THE CREDIT RISK INFORMATION DYNAMICS BETWEEEN THE CDS AND EQUITY MARKETS: EMPIRICAL EVIDENCE AND APPLICATION TO CAPITAL STRUCTURE ARBITRAGE

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A Thesis Submitted in Total Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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September 2012

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Abstract

An information link exists between the credit default swap (CDS) and equity markets. The CDS spread is an observable price of a reference firm's credit risk. The same credit risk information is also reflected in its equity price. According to the structural credit risk pricing approach, equity is analogous to a call option written on firm assets, with the face value of the debt as the strike price. Accordingly, the probability of non-exercise equals the probability of default. Any information that affects a firm's creditworthiness affects the value of this call option and hence the stock price.

This thesis examines the credit risk information dynamics between the CDS and equity markets. Unlike existing studies, we do not model the interaction between the change of CDS spread and stock return. This is because stock returns also reflect non–credit-related information. Instead, we utilise the CreditGrades model, which belongs to the structural credit risk pricing approach, to extract the implied credit default spread (ICDS) from a firm's equity price. The pairwise CDS spread and ICDS thus represent price of credit risk from the CDS and equity markets, respectively.

We propose a new approach to calibrate the CreditGrades model to extract the ICDS. First, we make a less arbitrary assumption regarding unobservable parameters that describe the stochastic recovery process of the firm. Second, we calibrate unobservable parameters on a more frequent basis. Third, we recalibrate model parameters to incorporate newly released accounting figures, since the recovery process is determined by a firm's capital structure fundamental. We document strong evidence that our calibration approach generates more accurate ICDS estimates than those used by previous studies. The more accurate ICDS estimates facilitate a cleaner study of credit risk information flow between the CDS and equity markets.

We analyse the nature of information linkage between the CDS and equity markets for a sample of 174 U.S. investment-grade firms. We document strong cointegration between the CDS spread and ICDS, suggesting a long-run credit risk pricing equilibrium between the two markets. Using Gonzalo and Granger (1995) and Hasbrouck (1995) measures, we sort firms into five categories of credit risk price discovery. When forward-shifting the estimation window, we uncover an interesting transmigration pattern. From January 2005 to June 2007, the CDS market influenced price discovery for 92 firms. From January 2006 to June 2008, with the onset of the global financial crisis (GFC), that number increased to 159. As we move away from the height of the GFC, the number of CDS-influenced firms diminishes but remains high compared to the pre-GFC period. Using CDS spreads as trading signals, a conditional portfolio strategy that updates the list of CDS-influenced firms produces a significant alpha against Fama–French factors. It also outperforms buy-and-hold, momentum, and dividend yield strategies.

Finally, we propose a new trading algorithm to implement capital structure arbitrage, a convergent-type strategy that exploits mispricing between the CDS and equity markets. Our trading algorithm incorporates both long-run credit risk pricing equilibrium and short-run price discovery process between the two markets. Using our trading algorithm, the arbitrageur avoids the risk of non-convergence and of incurring substantial losses. We confirm that most of the trading profits are generated by conditioning the strategy on firms for which the CDS market dominates the price discovery process. Despite the fact that our trading sample covers the entire GFC, the conditional trading strategy produces a Sharpe ratio that is comparable to that of other fixed income arbitrage strategies.

Acknowledgements

I would like to express my deepest appreciation to my supervisor, associate professor Victor Fang. Without his inspiration and encouragement, I would not have been brave enough to pursue the PhD I once dreamt of. He continually motivated, encouraged, and advised me throughout my entire PhD candidature. His efforts in making time readily available for me are also deeply appreciated.

This thesis would not have been possible without the help and guidance from associate professor Michael Chng. Despite not being my official supervisor, he spent great amounts of time with me, discussing this research project. I am indeed in his debt for his insightful advice, patience with my questions, and sharing his knowledge of financial economics as relevant to my study. This help will never be forgotten.

I also would like to thank Dr. Piyadasa Edirisuriva, who was my associate supervisor and became my main supervisor after Victor left Monash University. I am grateful for thank Dr. Edirisuriva continuous support. I also thank Professors George Tanewski and Professor Robyn Moroney, who encouraged me to start and provided me administrative support during my candidature.

In addition, I would like to thank my friends Sharon Shen, Lawrence Bai, Mary Wang, and Jian Liu for bringing me joy during the last four years and providing balance to my life during this challenging PhD research project. I must also thank my girlfriend, Grace Wu. Her kind support and understanding were invaluable in the completion of this thesis.

Finally, I wish to thank my mother and father for everything they have provided to me. I will never know how much love they have given me and how many personal sacrifices they have made for me. I wish I could give my love back, as a son.

STATEMENT OF AUTHORSHIP

This thesis contains no material, except where reference is made in the text, which has been published elsewhere by me for another degree or diploma.

To the best of my knowledge, no other person's work has been used without due acknowledgement in the main text of this thesis.

This thesis has not been submitted for award of any degree or diploma in any other tertiary institution.

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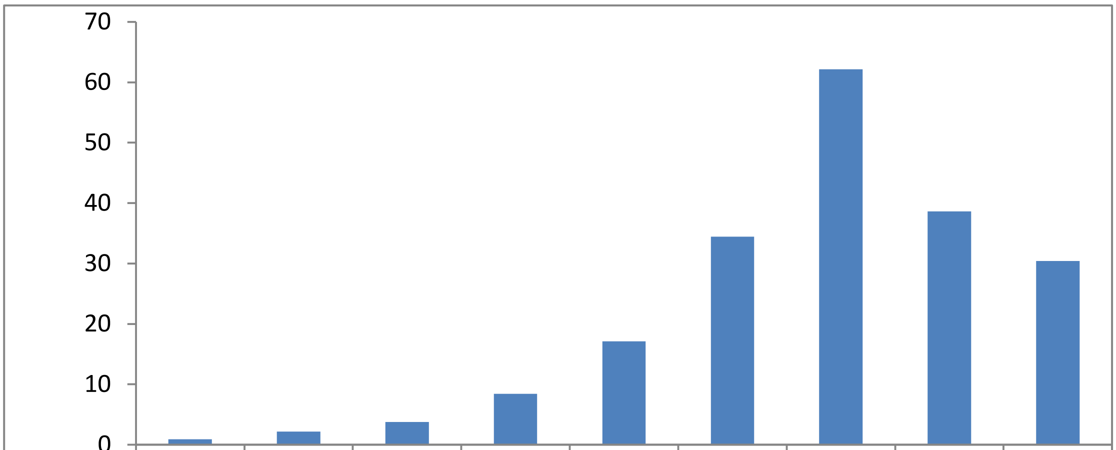
August 2012

Chapter 1: Introduction

1.1 The CDS market and background

The credit default swap (CDS) is one of the most prominent financial innovations of the last two decades. The first CDS contract can be traced back to the mid-1990s and the CDS market has experienced remarkable growth since then. According to a survey by the International Swaps and Derivatives Association (ISDA (2008)), the notional amount outstanding of CDS contracts increased from USD 0.92 trillion in 2001 to USD 62.17 trillion in 2007. In 2009 the CDS market was comparable in size to the U.S. bond market – USD 30.4 trillion versus USD 31.2 trillion notional outstanding – and this despite microstructural changes that had reduced the CDS market[1] (Bank for International Settlements (2008)). Figure 1 shows the notional amount outstanding of the CDS market from 2001 to 2009.

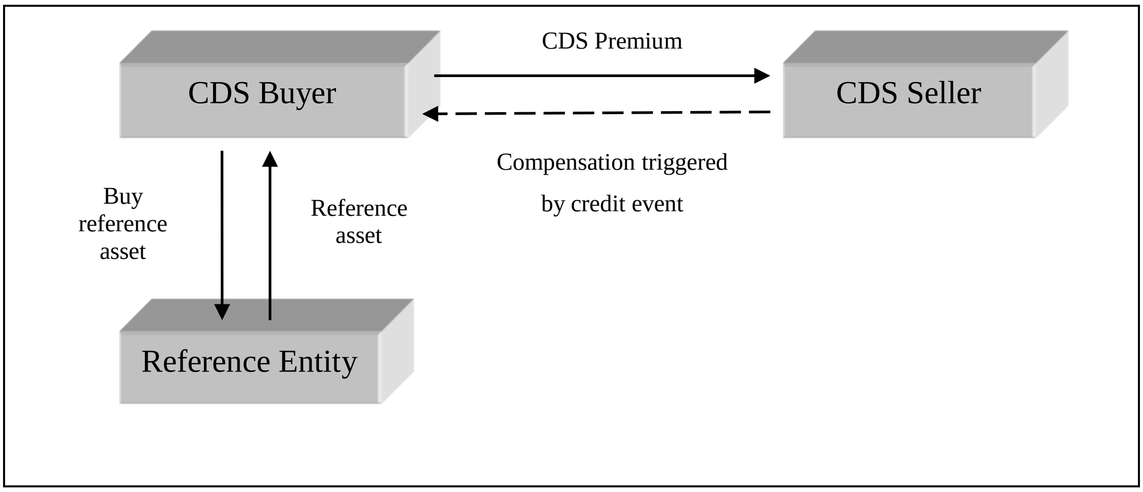
Figure 1.1: CDS contract notional amount outstanding (USD trillions)



	2001	2002	2003	2004	2005	2006	2007	2008	2009
Amount	0.919	2.192	3.779	8.422	17.096	34.423	62.173	38.6	30.4

[1] In 2008, the ISDA required major CDS market dealers, including TriOptima, Creditex, and Markit, to launch CDS compression services to terminate existing trades and replace them with smaller numbers of transactions with the same risk and cash flow profile. This process reduced the gross notional amount for the market participants and resulted in less regulatory capital to be held (Platt (2008), p. 70).

A CDS contract is a bilateral agreement that protects the buyer from losses on underlying assets due to a credit event of a reference entity. The underlying assets can be bonds, loans, or other structured products, for example, mortgage-backed securities, and the reference entity can be a corporation, municipality, or sovereign government. The diagram below illustrates the cash flow structure in a hypothetical CDS transaction. The CDS buyer makes periodic payments, known as premiums or spreads, to the seller until a credit event occurs or the contract expires, whichever comes first. Credit events are defined by a combination of some or all of the following: bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation/moratorium, and restructuring (ISDA (2003)). When a credit event happens, the seller is obliged to compensate the buyer through either a physical settlement or a cash settlement. Under a physical settlement, the buyer delivers the underlying asset to the seller in exchange for the face value of the asset. For a cash settlement, the seller compensates the buyer with the difference between the face value and the post-default market value of the underlying asset. This procedure has been applied to settle recent credit events, including the defaults of Tembec, Fannie Mae, Freddie Mac, and Lehman Brothers.



Since the payoff from a CDS contract is triggered by a default event, in effect the CDS market allows a firm's credit risk to be tradable at an observable price. Over the years, the CDS spread is increasingly being regarded as a benchmark indicator for the credit risk of the underlying reference entity. Hull et al. (2004) explain two reasons the CDS spread is better than the bond yield spread as a credit risk measure. First, the CDS spread quote provided by the market dealer represents a price at which the dealer is committed to trade. By contrast, the bond yield spread is not a binding price. Second, the CDS spread requires little adjustment since they are already a credit spread. However, the bond yield must be matched to the appropriate benchmark risk-free rate to obtain the bond yield spread.

Besides these two reasons, the CDS is a credit derivative contract, so the traders are not required to have physical exposure to the underlying assets when trading credit risk. This feature further enhances the liquidity of the CDS market as well. According to the British Bankers' Association (BBA) credit derivatives report (2006), one-third of the CDS contracts are used by banks to hedge their credit exposure. The rest are mainly investors and speculators who use the CDS market to fulfil their credit risk trading demand.

1.2 Motivation

Indeed, an information linkage exists across the CDS and equity markets. While firm credit risk is directly measured by CDS spreads, the equity market also reveals information related to the credit risk indirectly. Conceptually, equity investors hold only a residual claim on the firm's assets in the case of default, that is, they receive last priority to be compensated behind the debt holders. As a result, the equity investors bear the ultimate default risk of the firm and the equity price should react to credit risk-related information.

Theoretically, the structural credit risk pricing approach pioneered by Merton (1974) establishes an economic link between firm's equity value and default risk measured by the probability of default. According to the seminal work of Merton (1974), the equity can be viewed as a call option written on a firm's assets, with the strike price equal to the face value of the debt. The probability of default event, when the asset value falls under the debt value, is equivalent to the probability of such a call option not being exercised. Therefore, the equity price also implicitly reflects the firm's default risk.

This thesis is motivated by the significant gaps in the literature with respect to the information linkage across the CDS and equity markets. Despite the theoretical relation between the CDS and equity markets being established by the structural credit risk pricing approach, there have been few empirical studies on these cross-market credit risk information dynamics. In contrast, research has examined the dynamic relation between the CDS and bond markets. Blanco et al. (2005), Zhu (2006), and Dotz (2007) document that, consistent with the theoretical relation derived by Duffie (1999), the CDS and bond markets achieve a credit risk pricing equilibrium in the long run. Moreover, these studies further document that the CDS market dominates the bond market in the short-run credit risk price discovery process. However, the credit risk price discovery process across the CDS and equity markets remains under-researched.

Several studies investigate the relations between the CDS and equity markets. They employ a vector autoregressive (VAR) model to examine the lead–lag relation between the change of CDS spreads and stock returns (see Longstaff et al. (2003), Norden and Weber (2009) and Fung et al. (2008)). It is noted, however, that modelling these two variables in a VAR setting may not be appropriate for two reasons. First, the information content of the CDS spreads and stock returns are different. While the former presents the price of default risk, the latter cannot be utilised to indicate default risk directly. Second, Acharya and Johnson (2007) point out that the relation between CDS spreads and stock returns is highly non-linear according to the structural credit risk pricing approach. However, the VAR model assumes a linear relationship and ignores the significant non-linearity effect. Therefore, these studies provide little insight regarding the economic link between the CDS and equity markets.

Furthermore, if the fundamental economic role of a derivative market is to provide price discovery, this should be during normal market conditions. An interesting question is whether this role of the derivative market ceases to function properly during extreme events. For example, during the Wall Street crash of October 1987, the price discovery function of index futures market was severely impaired by the lack of liquidity and market making to facilitate the trading process. During the recent global financial crisis (GFC) that stemmed from the U.S. credit market in mid-2007, the CDS market was heavily criticised for its lack of regulation and transparency. However, to my best knowledge, no study has yet examined the price discovery function performed by the CDS market and its dynamic relation with the stock market during the course of the GFC.

Finally, although the CDS market has been heavily utilised for credit risk trading purposes,[2] only a few studies examine the trading applications of the CDS contract. Yu (2006), Duarte et al. (2007), and Bajlum and Larsen (2008) analyse the performance of a capital structure arbitrage strategy. This strategy is a convergent-type strategy that exploits temporal credit risk mispricing across the CDS and equity markets. However, the results documented by these studies seem to contradict the basic concept of capital structure arbitrage. While arbitrageurs may frequently lose their entire invested capital, the vast majority of trades executed do not converge. However, none of these studies ever discusses what really causes this non-convergence problem and how to overcome this difficulty.

1.3 Research objectives

Motivated by the gaps in the literature discussed above, this thesis examines the credit risk information linkage between the CDS and equity markets established by the structural credit risk pricing approach. This study has five conceptually related objectives. First, it implements the CreditGrades model[3] under the structural credit risk pricing approach to extract an implied credit default spread (ICDS) embedded in the firm's stock price. The ICDS is a credit risk measure from the equity market, with based on which we compare with the observable CDS spreads to investigate the credit risk information dynamics across the CDS and equity markets. Since the CreditGrades

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[2] According to the British Bankers' Association (BBA) credit derivatives report (2006), two-thirds of the CDS market is used by hedge funds and banks' proprietary trading desks for credit risk trading.

[3] The CreditGrades model was jointly developed by the leading institutions in the credit market, including RiskMetrics, J.P. Morgan, Goldman Sachs, and Deutsche Bank. In Finger et al. (2002, p. 5), the purpose of the CreditGrades model is to establish a robust but simple framework linking the credit and equity markets. It has been utilised as a benchmark model by both industry practitioners and academic researchers (see Currie and Morris (2002), Yu(2006), Bystrom (2006) and Duarte et al. (2007)). The model and procedures to extract *ICDS* are discussed in Chapter 4.

model needs to be calibrated with respect to non-observable parameters that describe the firm's recovery process, the calibration procedure becomes a non-trivial issue that affects the accuracy of the ICDS estimate. We propose a novel approach to calibrate the CreditGrades model. Our calibration approach provides a more accurate ICDS estimate, which in turn facilitates a cleaner study of cross-market credit risk dynamics between the CDS and equity markets.

