

The descriptive statistics of the synthetic 5-year iTraxx index, the synthetic 5-year iBoxx index and 5-year Euro swap rate are shown.

	Mean	Median	Max	Min	Std	Skewness	Kurtosis	Obs
Syn iTraxx Index (bp)	34.75	35.88	60.11	22.63	6.03	0.20	3.68	668
Syn iBoxx Index	140.92	142.00	145.48	131.00	3.45	-1.16	3.49	668
Euro Swap Rate (%)	3.41	3.34	4.26	2.62	0.44	0.02	1.78	668

The iTraxx index is composed of 125 single-name CDS, 25 names from the financial sector and 100 names from the non-financial sector. The names in the latter can be further sorted as Autos (10 names), Consumers (30), Energy (20), Industrials (20) and Telecommunications, Media and Technology (TMT) (20). Compared with the iTraxx Europe Series 5, which was inaugurated 6 months before the inauguration date of Series 6, eight names were substituted.

[31] Government bonds, such as the Bundesobligation, is deemed to be riskfree and are usually among the most liquid financial instruments in the market. Hence, the yield of the government bond is usually lower than the "true" riskfree rate.

[32] We omit the "synthetic" prefix in the coming sections for brevity.

The iBoxx EUR Corporates Overall 3-5 year and 5-7 indices have 213 and 177 names, whereof 113 and 86 names are financial, and 110 and 91 names are non-financial. The names in the non-financial sector are Autos (12 and 8 names), Consumers (16 and 16), Energy (22 and 23), Industrials (24 and 21) and TMT (26 and 23)[33], for 3-5 year and 5-7 year indices, respectively. The time to maturity of the 3-5 year and 5-7 year indices are 4.01 and 6.04 years[34], respectively. Hence, it is reasonable to take the average of them to form the synthetic 5-year index.

4.5 Results and Analysis

4.5.1 Unit Root Test and Order of Lagged Variables

It is essential to investigate whether the time series are integrated of order one or not, to avoid spurious regression. Since we are interested in the cointegrating relationships among the time series, any time series that is not $I(1)$ does not qualify. Therefore, we check the stationarity of both the level and the first-difference of the iTraxx index, plus the logarithm of iBoxx index and the swap rate, using both the augmented Dickey-Fuller test and the Phillips-Perron test.

The augmented Dickey-Fuller test is based on the regression:

$$\Delta y_t = \alpha y_{t-1} + x_t\delta^{'} + \beta_1 \Delta y_{t-1} + ... + \beta_p \Delta y_{t-p} + v_t, \tag{4.6}$$

where α is 1- ρ[35], δ is the coefficient vector to be estimated for the regressor x_t, which consists of the intercept and the trend, β is a vector of the coefficients to be estimated for the lagged variables y_{t-s}, $s = 1, ..., p$, p is the order of lagged difference which is determined by the Bayesian criteria and v_t is the error term.

The Phillips-Perron test is based on the non-augmented Dickey-Fuller test with

[33] The sectors used in iBoxx EUR Corporate index are different from those in iTraxx CDS Europe index. Hence, we merge some of the sectors in the iBoxx EUR Corporate index to make the results comparable with those of the iTraxx CDS Europe index.

[34] The time to maturity is calculated on Jan 31st, 2007. Since the bonds are rebalanced monthly, the time to maturity of indices also varies.

[35] For the time series $y_t = \rho y_{t-1} + x_t\delta' + \epsilon_t$, y_t is stationary if $|\rho| < 1$.

Table 4.4: Unit Root Tests

The table presents the augmented Dickey-Fuller test and Phillips-Perron test. The null hypothesis is the time series has unit root. The first-difference of the time series is also checked for possible high-order integration. We include both time trend and intercept in these two tests.