Second, this study examines the dynamic relation between the CDS and equity markets with respect to credit risk pricing. Specifically, we intend to answer the following two questions: i) Does a credit risk pricing equilibrium exist across the CDS and equity markets? ii) Which market is more efficient in reflecting credit risk-related information and hence leads in the credit risk price discovery process? In effect, we analyse the long-run relation in the first question and focus on the short-run dynamics in the second question.

Third, this study investigates the impacts of the GFC on these cross-market credit risk information dynamics. If there is a perceived credit risk pricing equilibrium across the CDS and equity markets, would the unprecedented GFC that stemmed from the U.S. credit market break this information linkage and cause a persistent disequilibrium? Furthermore, does the GFC impair the price discovery function of these two markets and how did the credit risk price discovery mechanism evolve as we approached the GFC and how is it evolving as we continue past it?

Fourth, apart from the statistical results, the study ascertains the economic significance of these cross-market credit risk information dynamics between the CDS and equity markets. Our idea is simple, if there is a pattern regarding the credit risk information flows across the CDS and equity markets, can we make use of it to generate economic profits? In that regard, we design and test a set of portfolio strategies that extract trading signals from the CDS market to trade corresponding stocks.

Fifth, this thesis examines the risk–return profile of a capital structure arbitrage strategy. The strategy is designed to exploit temporary credit risk mispricing across the CDS and equity markets, based on the assumption that long-run co-movement enforces price convergence between these two markets. Accordingly, the long-run credit risk pricing equilibrium and short-run price discovery mechanism has important implications for this strategy's success. We point out the problems in the existing trading algorithm and propose a novel capital structure arbitrage algorithm by incorporating the credit risk information dynamics across the CDS and equity markets.

1.4 Contributions

This study makes several significant contributions to the existing literature. First, we address the gap in the literature with respect to the dynamic relationship between the CDS and equity markets. Unlike previous studies that utilise VAR to model the change of CDS spreads and stock returns, we pay particular attention to the inherent economic linkage across these two markets in credit risk pricing. In that regard, we follow the structural credit risk pricing approach to extract the implied credit default spreads (ICDS) from a firm's stock price, which would match the firm's CDS spreads. The pairwise spreads ($CDS_{i,t}, ICDS_{i,t}$) thus represent prices of credit risk from the CDS and equity markets, respectively. Accordingly, we model the dynamics of the pairwise spreads ($CDS_{i,t}, ICDS_{i,t}$) to uncover the relationship between the CDS and equity markets in credit risk pricing. Unlike Bystrom (2006), who examines this relationship at the index level, we analyse the credit risk information dynamics at the firm level, where the inherent $(CDS_{i,t}, ICDS_{i,t})$ linkage would be less impaired by market frictions associated with having to trade in index constituents.

Second, this study undertakes a comprehensive examination of the dynamics relationship between the CDS and equity markets. Since these two markets react to the credit risk-related information simultaneously, we start our analysis by ascertaining whether the CDS and equity markets price credit risk equally in the long run, that is, is there a long-run credit risk pricing equilibrium across these two markets? We then shift our focus from the long run to the short run and explore the credit risk price discovery mechanism across the CDS and equity markets. The market that is more informational efficient will react to the news more quickly than the less efficient market and will thus lead in the price discovery process. Therefore our study also contributes to the inclusive results in the literature regarding the relative informational efficiency between the CDS and equity markets. Furthermore, this study provides results that complement those of Blanco et al. (2005) and Zhu (2006), who examine long-run credit risk pricing and the short-run credit risk price discovery process across the CDS and corporate bond markets.

Third, our sample encompasses the entire period during which the credit crunch deteriorated into the global financial crisis (GFC). This allows us to pay particular attention to the time-varying nature of the information dynamics between the CDS and equity markets. Our study offers comprehensive understanding of the cross-market credit risk information flow between these two markets before, during, and after the GFC. Indeed, we are not merely testing whether the GFC has imposed some structural break on cross-market credit-risk price discovery; rather, our study offers insight into the nature of the structural break itself.

Fourth, compared to prior studies, our study covers a comprehensive sample of CDS and equity markets for 174 U.S. investment-grade firms. This large firm sample allows us to document cross-sectional evidence regarding how the price discovery mechanism evolves over time. Using Gonzalo and Granger (1995) and Hasbrouck (1995) measures of price discovery, we classify the firms into five price discovery categories {C1,…,C5}. By updating the categorisation results with a quarterly rolling -window, we are able to track the transmigration patterns of firms across {C1,..,C5}. Our documented findings on transmigration patterns across price discovery categories can only come from measuring and updating Gonzalo and Granger (1995) and Hasbrouck (1995) measures on a quarterly basis for a large firm sample.

Fifth, this study contributes to the literature on the trading implications of the CDS market. While academic research in the CDS market is growing rapidly, only a few studies consider its trading applications. Unlike Yu (2006) and Duarte et al. (2007), who examine a capital structure arbitrage strategy, we discuss the trading implications of the CDS market within the context of cross-market information flows. We propose a set of portfolio strategies to ascertain the economic significance of documented price discovery results. All strategies utilise the CDS spreads as trading signals to trade the underlying stocks. The portfolio that identifies and updates the firm list in which the CDS market possesses price leadership outperforms the other portfolios. This strategy also generates a significant alpha against Fama–French factors and has superior performance compared to other proven portfolio approaches, including the buy-and-hold, momentum, and dividend yield strategies. The results can assist traders exploit trading opportunities on the basis of cross-market information flows between the CDS and equity markets.

Sixth, this study adds to the limited literature on the performance of a capital structure arbitrage strategy. We discuss several issues that lead to its poor performance, as documented in Yu (2006) and Bajlum and Larsen (2008), for example, the risk of incurring large losses and the non-convergence of arbitrage positions. We then propose a novel capital structure arbitrage trading algorithm to improve trading performance. Our trading algorithm incorporates the dynamics of the CDS and equity markets in credit risk pricing. Compared with the existing trading algorithm in the literature, our trading algorithm allows us to i) verify the fundamental convergence condition that underlies the concept of capital structure arbitrage trading, ii) identify the cross-market credit risk pricing disequilibrium situation that indicates the arbitrage opportunity, and iii) ascertain the adjustment dynamics in the CDS and equity markets after pricing disequilibrium occurs, based on which we can form the arbitrage positions.

Seventh, a significant contribution is also made with respect to the CreditGrades model calibration. Our calibration approach involves less ad hoc parameter setting and more frequent updating of the parameters to reflect new balance sheet information. The graphical and statistical evaluations demonstrate that the ICDS estimate obtained using our calibration procedure is able to capture more credit risk dynamics than using the previous approach of Yu (2006) and Duarte et al. (2007). Our detailed description of the calibration procedure can be utilised as an implementation manual for future academic research that uses the CreditGrades model to extract implied credit risk measure from a firm’s stock price.

1.5 Organisation

The thesis contains seven chapters, including this introduction Chapter 1. To follow, Chapter 2 reviews the literatures that are relevant to the studies in this thesis. We start by reviewing the principle of CDS pricing, where the probability of default is the key input. While the structural credit risk pricing and reduced form approaches are two well-accepted ways to model the probability of default, the former approach pioneered by Merton (1974) establishes an economic linkage between the credit risk and equity value and hence provides a theoretical foundation for this thesis. Since our studies are empirical, we focus on the intuition when reviewing these two theoretical credit risk pricing approaches. Chapter 2 also contains a review of the empirical literatures that examine i) the relationship between the CDS and other financial markets, ii) informational efficiency between the CDS and equity markets, and iii) the risk–return profile of the capital structure arbitrage strategy. The findings of these studies are presented meanwhile the problems are also identified and discussed. Finally, we review two methods of measuring the cross-market price discovery contribution, namely, Gonzalo and Granger (1995) common factor weight and Hasbrouck (1995) information share, based on which we examine the short-run price discovery mechanism between the CDS and equity markets.

Chapter 3 describes the data and sample for our empirical studies. To examine the credit risk information dynamics across the CDS and equity markets, we need credit risk measures from these two markets. For the CDS market, the CDS spread ($CDS_{i,t}$) is an observable price of credit risk for the underlying firm, while for the equity market we implement the CreditGrades model to extract the ICDS ($ICDS_{i,t}$)

embedded in the firm's stock price. We introduce the data sources and variables to construct the pairwise credit risk measures ($CDS_{i,t}, ICDS_{i,t}$). Chapter 3 also outlines the basic characteristics and descriptive statistics for our firm sample.

In Chapter 4, we introduce our improved approach to calibrate the CreditGrades model to extract the $ICDS_{i,t}$embedded in the firm's stock price. The chapter begins by providing a detailed description of the CreditGrades model and its mathematical procedures to calculate the $ICDS_{i,t}$. Next, we propose and explain our calibration methodology. We provide graphical and statistical evaluations between the $ICDS_{i,t}$ using our calibration and $ICDS^{*}_{\mathrm{i,t}}$ using the previous calibration approach of Yu (2006) and Duarte et al. (2007). Our model calibration generates a more accurate measure of $ICDS_{i,t}$, which facilitate a cleaner study on the cross-market credit risk information flows between the CDS and equity markets.

In Chapter 5, we undertake a comprehensive analysis of the dynamic relationship between the CDS and equity markets with respect to credit risk pricing. We first examine whether these two markets have a long-run credit risk pricing equilibrium and then shift our focus to explore the short-run cross-market credit risk price discovery mechanism. We report the results for the overall sample period as well as the pre-GFC and GFC subsample periods. Using Gonzalo and Granger (1995) and Hasbrouck (1995) price discovery measures, we classify firms into five mutually exclusive price discovery categories {C1,…,C5}. We uncover the time-varying nature of the information dynamics across these two markets by comparing dissimilar categorisation results over the pre-GFC and GFC subsamples. To obtain more insights regarding the impact of the GFC on the price discovery ability of each market, we employ a rolling-window analysis to update the categorisation results and track the transmigration patterns across {C1,…,C5} on a quarterly basis. Finally, we ascertain the economic significance of the results with portfolio strategies that draw trading signals from the CDS market. Profit and loss results confirm that the portfolio strategy identifying and updating the list of firms in which the CDS market leads in the price discovery process outperforms all other benchmarks, including buy and hold, momentum, and dividend yield.

Chapter 6 examines the performance of capital structure arbitrage, a convergent-type strategy that exploits temporary mispricing across the CDS and equity markets. We replicate the trading algorithm of existing studies and document a similar problem of non-convergence, which contradicts the basic concept of capital structure arbitrage. We then propose and redesign the trading algorithm by incorporating the dynamic relations between the CDS and equity markets. Since the price discovery mechanism indicates the adjustment process of divergent prices, we further decompose the overall strategy into five conditional strategies based on the price discovery categorisation results. The trading results are discussed for both the individual trade and portfolio levels. Finally, using the procedures proposed by Hogan et al. (2004), we test whether the capital structure arbitrage strategy gives rise to statistical arbitrage.

The thesis concludes with Chapter 7, in which we summarise the key findings and outline some implications for future research. The references and appendices follow this chapter.

1.6 Summary

According to the structure credit risk pricing approach, an information linkage exists between the CDS and equity markets. While the CDS market provides an observable price of credit risk for the underlying firm, the equity price also reflects default risk information indirectly. The objective of this thesis is to examine the credit risk information dynamics across the CDS and equity markets.

Motivated by the gaps in the literature, we undertake a comprehensive analysis of the long-run credit risk pricing equilibrium and short-run credit risk price discovery mechanism across the CDS and equity markets. In particular, we investigate the time-varying nature of these cross-market information dynamics and explore the price discovery function performed by the two markets before, during, and after the GFC. Using portfolio strategies, we demonstrate the economic significance of the documented statistical results regarding the cross-market credit risk price discovery findings. Finally, we propose a new trading algorithm for capital structure arbitrage trading by incorporating long-run and short-run credit risk dynamics across the CDS and equity markets.

Chapter 2: Literature review

2.1 Introduction

This chapter reviews the literatures that are relevant to this thesis. The first area concerns credit risk pricing, which underpins the pricing of CDS contracts. The basic principles of CDS pricing are discussed first, followed by a review of the two main approaches of credit risk modelling, namely, the structural models and the reduced form models. Since our studies are empirical, we focus on the intuition when reviewing these pricing models, which are highly technical in nature. We choose to use the CreditGrades model to extract implied credit default spreads (ICDS) from a firm's stock price. Chapter 4 discusses this structural model in detail.

The second area of the literature relates to studies on the cross-market information flows between the CDS and other financial markets. Using a reduced form of the credit risk pricing approach, Duffie (1999) demonstrates a theoretical relation between the CDS and bond markets. Furthermore, the structural credit risk pricing approach pioneered by Merton (1974) establishes a linkage between credit risk (probability of default) and equity value. Accordingly, the credit risk information is reflected in the CDS, bond, and equity markets. We review studies that analyse the dynamic relationship between the CDS and bond/equity markets. This is followed by a discussion of empirical studies that investigate the relative informational efficiency among these markets in reflecting credit risk information.

Third, we review prior studies on capital structure arbitrage, a convergent-type strategy that takes advantage of temporary mispricing across the CDS and equity markets. The implementation procedures are discussed and some issues of concerns are raised for potential improvement.

Finally, we revisit two well-accepted methods to measure price discovery contribution, namely, the Gonzalo and Granger (1995) common factor weight and Hasbrouck (1995) information share. The concepts of these two methods are briefly discussed. Using an example of two assets, we demonstrate how these two methods are applied to quantify the price discovery contribution performed by each market.

2.2 Credit risk pricing

2.2.1 CDS pricing

CDS pricing is about computing a regular fee or spread as a percentage of the notional value. Based on the cash flow streams in a CDS transaction, similar to swap pricing, CDS pricing involves finding the spread that equates the present value of expected CDS spreads payments, conditional on survival probability, with the present value of the expected compensation, which depends on the default probability and loss given default.[4] Based on a $1 notional principal, the present value of the expected CDS spreads payment can be expressed as

$$c\int_0^T P_{(s)}e^{-rs}ds \tag{2.1}$$

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[4] See, for example, Duffie (1999) and Hull and White (2000) and others.

where c is the annualised CDS spread, assuming continuous payment of fees for tractability purposes; $P_{(s)}$ is the probability of survival till time s, and r is the continuous risk-free rate.

The present value of the expected compensation payment at default can be expressed as

$$(1-\mathrm{R})\int_0^T f(s)e^{-rs}ds \tag{2.2}$$

where R is the recovery amount for the underlying assets and $f(s)$ is the default density function.

Upon initiation, the CDS contract has zero market value, that is, the present value of the expected CDS spread payment to the seller equals the present value of the expected default compensation payment made by the seller. Therefore the CDS spread is determined by setting these two present values equal to each other:

$$c\int_0^T P_{(s)}e^{-rs}ds = (1-\mathrm{R})\int_0^T f(s)e^{-rs}ds \tag{2.3}$$

From equation (2.3), the pricing of CDS spreads is determined by the survival probability $P_{(s)}$, the risk-neutral default density function $f(s)$, the recovery rate of the underlying asset R, and the risk-free rate r. The integral on the left-hand side reflects the summation over the stream of payments, whereas the integral on the right-hand side is due to the fact that the cumulative probability of default is an integration of the probability density function.[5]

Both the structural and reduced form approaches can be used to price CDS spreads, the only difference being in the stage of calculating the conditional default/survival probability. Using the reduced form approach, Duffie (1999) derives a theoretical relation between the CDS spreads and bond yield spreads. Hull et al. (2004), Blanco et al. (2005), and Zhu (2006) document that despite temporary violation in the short run, the theoretical relationship is valid in the long run. For the structural approach, its CDS pricing ability is confirmed by Eom et al. (2004), Arora et al. (2005), and Ericsson et al. (2009). In addition, Blanco et al. (2005), Ericsson et al. (2009), and Greatrex (2009) confirm that the variables suggested by the structural credit risk pricing model are highly significant in explaining the changes of CDS spreads. These variables include firm leverage, stock returns, and its volatility, the level of interest rate, and slope of the yield curve. The presence of significant explanatory power provides further support for applying the structural credit risk model to CDS pricing.

2.2.2 Overview of credit risk pricing

The structural credit risk pricing approach is pioneered by Merton (1974), in which default is defined as occurring when a firm's asset value falls below a certain critical point. This approach assumes the firm's assets value V_t follows a geometric Brownian motion

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[5] The survival probability $P_{(t)}$ and risk neutral default density function are related as $f(t) = -\frac{dP_{(t)}}{dt}$ (Duffie and Singleton (2003)).

$$\frac{dV_t}{V_t} = \mu dt + \sigma dW_t \tag{2.4}$$

where μ is asset drift, σ is asset volatility, and W_t is a standard Brownian motion. Merton (1974) views the firm's debt as a risk-free bond plus a short put option on the firm's assets and the firm's equity as equivalent to a call option written on the firm's asset with the strike price equal to the face value of liabilities. Accordingly, the firm's liabilities and equity can be priced using the Black–Scholes–Merton option pricing framework. In that regard, the survival probability, the key input to credit risk-sensitive instruments, is simply the (risk-neutral) probability of the asset value *V* not falling below the liability at maturity *T*. Assuming a simple capital structure with only a single zero coupon debt, this probability is

$$P_{(T)} = \Phi\left(\frac{\ln\left[\frac{V_0}{De^{-rT}}\right] - \frac{1}{2}\sigma^2 T}{\sigma\sqrt{T}}\right) \tag{2.5}$$

where $P_{(T)}$ is the survival probability up to *T*, $\Phi(\cdot)$ is the cumulative normal distribution function, V_0 is the current asset value, *D* is the face value of debt, r is the risk-free rate, and σ is annualised asset volatility.

The first-passage models extend Merton (1974) approach to accommodate the fact that the default event may occur prior to debt maturity. This class of models makes use of the distribution of first-passage time of Brownian motion to obtain analytical pricing formulas for the survival probability. For the Brownian motion process $dY_t = adt + bdW_t$, the probability of Y_t greater than an arbitrary point y (the default barrier) is calculated as in (2.6) (see Musieala and Rutkowski (2005))

$$P\{Y_s > y, \forall\, s < t\} = \Phi\left(\frac{at - y}{b\sqrt{t}}\right) - e^{2ay/b^2}\Phi\left(\frac{at + y}{b\sqrt{t}}\right) \tag{2.6}$$

Applying this result to the asset return process in (2.1) with y as the default barrier leads to an analytical formula for the risk-neutral probability of survival. Variants of first-passage models differ in the specification of the threshold for the default barrier. Black and Cox (1976) determine this threshold exogenously from the firm's capital structure. Longstaff and Schwartz (1995) adjust the deterministic interest rate to follow a stochastic process and allow it to correlate with the stochastic asset value process. Leland and Toft (1996) treat the default barrier as endogenously determined by the firm's capital structure such that equity holders will declare bankruptcy whenever the cost of servicing debt obligations is no longer justified by the corresponding increase in equity value.

Despite the elegance and tractability of the above structural models, they fail to reproduce the credit price of short maturities simply because assets that begin above the barrier cannot immediately, or within a short period of time, reach the barrier by diffusion only. This underpricing issue is documented in, for example, Jones et al. (1984), Ogden (1987), Lyden and Saranati (2000), and Ericsson et al. (2005).

Motivated by this underpricing issue, leading institutions in the credit market – including RiskMetrics, JP Morgan, Goldman Sachs, and Deutsche Bank – jointly develop their CreditGrades model. The CreditGrades model increases short-horizon credit prices by introducing uncertainty to the default barrier so that the chance of the stochastic asset process crossing the default barrier is more likely. This approach is analogous to the class of stochastic volatility models seeking to introduce fat-tailness to equity returns by making the 'spot' volatility random through time.

Given its practical implementation, the CreditGrades model has been considered the industry benchmark model[6] and is commonly utilised in empirical research. Yu (2006) and Duarte et al. (2007) use the CreditGrades model to examine the profitability of a capital structure arbitrage strategy. Bystrom (2006) uses this model to construct a stock price-implied CDS index that mimics the iTraxx CDS index and analyses the lead–lag relation between these two indexes. Bedendo et al. (2011) examine the cause of the cap between CDS spreads and corresponding spreads obtained using the CreditGrades model. We discuss the CreditGrades model in detail in Chapter 4.

The second approach to credit risk modelling is the reduced form model or intensity-based models. This approach includes the models of Jarrow and Turnbull (1995), Jarrow et al. (1997), and Duffie and Singleton (1999), and among others. Unlike structural models, reduced form models do not link the default probability to a firm's financial fundamentals but, instead, assumes default time as an exogenous random event whose distribution can be calibrated to the price of credit instruments. For example, a basic reduced form model defines default as the first arrival time of a Poisson process with constant mean arrival rate λ. Accordingly, the probability of survival till time t is $p(t) = e^{-\lambda t}$. The sophisticated models allow λ following a stochastic process $\lambda(t)$ (see Duffie and Singleton (2003)). Regardless of specification, all reduced form models do not explain theoretically why debts are defaulted; hence they are not suitable for research that examines the linkages between credit risk and equity value.

[6] See Currie and Morris (2002), Yu (2006), and Bajlum and Larsen (2008).

2.3 Cross-market credit risk information flows

2.3.1 Long-run equilibrium and short-run lead–lag relation

Empirical research in this area uses time-series analysis to examine the long-run equilibrium and short-run lead–lag relationship between the CDS, equity, and bond markets. Results consistently show that the CDS market leads the bond market (Blanco et al. (2005), Zhu (2006), Dotz (2007)). However, results on the relationship between the equity and CDS market remain inconclusive.

Blanco et al. (2005) analyse the dynamic relationship between CDS spreads and bond yield spreads for a sample of 17 U.S. and 16 European investment-grade firms. Their daily sample covers an 18-month period from January 2001 to June 2002. They find that in all U.S. firms and 10 European firms, the CDS spreads and bond yield spreads are cointegrated. The perceived cointegration suggests there is a long-run credit risk pricing equilibrium across the CDS and bond markets. Similar results are also documented by Zhu (2006), who examines an international sample of 24 firms between 1999 and 2002. These results confirm the theoretical relation between the CDS and bond yield spreads as derived by Duffie (1999).

After documenting the long-run credit risk pricing equilibrium relation, Blanco et al. (2005) examine the short-run credit risk price discovery process across the CDS and bond markets. They model the dynamics between the CDS and bond yield spreads as a bivariate vector error correction model (VECM). The VECM parameters allow them to compute Gonzalo–Granger (1995) and Hasbrouck (1995) measures to ascertain the relative price discovery contribution of each market. Blanco et al. (2005) find that the CDS market dominates the bond market in the price discovery process and 80% of the credit risk price discovery is indeed performed by the CDS market. They attribute this strength to the institutional features of the CDS market, including the ability to sell short, larger transaction sizes, and more sophisticated market participants. Utilising a similar methodology, Zhu (2006) also documents evident results that the CDS market performs a greater price discovery function than the bond market.

Dotz (2007) analyses a sample of 36 European firms from January 2003 to October, 2006 and finds that the price discovery mechanism between the CDS and bond markets is time varying. Converting the VECM model into a state-space form model, the author estimates the time-varying factor loadings of the error correction term and updates the Gonzalo–Granger (1995) and Hasbrouck (1995) measures. Dotz (2007) shows that while the CDS market dominates slightly in the price discovery process, its contribution was significantly reduced during the credit market turbulence in 2005.

Given the fact that the value of equity, bond, and CDS contracts depends on firm asset value, studies also investigate the empirical relationships among these three markets. Using Vector Autoregressive (VAR) model, Longstaff et al. (2003) examine the intertemporal relationships between the CDS, stock, and bond markets at individual firm level. Their weekly sample contains 68 U.S. firms from March 2001 to October 2002. They also find that the CDS spread change and stock return Granger-cause the change of the bond yield spread, suggesting the information arrives at the CDS and equity markets first before it is incorporated by the bond market. However, the authors did not find any evident result regarding the lead–lag relation between the CDS and equity markets.

Using an international sample of 58 firms, Norden and Weber (2009) analyse the lead–lag relationship between the CDS, bond, and equity markets at monthly, weekly, and daily frequencies. Their findings confirm the result of Longstaff et al. (2003), that the CDS and equity markets lead the bond market. In contrast, Norden and Weber (2009) also document a Granger causality effect of the stock return on the change of CDS spreads and this effect is more pronounced for a daily frequency. For example, the stock return Granger-causes the changes of the CDS spread in 39 firms, but the reverse effect is only found in 5 firms. This result reveals some evidence that favours the informational efficiency of the equity market over the CDS market.

Unlike Longstaff et al. (2003) and Norden and Weber (2009), Fung et al. (2008) examine the lead–lag relationship between the CDS and equity markets at the index level.[7] They divide the sample into investment-grade sector and high-yield sectors, where the investment-grade sector is captured by the CDX.NA.IG index and the high-yield sector is captured by the CDX.NA.HY index. For the investment-grade sector, Fung et al. (2008) find that the S&P 500 index returns and self-constructed investment-grade stock index returns Granger-cause change in the CDX.NA.IG index, but the reverse effects remain insignificant. For the high-yield sector, bi-directional Granger causality is detected between the stock index returns and CDX.NA.HY index change. Accordingly, the authors conclude that the stock market is more efficient than the CDS market in reflecting default risk-related information.

[7] For the CDS index, Fung et al. (2008) use the Dow Jones Investment Grade CDX index (CDX.NA.IG) and the Dow Jones High Yield CDX index (CDX.NA.HY). The CDX.NA.IG index is an equal-weighted CDS index composed from CDS contracts on 125 North American firms with the most liquid investment-grade credit. The CDX.NA.HY index is an equal-weighted CDS index composed from CDS contracts on 100 North American firms with the most liquid high-yield credit. For the stock index, the authors use the Standard & Poor's (S&P) 500 stock index. To fully replicate the entities in the CDX indices, they also construct two mimicking stock indices using relevant entities in the CDS indices.

While the results of Longstaff et al. (2003), Norden and Weber (2009) and Fung et al. (2008) are inconclusive, their modelling approach also offer little insight regarding the economic link between the CDS and equity markets. These studies utilise VAR to model the co-movement of the CDS spread changes and stock returns. However, these two variables indeed convey very different information. The CDS spreads represent the price of credit risk for the underlying firm but the stock return is not indicative of default risk. Furthermore, the relationship between the CDS spreads (price of default risk) and stock returns is inherently non-linear according to the structural credit risk pricing approach (see Acharya and Johnson (2007)). It is therefore inappropriate to investigate their relationship in a linear model. Thus the VAR approach employed by these studies has a weak theoretical foundation.[8]

Considering this issue, Bystrom (2006) utilises the CreditGrades model, a structural credit risk pricing model, to extract an implied credit default spreads (ICDS) embedded in the firm's stock price. Using the stock prices of constituent firms, the author constructs an ICDS index mimicking the iTraxx CDS index. Both the ICDS index and iTraxx CDS index measure the aggregate credit risk level for the constituent firms. The author finds that the autocorrelation is significant for the change in iTraxx CDS index but not for the change in ICDS index, indicating that the iTraxx CDS index is inefficient since future index values can be forecasted using historical values. More importantly, the changes in the CDS index are significantly correlated with the contemporaneous and lagged changes of ICDS index. This result

[8] Empirical studies analysing the relationship between the CDS and bond yield spreads, however, are motivated by the theoretical relation derived by Duffie (1999). Using the reduced form credit risk pricing approach, the author proves that the CDS spreads equals bond yield spreads under certain conditions.

confirms the ability of the CreditGrades model to predict market CDS spreads. It also suggests that the ICDS index, the credit risk measure implied by the stock market, leads the CDS index in reflecting credit risk information.

2.3.2 Informational efficiency between the CDS and equity markets

In addition to those studies that analyse the dynamic relationship, there is a stream of empirical research that examines the relative informational efficiency between the CDS and other financial markets. Indeed, these two streams of research are related. The more efficient market will incorporate the new information into prices more quickly. As a result, the more efficient market will dominate the less efficient market in the price discovery process.

Hull et al. (2004) examine the reaction of the CDS market to Moody credit rating announcements. Their sample covers a five-year period, from October 1998 to May 2002. They first analyse the CDS spread changes conditional on the rating announcement events and find that the CDS market is able to anticipate downgrades, reviews for downgrade, and negative outlook events. Furthermore, the authors study the possibility of credit rating announcements after large CDS spread changes. Their finding show that a significant proportion of rating events, for example, 50.9% of negative outlook events and 42.6% of downgrade events, are associated with the prior 30 days' top quartile CDS spread changes. Although their results suggest the CDS market is utilised by the rating agency as an information source for rating announcement decisions, the relative informational efficiency of the CDS market compared to other financial markets, for example, the stock market, still remains unclear.

Using event study methodology, Norden and Weber (2004) compare the relative reactions of the CDS and equity markets to credit rating events[9] during 2000 to 2002. They find abnormal price reactions in the CDS and stock markets before reviews for downgrade and actual downgrade events. To ascertain relative informational efficiency, they compare the percentage price run-up in the CDS and equity markets. The percentage price run-up is defined as the percentage change in the abnormal price change during an event window relative to the cumulative abnormal price change on the announcement day. The market with the larger and earlier run-up is considered the more informational efficient. The authors find dissimilar results for different types of rating events. The CDS market is associated with greater daily run-ups than the stock market before reviews for downgrade events, indicating the CDS market is able to incorporate more information. On the other hand, the stock market has larger run-ups than the CDS market prior to actual downgrade events. Given the fact that most of the reviews for downgrade events are eventually followed by actual downgrade events and it is the CDS market that has the pronounced reaction before a review for downgrade event, Norden and Weber (2004) conclude that the CDS market is more efficient than the stock market in processing credit risk-related information.

Using the same methodology, Greatrex (2008) compares the reactions of these two markets to the earnings announcement event. Unlike Norden and Weber (2004), Greatrex (2008) does not document any significant difference in the daily run-up measures between the CDS and stock markets. Thus the author concludes that the

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[9] Norden and Weber (2004) consider the credit-rating events of actual downgrades, reviews for downgrade, actual upgrades, and reviews for upgrade made by S&P, Moody's, and Fitch.

stock market is no less efficient than the CDS market in processing earnings news and vice versa.

Acharya and Johnson (2007) examine the link between insider trading and information transmission between the CDS and equity markets. They find that insider trading in the CDS market may provide an informational advantage to the CDS market over the stock market. Insiders who possess private information regarding a firm's creditworthiness will realise their informational advantage in the CDS market first, [10] before this information is transmitted to the stock market. The authors document that the shocks in the CDS market have significant predictive power on the future stock returns and this effect becomes more pronounced as the number of insiders increases. Accordingly, the incremental information revelation from the CDS market to the stock market is caused by informed trading activities. The authors further demonstrate that this insider trading-induced information flow only exists prior to a credit deterioration event, suggesting the information revelation is conditional on future negative credit risk shocks.

2.4 Capital structure arbitrage

Despite it having been designed as a hedging instrument against credit risk exposure, the CDS contract has been often utilised by market participants to fulfil trading purposes. Among trading applications, capital structure arbitrage has become one of the fast-growing areas attracting attention from hedge funds and bank's proprietary trading desks (Currie and Morris (2002)). In essence, the capital structure arbitrage

[10] In the study insiders mainly refers to the lead banks in a syndicated loan transaction. Acharya and Johnson (2007) point out that these banks also have trading desks in the CDS market.

strategy is a convergent-type strategy that takes advantage of credit risk mispricing across different instruments written on the firm. While the CDS spreads provide an observable price for credit risk, the stock price also indicates the level of credit risk indirectly, according to the structural credit risk pricing approach. Accordingly, the CDS and equity markets become the main trading venues for capital structure arbitrageurs.

2.4.1 Empirical results of the capital structure arbitrage strategy

Empirical research in capital structure arbitrage strategies is still in the early stage, with only Yu (2006) and Duarte et al. (2007) being the only published studies. Yu (2006) examines the profitability of capital structure arbitrage strategies using a sample of 261 North American firms from 2001 to 2004. Adopting the same trading algorithm as Yu (2006), Duarte et al. (2007) compares the performance of capital structure arbitrage with other common fixed-income arbitrage strategies.

Using the CreditGrades model, Yu (2006) estimates the ICDS embedded in the firm's stock price. The difference between CDS spreads and the ICDS indicates credit risk mispricing across the CDS and equity markets. A trading opportunity presents if

$$CDS_t > (1+\alpha) \times ICDS_t \tag{2.7}$$

or

$$ICDS_t > (1+\alpha) \times CDS_t \tag{2.8}$$

where α is a trading trigger[11] that allows divergent prices to be sufficient. In the case of (2.7), if the mispricing is caused by an overvalued CDS_t, the arbitrageur should take a short position on the CDS contract. But if divergent prices are driven by an undervalued $ICDS_t$ due to an inflated stock price, the arbitrageur should short stocks. However, without knowledge about credit risk pricing dynamics between the CDS and equity markets, the arbitrageur could not ascertain which market is more efficient in reflecting updated credit risk levels and which market is being mispriced. As a result, Yu (2006) decides to take short positions on the CDS contract and the stocks simultaneously in the case of (2.7). Analogously, for the divergent situation of (2.8), the arbitrageur takes long positions on both the CDS contract and the stocks.

Yu (2006) further explains that the equity position is indeed a hedge for the CDS position and vice versa. An equity delta (δ) is utilised to determine the combination of the CDS contract and stocks.[12] For each dollar in the CDS contract, $-\delta$ shares are matched.[13] At convergence, defined as $CDS_t = ICDS_t$, the arbitrageur unwinds the positions. If divergent prices do not converge, the positions are liquidated at the end of the holding period.[14] For risk management purposes, the positions are mark to market on a daily basis and close immediately when the total value becomes negative.