Panel A: Augmented Dickey-Fuller Test

	iTraxx	log(iBoxx)	Swap	ΔiTraxx	Δ log(iBoxx)	ΔSwap
test-stat	-3.31	-2.38	-2.00	-10.15	-25.43	-25.31
p-value	0.06	0.39	0.60	0.00	0.00	0.00

Panel B: Phillips-Perron Test

	iTraxx	log(iBoxx)	Swap	ΔiTraxx	Δlog(iBoxx)	ΔSwap
test-stat	-2.99	-2.38	-2.00	-17.34	-25.44	-25.30
p-value	0.14	0.39	0.60	0.00	0.00	0.00

adjusted statistic:

$$\hat{t}_\alpha = t_\alpha(\frac{\gamma_0}{f_0})^{\frac{1}{2}} - \frac{T(f_0 - \gamma_0)(se(\hat{\alpha}))}{2f_0^{1/2}s} \tag{4.7}$$

where $\hat{t}_\alpha$ is the t-stat of the estimated α, $se(\hat{\alpha})$ is the coefficient standard error and s is the standard error of the test regression. γ_0 and f_0 are the consistent estimator of the error variance of non-augmented Dickey-Fuller test and the estimator of the residual spectrum at frequency zero, respectively.

Table 4.4 reports the results of the unit root test. In Panel A, the null hypothesis that there is a unit root in the level of the iTraxx index, the logarithm of iBoxx index and the swap rate cannot be rejected at the 5% critical level. After first-differencing, the t-statistics are -10.15, -25.43 and -25.31, showing that the null hypothesis can be rejected. Panel B presents the output with the Phillips-Perron test, which have similar results. The test statistic of iTraxx index is -17.34, which rejects the null hypothesis of $I(1)$ process at the 1% level; the test statistic of the logarithm of iBoxx index and the swap rate are -25.39 and -25.44, respectively, which also rejects the unit root hypothesis at the 1% statistical level. The series are thus $I(1)$ series, based on the unit root test.

Before we step into the error-correction model, we will specify the order of lagged variables k in Equation 4.4 using the Bayesian criteria. The model is specified as following:

$$\Delta Y_t = \Gamma_1 Y_{t-1} + \Pi Y_{t-2} + E_t, \qquad t = 1, ...T, \tag{4.8}$$

where the Γ_1 and Π are defined as $-(I - A_1)$ and $-(I - A_1 - A_2)$, respectively. The Y vector consists of the iTraxx index, the logarithm of iBoxx index and the swap rate. E_t is a vector of i.i.d. error terms[36].

4.5.2 Cointegration Test

Cointegration Test

Table 4.5 presents the Johansen cointegration test results. Panel A reports the trace test with intercept and trend in the cointegrating equation and linear deterministic trend in the level data. The trace test shows that the null hypothesis that there is no cointegrating equation, against the alternative hypothesis that there are 2 cointegrating equations, is rejected with trace statistic of 66.76. The null hypothesis that there is 1 cointegrating equation, which is against the same alternative hypothesis that there are 2 cointegrating equations, cannot be rejected with trace statistic of 17.23, given the 5% critical value is 25.32. Therefore, there is 1 cointegrating equation that drives the short-term dynamics among the three time series.

Panel B gives the results using the maximum eigenvalue test with intercept

[36] We use the level data of CDS in our analysis rather than the logarithm of the data. By definition, the return of the iTraxx CDS can be calculated using the product of the change of the spread level and the $DV01$ discounting factor. Investors could easily calculate the return themselves whilst the movement of the markets is predicted. The logarithm of the level data also contains unit root for each of them and the properties of the estimated VEC model do not vary much.

Table 4.5: Cointegration Test

The Johansen cointegration test is applied to estimate the cointegrating rank. We include the time trend and intercept in the test procedure to capture the time-varying phenomenon in the markets. Panel A reports the trace test results while the results using maximum eigenvalue are shown in Panel B.

Panel A: Trace Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 % Critical Value	1 % Critical Value
None	0.072	60.94	34.55	40.49
At most 1	0.016	12.61	18.17	23.46
At most 2	0.004	2.51	3.74	6.40

Panel B: Maximum Eigenvalue Test

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 % Critical Value	1 % Critical Value
None	0.072	48.33	23.78	28.83
At most 1	0.016	10.09	16.87	21.47
At most 2	0.004	2.51	3.74	6.40

and trend in cointegrating equation, and linear deterministic trend in the level data. The maximum eigenvalue statistic of 49.52 rejects the null hypothesis of no cointegrating equation against the alternative hypothesis of 1 cointegrating equation. Moreover, the null hypothesis of 1 cointegrating equation against the alternative hypothesis of 2 cointegrating equations cannot be rejected with a maximum eigenvalue statistic of 13.11. Hence, both the trace test and the maximum eigenvalue test identify 1 cointegrating equation among these three series.

VECM Parameters

The coefficients of the vector error correction model are estimated after the cointegrating rank is identified. The VEC model takes the cointegrating equation into account and restricts the long-run relationship among the series to converge to their cointegrating relationship, while allowing the short-run dynamics to adjust the deviation from the long-run relationship. If one of the time series moves substantially away from the long-run relationship, the short-run dynamics of these time series will pull it back on track. Hence, both the long-run relation and the short-run dynamics govern the movement of the whole system and are important in the decision-making process.

Table 4.6 presents the estimated coefficients, standard error and p-value of the VEC model. First, the coefficients of the cointegrating equation are reported. As there is 1 cointegrating equation, the β vector, which contains the swap rate, the iTraxx index, the logarithm of the iBoxx index, the time trend and a constant, where the coefficient of swap rate is normalized to 1[37], is $(1, 0.01, 22.92, -0.00, -116.20)'$. The t-statistics show that all of them are statistically significant.

The estimated coefficients of the lagged variables and the cointegrating equation are reported in the lower part of the table. The test statistics of the cointegrating equation are significant for the iTraxx index and the logarithm of the iBoxx index at the 5% confidence level. Contrarily, the coefficient of the swap rate is not significant at the 5% level. The change of the iTraxx and the logarithm of the iBoxx indices are strongly affected by the cointegrating equation, while the change of the swap rate is not influenced. The short-run dynamics of the iTraxx and the logarithm of the iBoxx indices, driven by the cointegrating equation, pull the iTraxx and the logarithm of the iBoxx series back to the long-run steady state when they have deviated from the long-run relationship.

The coefficients of the lagged variables have different statistical significance. None of the lagged variables have an impact on the change of the swap rate, including the autoregressive element of the swap rate[38]. The swap rate is thus hardly influenced by the change in the iTraxx and iBoxx indices. It confirms that the swap rate only has the interest rate risk, which is not associated with the credit risk from the credit derivatives market via the iTraxx index.

[37] The β vector is unrestricted and there are numerous possible values. However, these values are not linear independent. Hence, we normalize one element and obtain a representative vector that can be used to form other possible values for the cointegrating equation.

[38] We also perform the correlogram test for the first-difference of swap rate to exclude the impact of the cointegrating equation. The results stay the same.

Table 4.6: Estimation of Vector Error Correction Model

The table reports the estimation of the vector error correction model which is based on the cointegration test in the previous subsection. The Johansen method is used for the system containing the iTraxx index, the iBoxx index and swap rate. Panel A shows the estimation of the factor loading and cointegrating vector, whilst the coefficients on the cointegrating relation and other lagged variables are shown in Panel B. The standard deviation is presented under the coefficient, which is then followed by the t-statistic in bracket.

Panel A: Coefficients of Cointegrating Equation Variables

Swap(-1)	iTraxx(-1)	log(iBoxx)(-1)	Trend	C
1	0.01	22.92	0.00	-116.20
	0.0009	0.2620	0.0000	
	[15.2646]	[87.4973]	[-78.3939]	

Panel B: Coefficients of Lagged Endogenous Variables

Error Correction:	ΔSwap	ΔiTraxx	Δlog(iBoxx)
CointEq	0.07	-5.26	-0.01
	0.05	1.04	0.00
	[1.39]	[-5.04]	[-2.80]
ΔSwap(-1)	-0.08	-0.41	-0.01
	0.10	2.12	0.00
	[-0.78]	[-0.19]	[-2.88]
ΔiTraxx(-1)	0.00	0.37	0.00
	0.00	0.04	0.00
	[-1.38]	[9.65]	[-0.31]
Δlog iBoxx(-1)	-2.36	-23.34	-0.24
	2.29	49.38	0.09
	[-1.03]	[-0.47]	[-2.52]
C	0.00	-0.02	0.00
	0.00	0.03	0.00
	[0.52]	[-0.59]	[3.36]

The coefficients of the lagged variables on the change of iTraxx index are not significant except for the autoregressive element. The lagged change in the iTraxx index has a positive impact on the change in the iTraxx index, which shows that there is autocorrelation in the credit derivatives market. The change in the iTraxx index is driven by the short-run dynamics via the cointegrating equation and the autoregressive elements.

When we check the coefficients of lagged variables on the change in the logarithm of the iBoxx index, we find negative and significant coefficients from the lagged change of swap rate and the autoregressive change of the logarithm of the iBoxx index and the insignificant coefficient from the lagged change in the iTraxx index. The credit risk and interest rate risk in the logarithm of the iBoxx index are partly explained by the change in the lagged swap rate and itself.