Yu (2006) applies the strategy to 210 investment-grade firms and 51 speculative-grade firms and demonstrates that the strategy incurs substantial losses for both investment- and speculative-grade firms. For the investment-grade firms, the best

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[11] Yu (2006) considers trading triggers of 0.5, 1 and 2.
[12] The equity delta is calculated as the change in the CDS contract value relative to the change in equity price.
[13] The equity delta δ is negative.
[14] Holding periods of 30 and 180 days are considered.

outcome is obtained when implementing the strategy with a 180-day holding period and a trading trigger α = 2. Among 18,173 trades executed, 23% generate a holding period loss. The minimum, mean, and maximum holding period returns are -13.37%, 1.02%, and 104.41% respectively. However, if the strategy is implemented with a 30-day holding period and a trading trigger α = 0.5, the overall outcome significantly deteriorates. Among 57,621 trades executed, 49% incur a loss and the worst loss can reach -75.16%. For the speculative-grade firms, the outcome does not improve. For example, with a 180-day holding period and a trading trigger α = 0.5, 50% of 9,315 trades are associated with a holding period loss and the worst loss is -54.6%.

In a recent working paper, Bajlum and Larsen (2008) replicate Yu's (2006) trading algorithm and compare the trading performance by using i) two structural models and ii) different volatility inputs to generate ICDS estimates. For the structural model, the authors compare Leland and Toft (1996) and the CreditGrades models. For the volatility proxy, they consider historical and option-implied volatility. They demonstrate that, relative to the model choice, the volatility input has a larger impact on trading performance. The mean holding period return substantially improves from 2.64% to 4.61% when implied volatility instead of historical volatility is used as input to the CreditGrades model. Similarly, the implied volatility input increases the mean return from 3.14% to 5.47% when the Leland and Toft (1996) model is used. These results are consistent with the findings of Finger and Stamicar (2005) and Cao et al. (2010), where forward-looking option-implied volatility dominates historical volatility in credit risk pricing. Finally, Bajlum and Larsen (2008) confirm Yu's (2006) results that the strategy is quite risky: A substantial proportion of trades generate losses and arbitrageurs may even experience a complete drawdown of their invested capital.

2.4.2 Discussions of the current capital structure arbitrage trading algorithm

Besides the risky results mentioned above, current studies also document that divergent prices are more likely to drift apart rather than converge. Indeed, entire trades are closed without convergence. For example, Yu (2006) executes 57,621 trades on investment-grade companies with a holding period of 30 days and a trading trigger of 0.5, but only 372 trades, or 0.6 percent end with convergence. Even with a holding period of 180 days and a trading trigger of 2, only 142 out of 18,173 or 0.7 percent, of trades are closed at convergence. Similar results are also found by Bajlum and Larsen (2008).

Suffice to say, these results completely contradict the basic concept of capital structure arbitrage. Claimed to be a convergent-type trading strategy, producing converging trades should be a minimum requirement for the capital structure arbitrage trading algorithm. We address three issues in the trading algorithm employed by these studies that may contribute to the non-convergence problem.

First, the capital structure arbitrage strategy assumes that a credit risk pricing equilibrium exists across the CDS and equity markets so that any divergent prices are expected to revert. Indeed, whether these two markets tend to move together is an empirical issue. Therefore the arbitrageur needs to verify the pricing equilibrium condition before applying the trading strategy. Without a perceived cross-market pricing equilibrium, divergent prices do not indicate a mispricing situation and therefore should not be utilised as a signal for an arbitrage opportunity. However, existing studies do not consider this issue in their trading algorithm and explicitly assume the divergent price will be forced to revert.

Second, if equations (2.7) and (2.8) are utilised as the trading signals, the existing studies indeed arbitrarily set $CDS_t = ICDS_t$ as the credit risk pricing equilibrium relation. Despite both CDS_t and $ICDS_t$ measuring credit risk, the former is an observed price from the CDS market whereas the latter is an implied price embedded in the firm's stock price. The dissimilar institutional features in the CDS and equity markets may impede the equilibrium occurring at parity, $CDS_t = ICDS_t$. For example, Tang and Yan (2008) document a non-trivial liquidity component in the CDS spreads while Blanco et al. (2005) point out that the cheapest-to-deliver option in the CDS contract and counterparty risk factor may result in an overestimated CDS spread. Analysing long-run equilibrium across the CDS and bond markets, Blanco et al. (2005) demonstrate that the CDS spreads and bond yield spreads do not necessarily reach a parity relation at equilibrium. Analogously, the arbitrageur also needs to ascertain the specific equilibrium relation between CDS_t and $ICDS_t$, based on which the disequilibrium (trading signal) can be decided.

Third, existing studies have difficulties identifying a mispriced market. For example, when the trading signal occurs at $ICDS_t > (1 + \alpha) \times CDS_t$, this divergence could be caused by an undervalued CDS_t or an overvalued $ICDS_t$ due to a depressed stock price. The former (latter) implies the arbitrageur should take a long position on the CDS contract (stock). Without understanding the dynamic relation between the CDS and equity markets, the arbitrageur would not be able to ascertain the adjustment process of these two markets to clear the divergent prices. Therefore, existing studies have to bet on both sides and use an equity delta to match the positions. However, Yu (2006) points out that the low correlation between the CDS spreads and stock price changes finally invalidates the seemingly hedged positions.

In view of the above, we may redesign the capital structure arbitrage trading algorithm by incorporating the dynamic relation across the CDS and equity markets. These cross-market dynamics allow us to i) verify the assumption of a credit risk pricing equilibrium that enforces the co-movements of these two markets, ii) clarify the format of the equilibrium relation, based on the divergence signal, and iii) ascertain the short-run adjustment mechanism between CDS_t and $ICDS_t$ after a divergence, which allows us to form arbitrage positions. Chapter 6 presents our trading algorithm and examines its performance.

2.5 Measures of cross-market price discovery

The central issue underlying the cross-market information dynamics is to understand the price discovery mechanics. According to the efficient market hypothesis, price is a reflection of relevant information and is primarily determined by how information is processed and interpreted in that market. When closely related assets are traded in different venues, the inter-market arbitrage argument also asserts the prices in the different markets are moving towards the efficient price. But dissimilar informational efficiency will cause the new information to be reflected more quickly in the more efficient market than in the less efficient market. Therefore, the price discovery mechanics reveal how common relevant information transmits across related markets. Currently, there are two well-accepted approaches to ascertain the cross-market price discovery mechanics: Gonzalo and Granger (1995) common factor weight and Hasbrouck (1995) information share.

Both Gonzalo and Granger (1995) and Hasbrouck (1995) utilise the VECM to capture the price dynamics of related assets. Suppose in the case of two assets with prices $y_{1,t}$ and $y_{2,t}$, following an *I(1)* process, the bivariate VECM is written as

$$\Delta y_{1,t} = \lambda_1\left(y_{1,t-1} - \tau_0 - \tau_1 y_{2,t-1}\right) + \sum_{s=1}^{S}(\alpha_{1,s}\, \Delta y_{1,t-s} + \beta_{1,s}\Delta y_{2,t-s}) + \varepsilon_{1,t}$$

$$\Delta y_{2,t} = \lambda_2\left(y_{1,t-1} - \tau_0 - \tau_1 y_{2,t-1}\right) + \sum_{s=1}^{S}(\alpha_{2,s}\, \Delta y_{1,t-s} + \beta_{2,s}\Delta y_{2,t-s}) + \varepsilon_{2,t} \tag{2.9}$$

where $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are serially uncorrelated innovations with $\mathrm{E}\left(\varepsilon_{1,t}\right) = \mathrm{E}\left(\varepsilon_{2,t}\right) = 0$ and the covariance matrix of $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ is represented by the terms σ_1^2, σ_2^2, and $\sigma_{1,2}$. The VECM of (2.9) has two components: The first component is the error correction term $y_{1,t-1} - \tau_0 - \tau_1 y_{2,t-1}$. It describes the long-run equilibrium relation between the price series. The second component consists of the autoregressive term $\sum_{s=1}^{S}(\alpha_{1,s}\, \Delta y_{1,t-s} + \beta_{1,s}\Delta y_{2,t-s})$ or $\sum_{s=1}^{S}(\alpha_{2,s}\, \Delta y_{1,t-s} + \beta_{2,s}\Delta y_{2,t-s})$ that captures the short-run dynamics induced by market imperfections.

Gonzalo and Granger (1995) define the price discovery contribution of each market as a function of the market's error correction coefficients λ_1 and λ_2. They show that a common efficient price or common factor exists and can be identified by a linear combination of a common factor coefficient vector Γ with the price vector $(y_{1,t}, y_{2,t})'$. The authors further prove that the common coefficient vector Γ is indeed orthogonal to the error correction coefficient vector $(\lambda_1, \lambda_2)'$. For example, if $\lambda_1 = 0$ and $\lambda_2 = 1$, the common coefficient vector $\Gamma = (1,0)'$. In this case, the common efficient price does not include $y_{2,t}$, suggesting the change in $y_{2,t}$ imposes only transitory effects on the efficient price but the change in $y_{1,t}$ has permanent effects. Accordingly, $y_{1,t}$ contributes entirely to the price discovery process. When both λ_1 and λ_2 are significantly different from zero, $y_{1,t}$ and $y_{2,t}$ jointly have permanent effects on the efficient price. Then the magnitude of λ_1 and λ_2 will define the relative contribution of each market to the price discovery mechanism. According to Gonzalo and Granger (1995), the contributions performed by $y_{1,t}$ and $y_{2,t}$ are calculated as $\frac{\lambda_2}{\lambda_2-\lambda_1}$ and $\frac{-\lambda_1}{\lambda_2-\lambda_1}$, respectively.

In contrast, Hasbrouck (1995) defines the price discovery in terms of the variance of the innovations to the common factor. To identify the common factor (efficient price), the author transforms the VECM model into a vector moving average representation. The moving average terms and their corresponding coefficients jointly indicate the common factor or efficient price across the two markets. The author further argues the new information is indeed reflected by the volatility of the prices and therefore the price discovery contribution can be analysed from the contribution of each market to the variance of the innovation to the common factor (efficient price). The author provides a formula to calculate the upper and lower bounds of the price discovery contribution performed by each market. The calculation is based on the error correction coefficients λ_1 and λ_2, as well as the elements of the covariance matrix of

$\varepsilon_{1,t}$ and $\varepsilon_{2,t}$: σ_1^2, σ_2^2, and $\sigma_{1,2}$. According to Hasbrouck (1995), the lower bound (HAS_L) and upper bound (HAS_U) for the first market[15] are calculated as

$$HAS_L = \frac{\lambda_2({\sigma_1}^2 - \frac{{\sigma_{12}}^2}{{\sigma_2}^2})}{\lambda_2^2{\sigma_1}^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2{\sigma_2}^2} \qquad HAS_U = \frac{(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1})^2}{\lambda_2^2{\sigma_1}^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2{\sigma_2}^2} \tag{2.10}$$

Baillie et al. (2002) show that Gonzalo and Granger (1995) and Hasbrouck (1995) measures provide consistent results if the residuals (price innovations) in the VECM are not correlated. However, as the price innovations become contemporaneously correlated, the results can be very different. The inconsistent results are mainly due to non-consensus between the lower and upper bounds of Hasbrouck (1995) measures. Baillie et al. (2002) demonstrate that the gap between these two bounds is proportional to the contemporaneous correlation. A higher correlation is associated with a smaller (larger) lower (upper) bound. To avoid this impact, Baillie et al. (2002) suggest utilising the average of the upper and lower bounds.

Both Gonzalo and Granger (1995) and Hasbrouck (1995) measures are employed extensively to examine the information linkage between related financial markets: for example, by Ates and Wang (2005), Tao and Song (2010), and Hasbrouck (2003) examining the price discovery contributions between various equity futures exchanges, by Tse et al. (2006) studying the price discovery process in the foreign exchange market, and by Blanco et al. (2005) and Zhu (2006) investigating the credit risk price discovery contribution of the CDS and bond markets.

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[15] For the second market, the calculated HAS_L and HAS_U become the upper and lower bounds, respectively.

2.6 Summary

This chapter reviews the literature that is relevant to the studies in this thesis. It starts with a discussion on CDS contract pricing. As a credit derivative instrument, the CDS contract is utilised to hedge and trade the credit risk of the underlying reference entity. The price of the CDS contract is predominately determined by the probability of default. While the structural credit risk pricing approach pioneered by Merton (1974) can be employed to model the probability of default, it also links the latter with the firm's equity value (stock price). Therefore, the structural credit risk pricing approach indeed establishes a linkage across the CDS and equity markets.

Although empirical research has examined the relationship between the CDS and equity markets, the results remain inconclusive. Some of these studies model the CDS spread changes and stock returns in a VAR setting. However, these two variables are subject to different risk factors and therefore should not be directly comparable. Other studies employ event study methodology to compare reactions in the CDS and equity markets before credit rating or earnings announcements but cannot distinguish the relative informational efficiency between these two markets. In stark contrast, there is a general consensus regarding the relationship between the CDS and bond markets. For example, a credit risk pricing equilibrium exists across the CDS and bond markets and the CDS market dominates the bond market in the credit risk price discovery process.

Since the CDS and equity markets both reflect credit risk information, a convergent-type strategy, namely, capital structure arbitrage, has been developed to trade the CDS contract and stocks of the underlying firm. Only a few studies examine the risk–return profile of this trading strategy. However, the results seem to contradict the basic concept of this trading strategy: For example, most of the positions fail to converge. In addition, the trading algorithm fails to identify which market is being mispriced and the arbitrageur must subsequently take positions in both markets.

In view of the literature discussed in this chapter, we decide to examine the credit risk information dynamics across the CDS and equity markets. In particular, we have three related objectives. In Chapter 4, we utilise the CreditGrades model, a structural credit risk pricing model, to extract the ICDS embedded in the firm's stock price. In that regard, we propose a new calibration procedure for the CreditGrades model, which significantly improves the accuracy of ICDS estimates. In Chapter 5, we formally examine the dynamic relationship between the CDS and equity markets. After analysing the long-run credit risk pricing relation, we focus on the credit risk price discovery mechanism across these two markets. Using portfolio strategies, we ascertain the economic significance of the credit risk information flows across the CDS and equity markets. Finally, in Chapter 6, we propose a new algorithm for capital structure arbitrage. Our trading algorithm incorporates a long-run credit risk pricing relation and short-run credit risk price discovery mechanics. The former allows us to verify the convergence condition that underpins the concept of capital structure arbitrage trading while the latter guides us to identify the mispriced market in order to take advantage of credit risk pricing divergence across the CDS and equity markets.

Chapter 3: Data and sample

3.1 Introduction

The objective of this thesis is to examine credit risk information dynamics across the CDS and equity markets. Accordingly, we need credit risk measures from each market. While the CDS spread ($CDS_{i,t}$) is an observable price of credit risk for the underlying firm, the stock market does not provide observable prices of credit risk. Indeed, the structural credit risk pricing approach pioneered by Merton (1974) establishes an economic link between the equity value and credit risk.[16] We utilise the RiskMetrics (Finger et al. 2002) CreditGrades model to extract the ICDS ($ICDS_{i,t}$) embedded in the firm's stock price. Hence the pairwise ($CDS_{i,t}, ICDS_{i,t}$) becomes measures of credit risk from the CDS and equity markets. Section 3.2 summarises the data sources and variables to obtain $CDS_{i,t}$ and $ICDS_{i,t}$. Section 3.3 outlines the basic characteristics of our sample. Section 3.4 concludes.

3.2 Data sources and variables

Our empirical studies require a comprehensive database that includes daily observations for the pairwise ($CDS_{i,t}, ICDS_{i,t}$). We introduce the data sources for i) the CDS spreads and ii) the variables used to extract $ICDS_{i,t}$.

[16] Equity-holder is able to retire debt at maturity and claim firm ownership. This is akin to holding a call option against debt-holders on firm assets, with the face-value of debt as the strike price. Accordingly, the probability of non-exercise is analogous to the probability of default. Any information that affects a firm's creditworthiness will affect the value of equity-holders' embedded call options and hence its stock price.

3.2.1 The Credit default swap

As described in Chapter 1, a credit default swaps (CDS) is a credit derivative contract in which the payoff is triggered by a default event. Expanding rapidly since 2002, the CDS market has taken over the credit risk trading function from the bond market. Accordingly, CDS spreads ($CDS_{i,t}$) are regarded as a benchmark indicator of credit risk for the underlying reference entity. Hull et al. (2004) discuss the advantages of CDS spreads over bond yield spreads as a measure of credit risk.