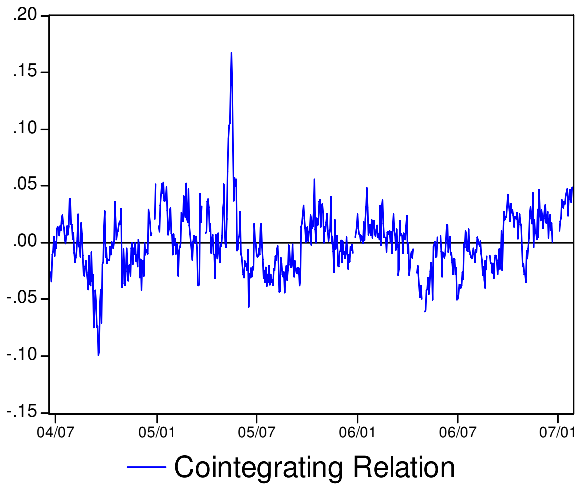
Hence, we can infer that the cointegrating equation drives the whole system, whilst the change of lagged variable also influence the equations of the iTraxx and the logarithm of the iBoxx indices.

GM and Ford downgraded to junk grade

Figure 4.3 shows the cointegrating relation generated with the estimated coefficients of the VEC model above. The line shows the numerical value of the cointegrating relation from June 21, 2004 to January 29, 2007. According to the VEC model estimation, all coefficients of the three series in the cointegrating relation are positive. I.e., an increase in any of the three series will raise the numerical value of the fitted cointegrating relation. The level of the cointegrating relation usually increases if markets are in turmoil and decreases when the stability returns. From the figure, we clearly find the peak around May, 2005, when S&P downgraded GM and Ford to non-investment grade.

Figure 4.3: Cointegrating Equation

The figure shows the fitted value of cointegrating equation using the estimated cointegrating vector. The x-axis shows the daily date reported and y-axis presents the numerical value of the cointegrating equation.



We give the story briefly here. After months of close observation of GM and Ford's outstanding debt, on May 5th, 2005, bond market investors found that S&P had downgraded GM and Ford to non-investment grade. The rating announcement came just one day after the reported news that the former Chrysler investor Kirk Kerkorian was offering $31 a share, about 13% above where the share closed the previous trading day, for up to 28 million GM shares through Tracinda Group[39].

In the credit derivative market, correlation trading, or "Equity vs Mezz" strategies, were widely used by hedge funds to sell protection on equity tranches and buy protection on mezzanine tranches. The correlation trading of single tranche synthetic CDOs are based on the one-factor Gaussian copula model, which was criticized after the shakeout because it malfunctioned. From May 5th onwards, investors needed to purchase protection against these two reference entities, which drove the CDS indices level dramatically. On May 17th, the CDS indices reached their peak and then began to drop, and had nearly recovered on May 26th. Some of the hedge funds fared badly in this market, according to the Merrill Lynch Report, the monthly return on correlation trading was as bad as -12%. The effect of the dealers' rush to hedge the unhedged bespoke mezzanine risks dominated that of the unwinding of long correlation trades by the hedge funds, which led to the widening of equity tranche spreads and the tightening of mezzanine tranche spreads.

[39]Tracinda has already owned 22 million GM shares before that day, or less than 4% of all the shares. Tracinda's statement said that the move was for investment purpose only. Neither GM nor Tracinda made any comment on the statement.

Figure 4.4: The Market Turmoil in May 2005

The figure shows the fitted value of cointegrating equation using the estimated cointegrating vector. The x-axis shows the daily date reported and y-axis presents the numerical value of the cointegrating equation.