We focus on the $CDS_{i,t}$ of five-year USD 10 million CDS contracts written on senior debt issued by U.S. firms. The U.S. CDS market is clearly larger, mature, and more liquid compared to the CDS markets in Europe and Asia-Pacific. The five-year contract represents the most liquid maturity on the term structure of the CDS market. Indeed, our choice on the CDS spreads data is consistent with key CDS market studies (e.g., Blanco et al. (2005); Acharya and Johnson (2007)). We use daily closing CDS spread data provided by CMA,[17] a leading data provider that specialises in the credit derivatives market. When constructing our sample, we cross-reference CDS data from both Bloomberg and Datastream for consistency.

3.2.2 Variables used to extract the ICDS

We use the CreditGrades model, under the structural credit risk pricing approach, to extract $ICDS_{i,t}$ embedded in the firm's stock price. The CreditGrades model requires the following model inputs: stock price ($S_{i,t}$), stock return volatility ($\sigma_{i,t}$), debt per

[17] CMA was founded in 2001 by a group of credit specialists and was acquired by the CME Group in 2008.

share ($D_{i,t}$), the risk-free rate ($r_{f,t}$), the mean ($\bar{\mathrm{L}}$) and volatility (λ) of the expected global recovery rate, and the recovery rate of reference bond (R). Among these input parameters, stock price, stock return volatility, debt per share, and the risk-free rate are observable. This section discusses the data sources for these observable parameters. The procedures to determine the value of the remaining unobservable parameters are explained in Chapter 4.

For the stock price ($S_{i,t}$), we use the daily stock files of the Center for Research in Security Prices (CRSP) to match firms against the reference entities in the CDS sample. Since the CDS contracts are denominated into U.S. dollars, we use share codes 10 and 11 to pull out those firms with common shares traded on U.S. exchanges. After matching, we download the CRSP daily closing prices.

For stock return volatility ($\sigma_{i,t}$), we compute the one-year historical volatility from CRSP adjusted daily returns. We are aware of that historical volatility may not be an efficient measure of volatility for CDS pricing. For example, Cao et al. (2010) find that option-implied volatility as an input to the CreditGrades model gives a more accurate measure of $ICDS_{i,t}$. However, our main objective in this thesis is to ascertain the credit risk information dynamics between the equity and CDS markets. By using option-implied volatility, the information content of $ICDS_{i,t}$ spans both the equity and option markets. This would contaminate the interpretation of our main results.

Following Yu (2006) and Duarte et al. (2007), we define debt per share ($D_{i,t}$) as total liabilities divided by common shares outstanding. We search the total liabilities of the matched firms in the Compustat North America files. These quarterly figures are lagged by one month from the end of the corresponding quarter to avoid any look-ahead bias. To construct a daily measure of debt per share ($D_{i,t}$), we download daily common shares outstanding from the CRSP, which have been adjusted for corporate events, for example, stock splits. However, if the quarterly number of shares outstanding is used, $ICDS_{i,t}$ will become significantly biased on the stock split day. This is because on the stock-split day, the share price will drop by around 50% but the quarterly number of shares remains unchanged. This will cause the per share debt–equity ratio to double. The debt–equity ratio is a key input parameter to determine the probability of default and back out $ICDS_{i,t}$

We use the five-year swap rate as a proxy for the risk-free rate. This choice is motivated by Blanco et al. (2005), who document that the swap rate is a better proxy of the risk-free rate for credit risk pricing. We download the daily five-year swap rates from Datastream.

3.3 Sample and summary statistics

After matching different data files at the firm level, our sample contains 174 firms over a five-year period between January 3, 2005, and December 31, 2009, or 1,259 observations per firm. To avoid anomalous results due to the GFC, our firm sample includes only investment-grade non-financial[18] firms with an S&P long-term debt rating better than BBB-. In preliminary analysis, we examine a pre-GFC sample period from January 2005 to June 2007. The GFC sub-sample runs from Jul 2007 to December 2009. The full list of companies is provided in Appendix 2.

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[18] The CreditGrades model requires capital structure information to calculate the ICDS. Due to the difficulties in calculating total liabilities and interpreting capital structures, following Yu (2006) and Duarte et al. (2007), we exclude firms in the banking and financial services sector.

Table 3.1: Industry classification and rating groups of the firm sample

	Number of Companies
Whole sample	174
AAA	5
AA	13
A	65
BBB	91
Basic materials	22
Communications	7
Consumer cyclical	35
Consumer non-cyclical	44
Energy	27
Industrial	33
Technology	6

Table 3.1 shows the industry classifications and credit ratings of our firm sample. Our sample covers seven industry sectors. There are 44, 35, and 33 consumer non-cyclical, consumer cyclical and industrial firms, respectively. Next are energy and basic materials, with 27 and 22 firms, respectively. Lastly, 7 firms are in technology and 6 communications. In terms of firm distribution across rating classes, 91 firms are rated BBB and 65 are A. Finally, our sample has 13 AA and five AAA firms.

Table 3.2: Summary statistics for the variables

Panel A: Overall sample period	Minimum	Maximum	Mean	Median	Standard Deviation
CDS spreads	1.0000	7871.9000	89.4561	46.1000	173.0411
Stock price	0.36	239.50	46.54	43.97	24.64
Debt per share	3.03	323.21	32.53	24.90	29.18
Stock return volatility	0.0986	1.9626	0.3373	0.0986	0.1990
Risk-free rate	0.0191	0.0576	0.0420	0.0440	0.0101
Panel B: Pre-GFC sample period	**Minimum**	**Maximum**	**Mean**	**Median**	**Standard Deviation**
CDS spreads	1.0000	622.5000	38.1991	30.0000	34.1444
Stock price	1.73	206.61	49.84	47.74	22.61
Debt per share	3.03	323.21	31.24	23.62	28.36
Stock return volatility	0.0986	0.4946	0.2365	0.2243	0.0705
Risk-free rate	0.0399	0.0576	0.0491	0.0499	0.0044
Panel C: GFC sample period	**Minimum**	**Maximum**	**Mean**	**Median**	**Standard Deviation**
CDS spreads	5.3000	7871.9000	140.3046	78.0000	230.8691
Stock price	0.36	239.50	43.27	38.89	26.09
Debt per share	3.64	308.74	31.24	26.34	29.92
Stock return volatility	0.1076	1.9626	0.4372	0.3754	0.2322
Risk-free rate	0.0191	0.0562	0.0350	0.0346	0.0093

Table 3.2 reports summary statistics for the variables used in this study. Panel A contains results for the whole sample period. The mean CDS spread is 89.4661 basis points (bps) across the entire firm sample. In terms of dollar value, on average, credit protection costs $89,456.1 per year for a standardised CDS contract with USD 10 million notional amount. We observe substantial variations in the CDS spreads in our sample. The minimum CDS spread is just 1 bps whereas the maximum reaches 7871.9 bps. This implies profuse credit risk profiles exist in our firm sample over the sample period. Table 3.2 also reports the input variables required for the CreditGrades model to extract the ICDS. For the stock price, the mean is $46.54 and the standard

deviation is $24.64. This can be compared with debt per share, for which the mean and standard deviation are $32.53 and $29.18, respectively. Lastly, the mean value for stock return volatility is 0.3373 and the average risk-free rate is 0.0420 per year.

Panels B and C of Table 3.2 report results for the pre-GFC and GFC sub-sample periods, respectively. During the pre-GFC sub-sample period, the mean CDS spread is 38.20 bps and the standard deviation is 34.14 bps. In stark contrast, the mean and standard deviation reach 140.30 bps and 230.87 bps, respectively, which constitute a greater than three-fold increase in the mean and a greater than six-fold increase in the standard deviation. These results indicate the credit risk profile of our firm sample differs substantially between the two sub-sample periods. During the pre-GFC sub-sample period, the CDS market is tranquil. During the GFC sub-sample period, heightened credit risk concern is associated with skyrocketing and extreme volatile CDS spreads.

3.4 Summary

This chapter summarises the data sources and variables used to construct pairwise credit risk measures ($CDS_{i,t}, ICDS_{i,t}$). This is followed by a description of the basic characteristic of our firm sample and summary statistics for the variables.

Chapter 4: The CreditGrades model, calibration, and the ICDS

4.1 Introduction

We utilise the RiskMetrics (Finger et al. (2002)) CreditGrades model to extract $ICDS_{i,t}$ embedded in firm i's stock price. While the model provides a simple analytical and closed-form solution to compute $ICDS_{i,t}$, some parameters are not directly observable. Therefore, the model needs to be calibrated with respect to the unknown parameters. Indeed, the calibration procedure is a non-trivial issue that affects the accuracy of the $ICDS_{i,t}$ estimate.

We propose a novel approach to calibrate the CreditGrades model. Our calibration approach differs from the previous benchmark approach used by Yu (2006) and Duarte et al. (2007). We impose less arbitrary assumptions on the unobservable parameters and adopt a frequent calibration approach. In particular, we treat corporate events carefully and update the values of unobservable parameters immediately once new accounting figures are released. The results demonstrate that our calibration approach significantly improves the accuracy of $ICDS_{i,t}$ from the previous calibration approach. A more accurate $ICDS_{i,t}$ measure facilitates a cleaner study of cross-market credit risk information dynamics between the CDS and equity markets, which is carried out in the following chapters.

This chapter is organised as follows. Section 4.2 reviews the CreditGrades model. Section 4.3 explains the calibration procedures and compares $ICDS_{i,t}$ with $ICDS^{*}_{i,t}$, obtained using the previous calibration procedure. Section 4.5 concludes with a summary.

4.2 The CreditGrades model

The CreditGrades model is jointly developed by four leading institutions in the credit market, including RiskMetrics, J.P. Morgan, Goldman Sachs, and Deutsche Bank. As stated in the CreditGrades technical document, ‘The purpose of the CreditGrades model is to establish a robust but simple framework linking the credit and equity markets’ (Finger et al. (2002), p. 5).

The CreditGrades model belongs to the structural credit risk pricing approach, pioneered by Merton (1974). Specifically, it models a firm’s default as the first time its assets value falls below a default barrier. In that regard, the CreditGrades model is an extension of the first-passage model of Black and Cox (1976). Innovatively, the CreditGrades model allows the default barrier, which is the recovery value, to follow a stochastic process. A default is triggered once two stochastic processes, namely, the asset value and the default barrier, hit each other. Allowing the default barrier to follow a stochastic process also increases the probability of the asset value hitting the default barrier, which addresses the underpricing problem commonly exist in other structural models. As a result, the short-term default probability and credit spreads obtained from the CreditGrades model are more realistic. The model can be summarised as follows.[19]

The CreditGrades model assumes that a firm’s asset value V_t follows a geometric Brownian motion without drift:

$$\frac{dV_t}{V_t} = \sigma dW_t \tag{4.1}$$

[19] See the CreditGrades technical document (Finger et al. (2002)) for a full description of the model.

A zero-drift assumption is consistent with evidence of stationary leverage ratios documented by Collin-Dufresne and Goldstein (2001). In the event of default, debt-holders receive a recovery amount LD, where L is the global average recovery rate and D is debt per share. In the CreditGrades model, the recovery amount upon default (LD) is defined as the default barrier and assumed to follow a stochastic process. More specifically, the model assumes that L follows a log-normal distribution, with $\log(L) \sim N(\mu, \lambda^2)$. Denote $\mathrm{E}(L) = \bar{L}$ and $\mathrm{Var}[\log(\mathrm{L})] = \lambda^2$. Using a standard normal random variable $Z \sim N(0,1)$, the default barrier can be expressed as

$$LD = \bar{L}D \cdot e^{(\lambda Z - \frac{\lambda^2}{2})} \tag{4.2}$$

This is because if $\bar{L} = e^{(\mu + \frac{\lambda^2}{2})}$, then $\bar{L}e^{(\lambda Z - \frac{\lambda^2}{2})} = e^{(\mu + \lambda Z)}$; since Z is a standard normal random variable, $\log e^{(\mu + \lambda Z)} \sim N(\mu, \lambda^2)$. Hence, $\bar{L}e^{(\lambda Z - \frac{\lambda^2}{2})}$ and L both follow a log-normal distribution and have matched moment conditions.

A default event is triggered once $V_t < LD$. Using Ito's lemma and given the initial asset value V_0, the firm will exist as long as the following equations are satisfied:

$$\begin{gathered} V_0 \cdot e^{\left(\sigma W_t - \frac{1}{2}\sigma^2 t\right)} > \bar{L} \cdot D \cdot e^{\left(\lambda Z - \frac{\lambda^2}{2}\right)} \\ \sigma W_t - \frac{1}{2}\sigma^2 t - \lambda Z + \frac{\lambda^2}{2} > log\left(\frac{\bar{L}D}{V_0}\right) \end{gathered} \tag{4.3}$$

Denote $\mathrm{X_t} = \sigma W_t - \frac{1}{2}\sigma^2 t - \lambda Z - \frac{\lambda^2}{2}$. It can be shown that $X_t \sim N[-\frac{\sigma^2}{2}\left(t + \frac{\lambda^2}{\sigma^2}\right), \sigma^2\left(t + \frac{\lambda^2}{\sigma^2}\right)$. Then $\mathrm{X_t}$can be approximated by a time-shifted Brownian motion $\widehat{\mathrm{X}}_\mathrm{t}$

that starts at $t_0 = -\frac{\lambda^2}{\sigma^2}$.[20] In that case, the default event is triggered once $\widehat{X}_t \leq \log\left(\frac{\bar{L}\cdot D}{V_0}\right) - \lambda^2$. Then the survival probability is the cumulative probability before $\widehat{X}_t$ hits and falls below a certain level of ($\log\left(\frac{\bar{L}\cdot D}{V_0}\right) - \lambda^2$) for the first time. Applying distributions for the first-hitting time of Brownian motion, the CreditGrades model provides the following closed-form solution in equation (4.4) to calculate the survival probability $P_{(t)}$ up to time t[21]:

$$P_{(t)} = \Phi\left(-\frac{A_t}{2} + \frac{log(d)}{A_t}\right) - d\Phi\left(-\frac{A_t}{2} - \frac{log(d)}{A_t}\right)$$

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L}D};\ A_t^2 = \sigma^2 t + \lambda^2 \tag{4.4}$$

The variable $P_{(t)}$ allows us to specify the ICDS. Denote R as the recovery rate for the underlying debt,[22] $f(t)$ as the default density function,[23] and r as the risk-free rate. The present value of expected compensation and expected CDS spread payments due to a default event are given, respectively, by the following equations:

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[20] Define a time-shifted Brownian motion process $\widehat{W}_t$that starts at $\hat{t}_0 = -\frac{\lambda^2}{\sigma^2}$. Then $\frac{d\widehat{X}_t}{\widehat{X}_t} = -\frac{\sigma^2}{2}d\hat{t} + \sigma d\widehat{W}_t$ also follows a time-shifted Brownian motion process with $\widehat{X}_{\hat{t}_0} = 0$; $E(\widehat{X}) = -\frac{\sigma^2}{2}\left(t + \frac{\lambda^2}{\sigma^2}\right)$ and $\mathrm{Vari}(\widehat{X}) = \sigma^2\left(t + \frac{\lambda^2}{\sigma^2}\right)$.

[21] The general formula for the probability of a Brownian motion process $Y_t = at + bW_t > y, \forall\, s < t$ is

$$\mathrm{P}\{Y_s > y, \forall\, s < t\} = \Phi\left(\frac{at - y}{b\sqrt{t}}\right) - e^{2ay/b^2}\Phi\left(\frac{at + y}{b\sqrt{t}}\right)$$

where $\Phi(\cdot)$ is a cumulative probability distribution function. The CreditGrades model considers the probability of a Brownian motion process $\widehat{X}_t = -\frac{\sigma^2}{2}\hat{t} + \sigma\widehat{W}_t$ greater than the fixed level of $log\left(\frac{\bar{L}\cdot D}{V_0}\right) - \lambda^2$.

[22] Here R is different from $\bar{L}$: R is the expected recovery rate for specific debt covered by the CDS contract, whereas $\bar{L}$ is the expected global recovery rate (i.e., the expected average recovery rate for all the company's debt).

[23] With survival probability $P_{(t)}$, the risk-neutral probability of the default density function can be defined as $f(t) = -\frac{dP_{(t)}}{dt}$.

$$(1-R)[1-P_{(0)}+\int_0^t f(s)e^{-rs}ds] \tag{4.5}$$

$$cds\int_0^t P_{(s)}e^{-rs}ds \tag{4.6}$$

On day τ, the value of CDS contract M_τ for the protection buyer is the difference between the present value of expected compensation and expected spread payments in the following equation:

$$M_\tau=(1-R)[1-P_{(0)}+\int_0^t f(s)e^{-rs}ds]-CDS\int_0^t P_{(s)}e^{-rs}ds \tag{4.7}$$

Since $\int_0^t P_{(s)}e^{-rs}ds=\frac{1}{r}\left(P_{(0)}-P_{(t)}e^{-rt}\right)-\frac{1}{r}\int_0^t f(s)e^{-rs}ds$, equation (4.7) can be re-expressed as equation(4.8).

$$\begin{aligned}M_\tau=(1-R)\left[1-P_{(0)}\right]-\frac{CDS}{r}\left(P_{(0)}-P_{(t)}\cdot e^{-rt}\right)\\+\left(1-R+\frac{cds}{r}\right)\int_0^t f(s)e^{-rs}ds\end{aligned} \tag{4.8}$$

Using equation (4.9), we rewrite equation (4.8) as equation (4.10), where $\xi=\lambda^2/\sigma^2$ and $z=\sqrt{\frac{1}{4}+2r/\sigma^2}$:

$$\begin{gathered}\int_0^t f(s)e^{-rs}ds=e^{\frac{r\lambda^2}{\sigma^2}}\left[G\left(t+\frac{\lambda^2}{\sigma^2}\right)-G\left(\frac{\lambda^2}{\sigma^2}\right)\right]\\ G(t)=d^{z+1/2}\Phi\left(-\frac{log(d)}{\sigma\sqrt{t}}-z\sigma\sqrt{t}\right)+d^{-z+1/2}\Phi\left(-\frac{log(d)}{\sigma\sqrt{t}}+z\sigma\sqrt{t}\right)\end{gathered} \tag{4.9}$$

$$\begin{aligned}M_\tau=(1-R)\left(1-P_{(0)}\right)-\frac{cds}{r}\left(P_{(0)}-P_{(t)}e^{-rt}\right)+\left(1-R+\frac{cds}{r}\right)e^{r\xi}[G(t+\xi)\\-G(\xi)]\end{aligned} \tag{4.10}$$

On the contract initiation date, the CDS contract has zero market value, that is, $M_\tau=0$. Accordingly, by setting $M_\tau=0$, we obtain the closed-form solution for CDS: in equation (4.11).

$$CDS = r(1-R)\frac{1-P_{(0)}+e^{r\xi}(G(t+\xi)-G(\xi))}{P_{(0)}-P_{(t)}e^{-rt}-e^{r\xi}(G(t+\xi)-G(\xi))} \quad (4.11)$$

To solve CDS in equation (4.11), we need the parameters $\mathrm{V}_0, \sigma, \mathrm{D}, \bar{\mathrm{L}}, \lambda$, and r. The CreditGrades model uses a linear approximation to relate the asset value V_0 to the equity value S_0, as written in equation (4.12):

$$V_0 = S_0 + \bar{L}D \quad (4.12)$$

This equation further implies that asset volatility σ can be expressed using equity volatility σ_s:

$$\sigma = \sigma_s \frac{S}{S+\bar{L}D} \quad (4.13)$$

Hence, the value of credit default spreads in equation (4.11) is largely determined by stock price and return volatility.

4.3 The CreditGrades model calibration and the ICDS

To extract the stock price ICDS, the CreditGrades model requires the following input parameters: stock price ($S_{i,t}$), stock return volatility ($\sigma_{i,t}$), debt per share ($D_{i,t}$), the risk-free rate ($r_{f,t}$), the mean ($\bar{\mathrm{L}}$) and volatility (λ) of the expected global recovery rate, and the recovery rate of the reference bond (R). It is noted that the mean and volatility of the expected global recovery rate ($\bar{L}$, λ), as well as the recovery rate of the reference bond (R) are not directly observable. Therefore, the CreditGrades model needs to be calibrated with respect to these unknown parameters before it is used to estimate the ICDS.

Following Hull et al. (2004) and Yu (2006), we set $R = 0.5$. This is based on an industry rule of thumb and is consistent with Moody's statistics on historical corporate bond recovery rates.[24] However, there are few guidelines for setting both $(\bar{L},\ \lambda)$. As a result, we calibrate the model with respect to $(\bar{L},\ \lambda)$. More specifically, using the prior 30 days' observations, we calibrate $(\bar{L},\ \lambda)$ to minimise the sum of the squared difference between $CDS_{i,t-j}$ and $ICDS_{i,t-j}$ in equation (4.14).

$$[\bar{L},\lambda] = \underset{\bar{L},\lambda\in[0,1]}{argmin} \sum_{j=1}^{30} (CDS_{i,t-j} - ICDS_{i,t-j})^2 \tag{4.14}$$

After $(\bar{L},\ \lambda)$ is calibrated, they are applied over the next 30 days to extract $ICDS_{i,t}$. In effect, our $ICDS_{i,t}$ estimates are obtained from a frequent calibration approach. At each calibration day, we use the prior 30 days as the calibration window to determine the values for $(\bar{L},\ \lambda)$. The values of the pairwise $(\bar{L},\ \lambda)$ together with other parameters are used as the model inputs to extract $ICDS_{i,t}$ over the next 30 days (the extraction window). At the end of the extraction window, we repeat the whole process.

We improve on the previous calibration approach in mainly two regards. First, we calibrate $(\bar{L},\ \lambda)$, whereas Yu (2006) and Duarte et al. (2007) assume $\lambda = 0.3$ and only calibrate the model with respect to $\bar{\mathrm{L}}$. Our $ICDS_{i,t}$ should contain less bias associated with the ad hoc setting of λ. Second, Bystrom (2006), Yu (2006), and Duarte et al. (2007) all calibrate the model once using 10 daily observations and then apply the calibrated parameter $\bar{\mathrm{L}}$ for the rest of the entire sample. In contrast, we recalibrate

[24] See Moody's Investors Service, Historical Default Rates of Corporate Bond Issuers, 1920–1999 (January 2000).

$(\bar{L},\ \lambda)$ every 30 days.[25] This allows us to update the value of $\bar{L}$ and λ, the key parameters that determine the recovery process, as well as the default barrier under the CreditGrades model. Furthermore, in accordance with Leland (1994) and Leland and Toft (1996), in that the recovery process depends on a firm's capital structure fundamental, if new accounting information on total liabilities is released during the 30-day extraction window, we immediately use the new accounting figures to update debt per share $(D_{i,t})$ and recalibrate $(\bar{L},\ \lambda)$ using the prior 30 days of data. The updated recovery parameters are then used for the remainder of that extraction window. We ensure that both the calibration and extraction of $ICDS_{i,t}$ utilise only past information to avoid introducing any look-ahead bias.

Apart from the calibration procedure, our choices on the observable parameters also differ from those of previous studies. First, Blanco et al. (2005) confirm that the swap rate is a better proxy of risk-free rate for credit risk pricing. Accordingly, we use a five-year swap rate as the risk-free rate $(r_{f,t})$ proxy. In contrast, Yu (2006) and Duarte et al. (2007) use the Treasury rate as a proxy for the risk-free rate. Second, for the equity volatility $\left(\sigma_{i,t}\right)$, we compute the one-year historical volatility using CRSP adjusted daily returns. Cao et al. (2010) find that option-implied volatility dominates historical volatility in explaining variation in CDS spread changes and yields more accurate ICDS estimates than historical volatility. However, our main objective in this thesis is to analyse credit risk information dynamics between the equity and CDS markets. By using option-implied volatility, the information content of $ICDS_{i,t}$ spans both the equity and option markets. This would contaminate the interpretation of our

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[25] See Bakshi et al. (1997) for a discussion on the benefits of frequent calibration on the option pricing model.

main results. Third, Yu (2006) define debt per share ($D_{i,t}$) as total liabilities divided by common shares outstanding. These quarterly figures are lagged one month from the end of the corresponding quarter to avoid any look-ahead bias. However, it is sub-optimal to use quarterly D figures to extract a daily time series of $ICDS_{i,t}$, especially when capital structure events, for example, stock splits, occur during the extraction window. On the stock split day, the share price will drop by around 50%, but the quarterly number of shares will remain unchanged. This will cause the per share debt–equity ratio to double. The debt–equity ratio is a key input parameter to determine the probability of default and back out $ICDS_{i,t}$. To construct a daily measure of $D_{i,t}$, we download daily common shares outstanding data from the CRSP, which has been adjusted for corporate events.

Figure 4.1: Time series plot of CDS spreads and ICDS for Caterpillar Inc.

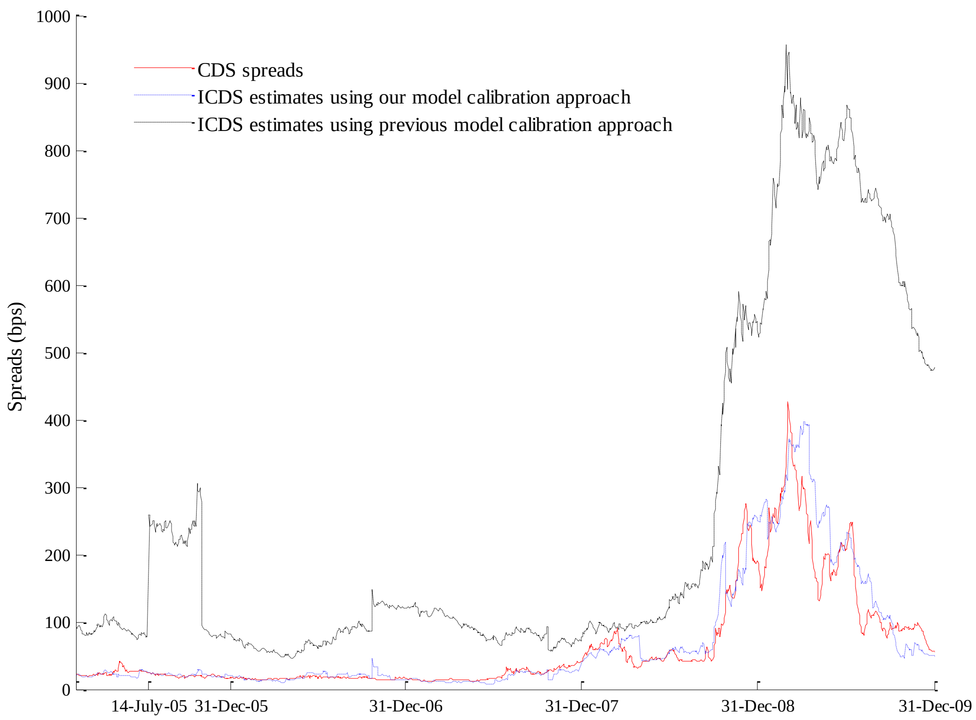


Figure 4.1 uses the stock split by Caterpillar Inc. on July 14, 2005, to illustrate the dissimilar impacts on $ICDS_{i,t}$ from quarterly versus daily measures of D. Using quarterly figures of D, $ICDS_{i,t}$ jumped from 78.54 bps to 242.89 bps. In contrast, our measure of $ICDS_{i,t}$ increased to 23.48 bps, which is much closer to that day's $CDS_{i,t}$ of 25.3 bps.

To demonstrate the claimed improvements, we replicate the previous calibration approach of Yu (2006) and Duarte et al. (2007) to obtain their ICDS measure $ICDS^{*}_{i,t}$, which we compare against $ICDS_{i,t}$. Panels A and B of Figure 4.2 plot the time-series graphs of the cross-sectional averages of $ICDS_{i,t}$, $CDS_{i,t}$, and $ICDS^{*}_{i,t}$ for the pre-GFC and GFC sub-samples,[26] respectively. Panel A of Figure 4.2 clearly shows that $ICDS_{i,t}$ tracks $CDS_{i,t}$ better than $ICDS^{*}_{i,t}$. The difference in tracking ability is further exemplified in Panel B, where the gap between $CDS_{i,t}$ and $ICDS^{*}_{i,t}$ widens substantially from October 2008 onwards.

[26] Recall from Chapter 3 that our sample contains 174 U.S. investment-grade firms over a five-year period between January 3, 2005, and December 31, 2009. For sub-sample analysis, we examine a pre-GFC sub-sample period from January 2005 to June 2007. The GFC sub-sample runs from July 2007 to December 2009.

Figure 4.2 (A) Cross-sectional average of CDS spreads and ICDS for the pre-GFC sub-sample

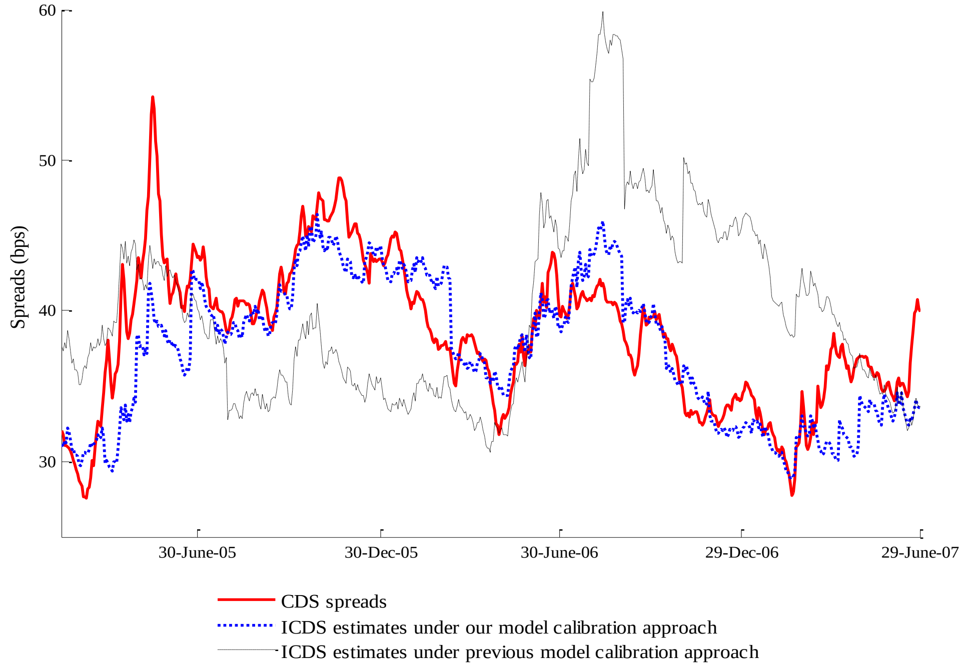
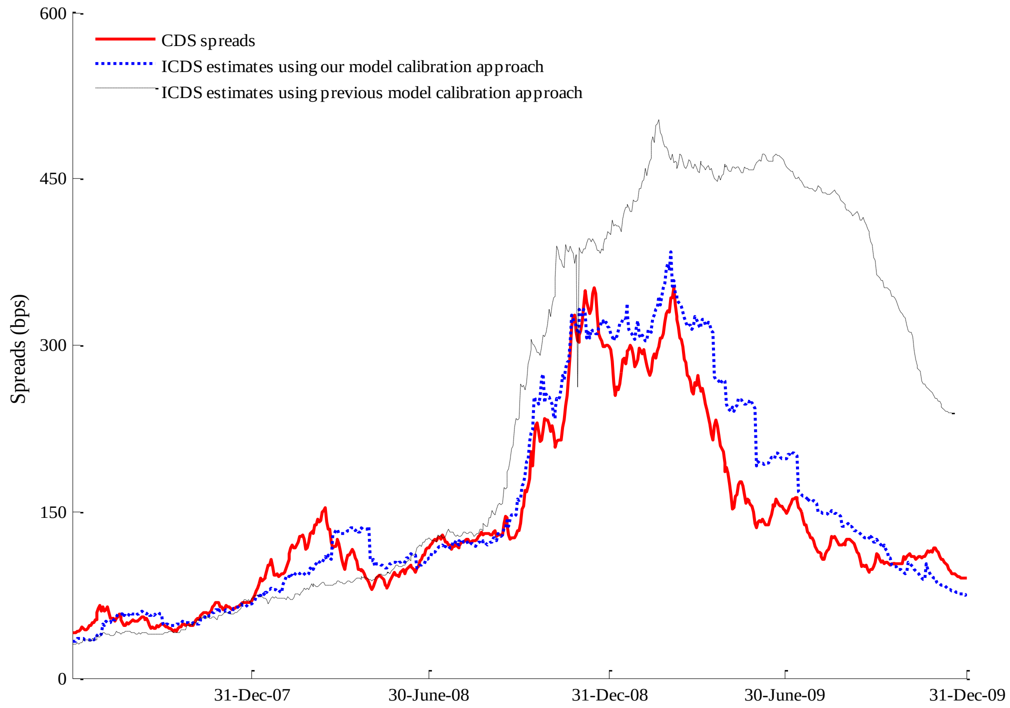


Figure 4.2 (B) Cross-sectional average of CDS spreads and ICDS for the GFC sub-sample



In addition, we use $CDS_{i,t}$ as the benchmark to compute the average absolute pricing errors (AAPEs) for each of the two ICDS measures in equation (4.15).

$$AAPE_i = \frac{1}{N} \sum_{t=1}^{N=1229} \left| CDS_{i,t} - ICDS_{i,t} \right| \tag{4.15}$$

Here $ICDS_{i,t}$ uses 20 more observations than $ICDS^*_{i,t}$ in the initial calibration. For consistency, we ignore the first 30 observations when computing the AAPEs for $ICDS_{i,t}$ and $ICDS^*_{i,t}$, such that the total number of observations $N = 1229$.