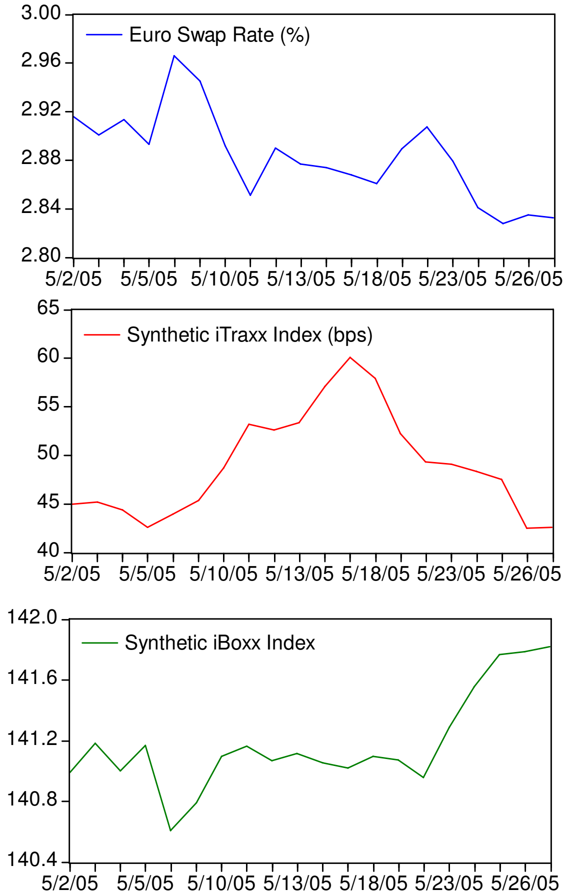


Figure 4.4 presents the level of series during May 2005. The variation in the iTraxx index is much higher than that in the swap rate and the iBoxx index. Moreover, the movement of the iTraxx index was the reverse of the swap rate and the iBoxx index. The iTraxx index had increased nearly 50% to its peak, while the swap rate and the iBoxx index had not changed substantially. The short-run dynamics had driven the credit derivative market, which deviated from the long-run steady state when the exogenous downgrading shock was present, back on track. In the CDS equation, the negative coefficient of the cointegrating relation led to a decreasing iTraxx index. The higher the iTraxx level, the stronger the impact of the cointegrating relation. When the iTraxx index was increasing dramatically due to the immense demand for credit protection, the level of the cointegrating relation also increased, to around three times the level before the crisis, to pull the deviating series back to the long-run steady state. The iTraxx index reached its peak on May 17th and had gone back to the normal level by the end of that month.

4.6 Conclusion

This paper uses the multiple time series technique to check the relationship between credit derivative and bond markets. To the best of our knowledge, this is the first paper to examine this relationship at market level.

We find that there is a cointegration relation among credit derivative market, bond market and swap rate. In the VEC model, credit derivative market is by far most affected by the cointegrating relation. We confirm that there are both long-term steady-state relationships and short-term dynamics in credit derivative market, cash bond market and interest rate. If one of the series goes substantially away from the long-term steady-state, the cointegration relation will pull it back to the steady-state. We believe the finding is important for the management of credit market investors' portfolios, and it also helps regulators to use the market information efficiently to avoid the possible crisis.

Further analysis could be developed to examine the market behavior before and after the GM crisis in May 2005. Since trading strategies were very much changed after the crisis, the relationship could also be different. Moreover, this paper uses only European market data in the multiple time series analysis, and North American markets were more affected by the crisis, making more in-depth research worth while.

Appendix

This table shows the structure of the whole iBoxx index family. The iBoxx Euro Overall is composed of the Sovereign Index and the non-sovereign index. In the sovereign index, the indices of 11 European nations are available and form the Sovereign Index. The Non-sovereign Index consists of Sub-sovereigns, Collateralized and Corporates indices, where there are further sub-indices in each of them. The indices are either real-time or daily data (End-of-Day), which depends on the desire of the market participants.

iBoxx Euro Overall			
Sovereign	Non-Sovereigns		
	Sub-sovereigns	Collateralized	Corporates
Germany	Agencies	Covered	Financials
Austria	Other Sovereigns	-Germany	Non-Financials
Belgium	Other Subsovereigns	-Ireland	Market Sectors
Finland	Public Banks	-France	Senior Subordinated
France	Regions	-Spain	
Greece	Supranational	-UK	
Ireland		Other Securitized	
Italy		Other Collateralized	
Netherlands			
Portugal			
Spain			

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Eidesstattliche Erklärung

Hiermit erkläre ich an Eides Statt, dass ich die Dissertation selbständig angefertigt und mich anderer als der in ihr angegebenen Hilfsmittel nicht bedient habe, insbesondere, dass aus anderen Schriften Entlehnungen, soweit sie in der Dissertation nicht ausdrücklich als solche gekennzeichnet und mit Quellenangaben versehen sind, nicht stattgefunden haben.

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