In Table 4.1, we compare the cross-sectional cumulative distribution of the AAPEs for $ICDS_{i,t}$ and $ICDS^*_{i,t}$ across deciles. The three panels of the table contain the full-sample, pre-GFC, and GFC sub-sample results. In Panel A, the mean AAPE is 21.92 bps for $ICDS_{i,t}$ and 117.75 for $ICDS^*_{i,t}$. The median AAPE for $ICDS^*_{i,t}$ is 93.12 bps, which is six times larger than the 15.57 bps median AAPE for $ICDS_{i,t}$. At the 10% level, the AAPE for $ICDS_{i,t}$ is 7.14 bps and 31.86 bps for $ICDS^*_{i,t}$. At the 90% level, the AAPE for $ICDS_{i,t}$ increases to 31.59 bps. For $ICDS^*_{i,t}$, the AAPE jumps to 224.16 bps. Put differently, 90% of firms have an AAPE of less than 31.59 bps using $ICDS_{i,t}$. In stark contrast, only less than 10% of firms have an AAPE of 31.86 bps or less based on $ICDS^*_{i,t}$.

Table 4.1: Average absolute pricing error statistics

Panel A: Full Sample	Cumulative Distribution									
	10%	20%	30%	40%	Median	60%	70%	80%	90%	Mean
AAPE using our approach	7.14	8.60	11.19	13.10	15.57	18.90	21.43	25.02	31.59	21.92
AAPE using previous approach	31.86	41.20	52.35	74.50	93.12	128.52	143.91	172.94	224.16	117.75
Panel B: Before Crisis	**Cumulative Distribution**									
	10%	20%	30%	40%	Median	60%	70%	80%	90%	Mean
AAPE using our approach	2.07	2.97	3.60	4.53	5.03	5.85	6.86	7.78	9.73	6.07
AAPE using previous approach	10.50	15.02	18.35	22.39	27.51	34.47	42.62	52.07	73.38	37.69
Panel C: During Crisis	**Cumulative Distribution**									
	10%	20%	30%	40%	Median	60%	70%	80%	90%	Mean
AAPE using our approach	10.89	13.57	16.47	20.34	25.17	31.23	35.59	41.64	54.93	36.89
AAPE using previous approach	48.05	58.20	74.61	115.17	155.69	211.16	255.89	297.66	375.49	193.39

The results from the pre-GFC sample in Panel B shows an even smaller AAPE for $ICDS_{i,t}$, with a mean and 90% cumulative distribution of 6.07 bps and 9.73 bps, respectively. For $ICDS_{i,t}^{*}$, the mean and 90% cumulative distribution of the AAPEs are 37.69 bps and 73.38bps, respectively. The improvement in the AAPEs is even more remarkable for the GFC sub-sample. The mean AAPE drops from 193.39 bps to 36.89 bps when we switch from $ICDS_{i,t}^{*}$ to $ICDS_{i,t}$. Similarly, the 90% cumulative distribution of AAPEs is sharply reduced from 375.49 bps to 54.93 bps. These results strongly suggest that our $ICDS_{i,t}$ measure is substantially improved over the $ICDS_{i,t}^{*}$

measure used by Bystrom (2006) and Duarte et al. (2007). This in turn facilitates a cleaner study of cross-market credit risk dynamics between the CDS and equity markets.

4.4 Summary

According to the structural credit risk pricing approach pioneered by Merton (1974), an economic link exists between the CDS and equity markets. This is because both CDS spreads and stock prices reveal the credit risk of the underlying firm. While CDS spreads have been accepted as a direct measure for credit risk, equity can be viewed as a call option written on a firm's asset, where the probability of non-exercise equals the probability of default. To examine the credit risk information dynamics across the CDS and equity markets, the first step is to extract the ICDS, a credit risk measure embedded in the firm's stock price. For this purpose, we utilise the CreditGrades model.

The chapter begins by providing a theoretical review of the CreditGrades model. The CreditGrades model belongs to the first-passage structural credit risk pricing approach. It models a firm's default as the first time its assets value falls below a default barrier. By allowing the default barrier to follow a stochastic process, the probability of the asset value hitting the default barrier is also increased, which addresses the underpricing problem confronted by other structural models. As a result, the CreditGrades model is able to provide more realistic short-term credit spreads. More importantly, the CreditGrades model provides a simple analytical approach and a closed-form solution to compute stock market ICDSs.

To extract the ICDS, the CreditGrades model needs to be calibrated with respect to unobservable parameters. We propose a new calibration procedure that differs from existing methods in two regards. First, we impose fewer assumptions on the values of the unobserved parameters. We let the data speak for themselves regarding the value of the mean and the volatility of the global recovery rate. Accordingly, our calibration results contain less bias associated with the ad hoc setting on unobserved parameters. Second, we adopt a frequent calibration approach to dynamically update the value of the unobservable parameters. This allows us to incorporate new information on capital structure into the recovery parameters. In addition to the new methodology for calibration, we carefully choose the observable parameters. We use the swap rate as a proxy for the risk-free rate and choose data on the daily number of common shares outstanding to avoid impacts on the debt per share due to corporate events such as stock splits. To make sure the variations in the ICDS are mainly driven by information from the stock market, we use historical volatility rather than option-implied volatility.

The graphical evaluation suggests better tracking ability for the ICDS estimates using our calibration approach than $ICDS^*$ obtained from the existing calibration method. The difference in tracking ability is further exemplified during the GFC sub-sample period. Furthermore, using CDS spreads as a benchmark, we calculate the AAPE for each of the two ICDS measures and provide statistical evaluations. The cross-sectional distribution of the AAPEs provides striking evidence that our calibration procedure generates more accurate ICDS estimates than the existing procedure. Indeed, using our calibration approach, 90% of the sample firm has an AAPE less than 31.59 bps, whereas a similar AAPE is only found in 10% of sample firms if the existing calibration method is adopted.

Our proposed calibration approach of the CreditGrades model improves the accuracy of ICDS estimates. This in turn facilitates us to further examine the cross-market information flows between the CDS and equity markets. Chapter 5 investigates the credit risk information dynamics across these two markets. Chapter 6 proposes a new capital structure arbitrage algorithm that incorporates cross-market information dynamics.

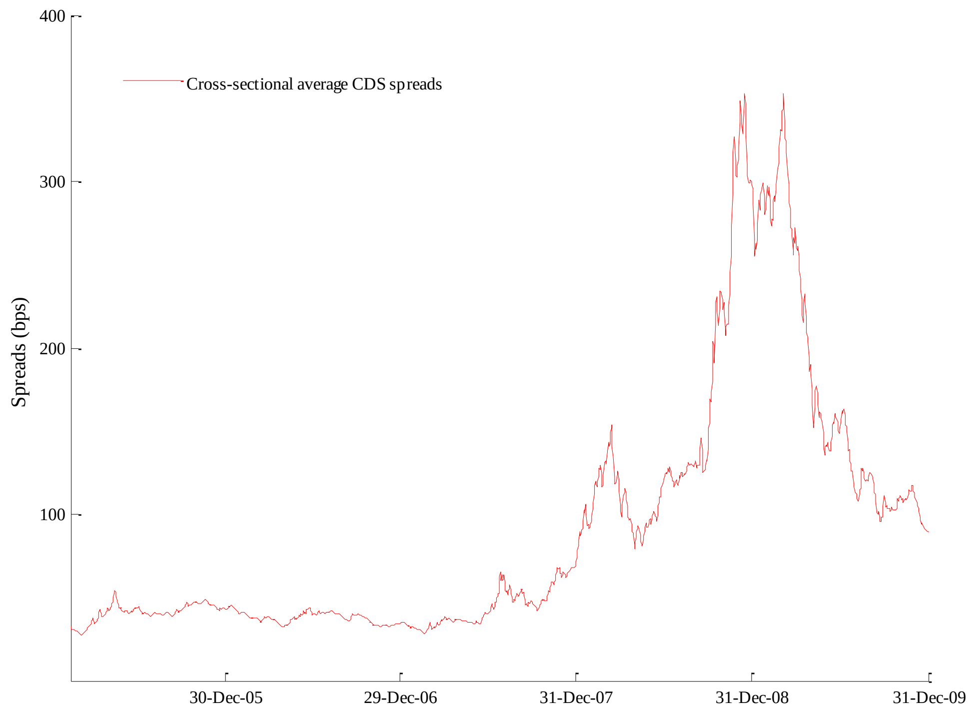
Chapter 5: Transmigration across price discovery categories: Evidence from the U.S. CDS and equity markets

5.1 Introduction

The fundamental economic role of a derivative market is to facilitate risk-sharing and price discovery. As Working (1953) argues, robust trading interactions between hedgers and more informed speculators constitute a successful and liquid derivative market. This can be said for derivative markets operating under normal circumstances, for example, index futures markets before the October 1987 crash and the CDS market before the 2008 GFC. Blanco et al. (2005) find that the CDS market is more efficient than the bond market in reflecting credit risk information. Acharya and Johnson (2007) document that negative private information is first revealed in the CDS market before it is transmitted to the stock market.

An interesting question is whether such a role of derivative markets ceases to function properly during extreme events. For example, during the crash of October 1987, the price discovery mechanism of index futures markets was severely hampered by the lack of liquidity and market-making to facilitate the trading process. Trade prices were few and far between and they were extremely volatile. Quote prices contained a huge premium for immediacy. During the GFC, when financial markets were gripped by a systemic credit crunch, we naturally expect CDS spreads to have been higher and more volatile as well. A time-series plot of the cross-sectional average CDS spreads for our firm sample in Figure 5.1 shows that this is indeed the case. Accordingly, one may draw an analogy between the two financial crises and expect the U.S. CDS market's risk sharing and price discovery mechanism to be similarly impaired during the GFC.

Figure 5.1: Time-series plot of cross-sectional average CDS spreads



In this chapter, we examine the credit risk information dynamics between the CDS and equity markets. Our daily sample consists of 174 U.S. non-financial investment-grade firms between January 2005 and December 2009. We use the RiskMetrics CreditGrades model to extract a time series of ICDSs ($ICDS_{i,t}$) from the stock prices of firm $i = 1,2,\dots,174$. This is aligned with the time series of the corresponding observable CDS spreads ($CDS_{i,t}$). The time-series variation in the pairwise credit risk measures ($CDS_{i,t}, ICDS_{i,t}$) informs us about the cross-market credit risk information flows between the CDS and equity markets.

We have four related objectives. First, we examine long-run credit risk pricing equilibrium between the CDS and equity markets. Blanco et al. (2005), Zhu (2006) and Dotz (2007) document an evident cross-market credit risk pricing equilibrium between the CDS and bond markets. Comparatively fewer studies examine this pricing relation across the CDS and equity markets. If both markets reflect credit risk information, the pairwise credit risk measures $(CDS_{i,t}, ICDS_{i,t})$ should be cointegrated. The cointegration between $CDS_{i,t}$ and $ICDS_{i,t}$ allows us to further ascertain the short-run credit risk price discovery mechanism across the CDS and equity markets.

Second, we apply both the Gonzalo–Granger (1995) common-factor weight (GG) and Hasbrouck (1995) information share (HAS) measures to determine the credit risk price discovery contribution by the CDS and equity markets. We sort firms into five price discovery categories {C1,…,C5}. The latter represents a spectrum of cross-market price discovery status. As we move from C1 to C5, the price discovery contribution shifts from the CDS market to the equity market.

Third, we are interested in tracking the transmigration patterns of firms across {C1,…, C5} when we forward-shift the estimation window towards and away from the midst of the GFC. The initial categorisation into {C1,…,C5} is based on the pre-GFC sample period from January 3, 2005, to June 30, 2007. We forward-shift the pre-GFC sample on a quarterly basis and recalculate the GG and HAS measures. This allows us to update and track firm migration across {C1,…,C5} during the GFC sample period from July 1, 2007, to December 30, 2009. The findings we document on transmigration patterns can only come from measuring and updating GG and HAS measures for a large firm sample.

Fourth, we ascertain the economic significance with five portfolio strategies {PS1,…,PS5}, all of which draw trading signals from the CDS market to trade corresponding stocks. These five strategies are designed to demonstrate incremental profit/loss from identifying and updating the list of firms for which the CDS market has price leadership. PS1 is an unconditional strategy that considers the entire firm sample. It disregards the price discovery dynamics between $CDS_{i,t}$ and $ICDS_{i,t}$. The strategy PS2 trades from a conditional but static list of firms for which the CDS market leads the stock market in the credit risk price discovery process during the initial estimation window. The strategy PS3 trades from a conditional but dynamic list of firms for which the CDS market processes price leadership. In that regard, the firm list for PS3 incorporates the documented cross-market price discovery transmigration patterns. We include control portfolio strategies PS4 and PS5, which trade from firm lists that are mutually exclusive to PS2 and PS3, respectively.

We evaluate the profit/loss results of {PS1,…,PS5} against two sets of benchmarks. First, we test the significance of each strategy's risk-adjusted realised returns using Jensen's alpha against Fama–French factors. Second, we benchmark our strategies against other proven strategies that are implemented using our firm sample over the same trading period, including buy-and-hold, momentum, and dividend yield strategies.

This chapter proceeds as follow. Section 5.2 describes the data and sample. Section 5.3 discusses in-sample statistical results. These include long-run credit risk pricing equilibrium, the price discovery contributions of the CDS and equity markets, and transmigration patterns across price discovery categories. The out-of-sample profit/loss results are provided in Section 5.4. Section 5.5 concludes with a summary.

5.2 Data and sample

The data sources and variables used in this study are introduced in Chapter 3. We summarise these variables in Table 5.1.

Table 5.1: Data description

Data	Description	Source
CDS spread: $CDS_{i,t}$	Five-year USD 10 million CDS contracts written on senior unsecured debt issued by U.S. firms.	Provided by CMA, downloaded from Bloomberg and Datastream.
Stock price: $S_{i,t}$	Daily closing price.	CRSP daily file.
Stock return volatility: $\sigma_{i,t}$	One-year historical volatility using CRSP adjusted daily returns.	CRSP daily file.
Debt per share: $D_{i,t}$	Total liabilities divided by common shares outstanding. We use the quarterly figure of total liabilities and daily observations of common shares outstanding.	We download quarterly total liabilities figures from the Compustat North America file. Daily observations on common shares outstanding are accessed from the CRSP daily file.
Risk-free rate: r_t^f	We use the five-year swap rate as a proxy for the risk-free rate.	Datastream.

The stock price ($S_{i,t}$), stock return volatility ($\sigma_{i,t}$), debt per share ($D_{i,t}$), and the risk-free rate (r_t^f) are the inputs to the CreditGrades model to estimate $ICDS_{i,t}$. The details of the CreditGrades model and the $ICDS_{i,t}$ estimation procedure[27] are discussed in Chapter 4.

After merging various data sources, our sample contains 174 U.S. investment-grade firms over a five-year period between January 3, 2005, and December 31, 2009. Each firm has pairwise credit risk measures $(CDS_{i,t}, ICDS_{i,t})$. To uncover cross-market price discovery transmigration patterns during the course of the GFC, the sample period is divided into a pre-GFC sub-sample from January 2005 to June 2007 and a GFC sub-sample from July 2007 to December 2009.

5.3 Empirical results

Our empirical analysis has three stages. First, we examine whether long-run credit risk pricing equilibrium exists across the CDS and equity markets. Second, we analyse the short-run credit risk price discovery process between these two markets. Using the Gonzalo–Granger (1995) and Hasbrouck (1995) measures of the cross-market price discovery contributions by $(CDS_{i,t}, ICDS_{i,t})$, we sort our firm sample into one of five price discovery categories. Third, using rolling-window estimation, we track the transmigration of firms across price discovery categories during the course of the GFC.

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[27] The CreditGrades model also requires the mean ($\bar{L}$)and volatility (λ)of the global recovery rate and bond-specific recovery rate (R) as model inputs. The values of these variables are not directly observable. Following Hull and White (2004) and Yu (2006), we set $R = 0.5$. For the values of $\bar{L}$ and λ, we use our proposed CreditGrades model calibration procedure, described in Chapter 4.

5.3.1 Long-run credit risk pricing equilibrium

If a long-run credit risk pricing equilibrium exists across the CDS and equity markets, the pairwise credit risk measures $(CDS_{i,t}, ICDS_{i,t})$ should be cointegrated. As a preliminary check, an Augmented Dickey–Fuller (ADF) unit root test confirms that $CDS_{i,t}$ and $ICDS_{i,t}$ are I(1) processes for every firm. We apply Johansen cointegration test to each firm's $(CDS_{i,t}, ICDS_{i,t})$. The results are presented in Table 5.2. Panel A reports the cointegration results for the full sample and the pre-GFC and GFC sub-samples. Panel B provides a further partitioning base on credit ratings.

Table 5.2: Long-run credit risk pricing equilibrium across the CDS and equity markets

	Total Number of Companies	Cointegrated at the 0.05 Level	Not Cointegrated at the 0.05 Level
Panel A: Full and Sub-Sample Periods			
Full Sample Period	174	173	1
Pre-GFC Sub-Sample Period	174	172	2
GFC Sub-Sample Period	174	165	9
Panel B: Rating Group			
Full Sample Period AAA Firms	5	5	0
Full Sample Period AA Firms	13	13	0
Full Sample Period A Firms	65	64	1
Full Sample Period BBB Firms	91	91	0
Pre-GFC Sample Period AAA Firms	5	5	0
Pre-GFC Sample Period AA Firms	13	12	1
Pre-GFC Sample Period A Firms	65	64	1
Pre-GFC Sample Period BBB Firms	91	91	0
GFC Sample Period AAA Firms	5	5	0
GFC Sample Period AA Firms	13	12	1
GFC Sample Period A Firms	65	64	1
GFC Sample Period BBB Firms	91	84	7

In Panel A of Table 5.2, the $(CDS_{i,t}, ICDS_{i,t})$ of 173 firms are cointegrated at the 0.05 level for the full sample period. In the pre-GFC sub-sample, the $(CDS_{i,t}, ICDS_{i,t})$ of only 2 firms are not cointegrated at the 0.05 level. While this increases to 9 firms in the GFC sub-sample, the cointegration link between the $CDS_{i,t}$ and $ICDS_{i,t}$ still prevails for the vast majority of our sample firms. This is despite investors' negative sentiment about credit risk and regulatory interventions, such as rescue packages and short-selling restrictions. The results strongly suggest the presence of a prevailing cross-market credit risk pricing equilibrium between the CDS and equity markets. Panel B does not reveal any systematic pattern cointegration results across the various rating groups. It shows the loss of cointegration in 7 additional firms in the GFC sub-sample are all rated BBB. Intuitively, if the GFC is expected to disrupt the credit risk pricing equilibrium between the CDS and equity markets, this is more likely to occur in BBB rather than AA firms.

5.3.2 Price discovery contributions of the CDS and equity markets

The presence of cointegration for the majority of our firm sample allows us to model the cross-market dynamics between $CDS_{i,t}$ and $ICDS_{i,t}$ as a bivariate VECM:

$$\Delta CDS_t = \sum_{s=1}^{S} (\alpha_{1,s}\, \Delta CDS_{t-s} + \beta_{1,s} \Delta ICDS_{t-s}) + \lambda_1 (CDS_{t-1} - \tau_0 - \tau_1 ICDS_{t-1}) + \varepsilon_{1,t}$$

$$\Delta ICDS_t = \sum_{s=1}^{S} (\alpha_{2,s}\, \Delta CDS_{t-s} + \beta_{2,s} \Delta ICDS_{t-s}) + \lambda_2 (CDS_{t-1} - \tau_0 - \tau_1 ICDS_{t-1}) + \varepsilon_{2,t} \quad (5.1)$$

This model assumes $\mathrm{E}(\varepsilon_{1,t}) = \mathrm{E}(\varepsilon_{2,t}) = 0$, $\mathrm{E}(\varepsilon_{1,t}^2) = \sigma_1^2, \mathrm{E}(\varepsilon_{2,t}^2) = \sigma_2^2$, and $\mathrm{E}(\varepsilon_{1,t}\varepsilon_{2,t}) = \sigma_{1,2}$. We use the Schwarz information criterion (SIC) to determine the VECM's optimal leg specification S on a firm-by firm basis.

In equation (5.1), the long-run credit risk pricing equilibrium is manifested in the error correction term $(CDS_{t-1} - \tau_0 - \tau_1 ICDS_{t-1})$. Any departure from this equilibrium relationship is both temporary and bounded. We do not impose the restriction $\tau_0 = 0$ and $\tau_1 = 1$. This is because the $CDS_{i,t}$ is a market-observed price of credit risk whereas the $ICDS_{i,t}$ is a measure of credit risk implied by the stock price. The institutional and microstructural features in the CDS and stock markets will have dissimilar effects on $CDS_{i,t}$ and $ICDS_{i,t}$.

The key parameters to ascertain the cross-market price discovery mechanism between the two markets are the error correction coefficients λ_1 and λ_2. If only $\lambda_1 < 0$ is significant, this suggests ΔCDS_t relies on the error correction variable to adjust for temporal deviations from the equilibrium pricing relation. This implies that the equity market solely dominates in the price discovery process. Analogously, if only $\lambda_2 > 0$ is significant, the $\Delta ICDS_t$ react to the temporal pricing disequilibrium and hence the CDS market solely dominates in the price discovery process.

If $\lambda_1 < 0$ and $\lambda_2 > 0$ are significant, this implies the CDS and equity markets both jointly contribute to the credit risk price discovery process. We compute the Gonzalo-Granger (1995) common-factor weight (GG) and Hasbrouck (1995) information-share (HAS) measures to determine the credit risk price discovery contribution by the CDS and equity markets. The GG measures for the CDS and equity markets are calculated as $\frac{\lambda_2}{\lambda_2 - \lambda_1}$ and $\frac{-\lambda_1}{\lambda_2 - \lambda_1}$, respectively. If the GG measure for one market exceeds 0.5, this implies a greater price discovery contribution. The HAS measure defines an upper bound ($\mathrm{HAS_U}$) and a lower bound ($\mathrm{HAS_L}$) for each market's price discovery contribution. Given our VECM specification in equation (5.1), $\mathrm{HAS_U}$ and $\mathrm{HAS_L}$ for the CDS market are calculated as

$$HAS_L = \frac{\lambda_2({\sigma_1}^2 - \frac{{\sigma_{12}}^2}{{\sigma_2}^2})}{\lambda_2^2{\sigma_1}^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2{\sigma_2}^2} \qquad HAS_U = \frac{(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1})^2}{\lambda_2^2{\sigma_1}^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2{\sigma_2}^2} \tag{5.2}$$

where ${\sigma_1}^2$, ${\sigma_2}^2$, and σ_{12} are the elements from the variance–covariance matrix of $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$.

Following Baillie et al. (2002) and Blanco et al. (2005), when $\frac{1}{2}(\mathrm{HAS_L}+\mathrm{HAS_U}) > 0.5$ and $\frac{\lambda_2}{\lambda_2-\lambda_1} > 0.5$, this indicates that the CDS market has a larger price discovery contribution than the equity market and vice versa. However, if there is no consensus between the GG and HAS measures, we regard the CDS and equity markets as contributing similarly to the credit risk price discovery process. This is a reasonable compromise between the two standard measures of cross-market price discovery.

The preceding discussion naturally implies five mutually exclusive price discovery categories {C1,…,C5}. C1 (Category 1) and C5 (Category 5) contain firms where the CDS and equity market solely dominates the price discovery process, respectively. When both markets contribute to the price discovery process, the categorisation is based on the GG and HAS measures. Firms where both the GG and HAS measures indicate the CDS (equity) market contributes more to the price discovery process are allocated in C2 (C4). Lastly, firms for which the two measures do not share a consensus are assigned to C3. Moving from C1 to C5, the relative contribution of the CDS market to the price discovery is declining but the equity market is becoming increasingly important. Hence, {C1,…,C5} can be viewed as a price discovery contribution spectrum with the CDS market dominating the price discovery at one end and the equity market dominating at the other.

Table 5.3: Credit risk price discovery across the CDS and equity markets

	Category 1 (C1)	Category 2 (C2)	Category 3 (C3)	Category 4 (C4)	Category 5 (C5)	Total
			Panel A: Whole Sample Period			
All Firms	74	57	14	16	12	173
AAA	2	3	0	0	0	5
AA	8	2	1	1	1	13
A	24	23	4	6	7	64
BBB	40	29	9	9	4	91
			Panel B: Pre-GFC Sample Period			
All Firms	52	40	18	47	15	172
AAA	1	0	0	4	0	5
AA	1	2	2	7	0	12
A	19	10	8	22	5	64
BBB	31	28	8	14	10	91
			Panel C: GFC Sample Period			
All Firms	90	28	13	11	23	165
AAA	4	1	0	0	0	5
AA	8	1	0	1	2	12
A	34	12	3	3	12	64
BBB	44	14	10	7	9	84

Table 5.3 presents the results for the full-sample period in Panel A and Panels B and C's results correspond to the pre-GFC and GFC sub-samples. Panel A shows that 131 firms, or 76% of the firm sample, are categorised as either C1 or C2, where the CDS market either dominates or leads the price discovery mechanism. However, the equity market also makes a non-trivial contribution to the price discovery process, with 28

firms are indeed categorised as C4 and C5 firms, which constitutes around 17% of the firm sample. Most of these firms have comparatively lower credit ratings of AA and BBB.

The results across Panels B and C reveal interesting dissimilarities in the categorisation results, implying the cross-market credit risk price discovery mechanism is time varying. In Panel B, 92 firms, or 53% of the firm sample, belong to either C1 or C2. The equity market holds its own with 62 firms, or 36%, belonging to either C4 or C5. In stark contrast, Panel C shows the CDS market dominates the credit risk price discovery during the credit-crunch induced GFC, with 118 firms, or 71.5%, categorised as either C1 or C2 firms.[28] This suggests that the CDS market actually became more efficient than the equity market at incorporating credit risk information during the GFC. With a heightened awareness of credit risk, the market for trading credit risk becomes all the more pertinent.

Our results, which are based on a cleaner measure of $ICDS_{i,t}$ over a large firm sample, provides strong evidence of informational efficiency in the CDS market. Prior studies by Norden and Weber (2004, 2009), Bystrom (2006), and Fung et al. (2008) document inconclusive findings on this issue. Acharya and Johnson (2007) find that the CDS market is more efficient at revealing negative private information. Our results show that this is also the case for a market-wide credit crunch. Blanco et al. (2005) confirm that the CDS market is more efficient than the corporate bond market in reflecting credit risk information. Our results show that the CDS market performs more credit risk price discovery than the equity market as well.

[28] We lose 7 additional firms when we move from Panel B to Panel C since their $CDS_{i,t}$ and $ICDS_{i,t}$ are not cointegrated in the GFC sub-sample.

We make a further comparison between Panels B and C. The number of firms in each category is unstable, going from the pre-GFC to GFC sample. For example, the number of C1 firms jumps from 52 to 90 and C5 firms increase slightly from 15 to 23. However, the number of C4 firms drops from 47 to 11 and C2 firms also reduces from 40 to 28. This suggests a shift in the price discovery mechanism towards C1 and C5, that is, the ends of the spectrum, where either the CDS or equity market dominates credit risk price discovery. Our findings thus far indicate possible transmigration of firms across price discovery categories as the sample progresses towards and away from the GFC. This motivates us to perform a more detailed analysis of firm categorisation in the next section.

5.3.3 Transmigration patterns across price discovery categories

The dissimilar results in Panels B and C of Table 5.3 indicate that the price discovery mechanism across the CDS and equity markets is time varying. However, it does not provide any insight on transmigration patterns in and out of each category. We report relevant details on the number and percentage of firms that migrate from one category into another in Panels A and B or Table 5.4, respectively. In both panels, the column headings are for the pre-GFC sub-sample and the row headings represent the GFC sub-sample. For example, in Panel A, at the intersection of the pre-GFC C2 and the GFC C1, 17 firms migrate from C2 to C1 price discovery, going from the pre-GFC to the GFC sub-sample. For completeness, we include C6, which represents firms for which no cointegration exists between $CDS_{i,t}$ and $ICDS_{i,t}$ in either of the two sub-samples.

Table 5.4: Transition of firms between price discovery categories

Panel A: Number of Firms	Pre-GFC C1	Pre-GFC C2	Pre-GFC C3	Pre-GFC C4	Pre-GFC C5	Pre-GFC C6	Total
GFC C1	**35**	17	12	20	4	2	90
GFC C2	4	**6**	2	10	6	0	28
GFC C3	3	6	**3**	1	0	0	13
GFC C4	2	4	0	**4**	1	0	11
GFC C5	6	5	0	10	**2**	0	23
GFC C6	2	2	1	2	2	**0**	9
Total	52	40	18	47	15	2	174

Panel B: Percentage of Firms in the Pre-GFC Category	Pre-GFC C1	Pre-GFC C2	Pre-GFC C3	Pre-GFC C4	Pre-GFC C5	Pre-GFC C6
GFC C1	**67.31%**	42.50%	66.67%	42.55%	26.67%	100.00%
GFC C2	7.69%	**15.00%**	11.11%	21.28%	40.00%	0.00%
GFC C3	5.77%	15.00%	**16.67%**	2.13%	0.00%	0.00%
GFC C4	3.85%	10.00%	0.00%	**8.51%**	6.67%	0.00%
GFC C5	11.54%	12.50%	0.00%	21.28%	**13.33%**	0.00%
GFC C6	3.85%	5.00%	5.56%	4.26%	13.33%	**0.00%**
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

We discuss the key findings from Panel B, which expresses the number of firms as a percentage of total firms in each category for the pre-GFC sample. If we perceive it as a transition matrix, the diagonal elements (in bold) indicate the percentage of firms remaining in the same category, as moving from the pre-GFC to the GFC sub-sample. For example, C1 retains 67% of firms from the pre-GFC to the GFC sub-sample. In stark contrast, less than 20% of firms remain in the other categories. There are 15% of C2 firms, 16.67% of C3 firms, 8.51% of C4 firms, and 13.33% of C5 firms remain in the same category, going from the pre-GFC to the GFC sub-sample.

Furthermore, C1 exerts a gravitational pull, drawing firms from other price discovery categories. As reported in Panel B, C1 absorbs 42% of C2 firms, 66.67% of C3 firms, 42.55% of C4 firms, and 26.67% of C5 firms from the pre-GFC to the GFC subsample.C1 and C2 have jointly attract more than half the entire firm sample. Specifically, 77.8% of pre-GFC C3 firms, 65.8% of pre-GFC C4 firms, and 66.7% of pre-GFC C5 firms have migrated to either the GFC C1 or C2 categories. These findings reinforce the presence of time-varying price discovery between the CDS and equity markets and the heightened price discovery role of the CDS market for an increasing number of firms during the GFC.

The results in Table 5.4 indicate a structural break in the credit risk dynamics for a large number of firms. If this structural break is caused by the credit-crunch induced GFC, we should further ascertain the transmigration patterns during the course of the GFC. Accordingly, we use rolling-window analysis to track the number of firms in {C1,…,C5} over the entire period of our GFC sub-sample. The categorisations are based on 11 rolling-window estimations {RW1,…,RW11} of the GG and HAS measures. Rolling-window 1 (RW1) is simply the pre-GFC sub-sample from January 3, 2005, to June 30, 2007; RW2 is from April 1, 2005, to September 30, 2007, and so on. Lastly, RW11 covers from October 1, 2007, to December 31, 2009 i.e. the same as the GFC sub-sample. In effect, we update the price discovery categorisation for each of 174 firms on a quarterly basis.

Table 5.5: Rolling-window credit risk price discovery categorisation

	RW1	RW2	RW3	RW4	RW5	RW6	RW7	RW8	RW9	RW10	RW11
Starting Date	2005/1/1	2005/4/1	2005/7/1	2005/10/1	2006/1/1	2006/4/1	2006/7/1	2006/10/1	2007/1/1	2007/4/1	2007/7/1
Ending Date	2007/6/30	2007/9/30	2007/12/31	2008/3/31	2008/6/30	2008/9/30	2008/12/31	2009/3/31	2009/6/30	2009/9/30	2009/12/31
C1 Firms	52	54	87	89	150	147	66	73	92	93	90
C2 Firms	40	48	40	37	9	9	30	29	36	32	28
C3 Firms	18	23	23	8	3	2	13	20	14	18	13
C4 Firms	47	37	20	12	1	2	17	20	12	10	11
C5 Firms	15	9	0	12	6	6	39	25	15	16	23
C6 Firms	2	3	4	16	5	8	9	7	5	5	9
Total	174	174	174	174	174	174	174	174	174	174	174

The results in Table 5.5 demonstrate a clear transmigration patterns in the price discovery categories as we progress towards and away from the midst of the GFC. The CDS market has an evident gravitational pull, with the number of C1 and C2 firms increasing sharply from 92 in RW1 to 159 in RW5 and to 156 in RW6. The latter rolling window constitutes the onset of the GFC. From RW7 onwards, the number of C1 and C2 firms decrease substantially but remain high compared to RW1 i.e. the pre-GFC sub-sample period.

Figure 5.2: Number of C1 and C2 firms across eleven rolling windows (RW)

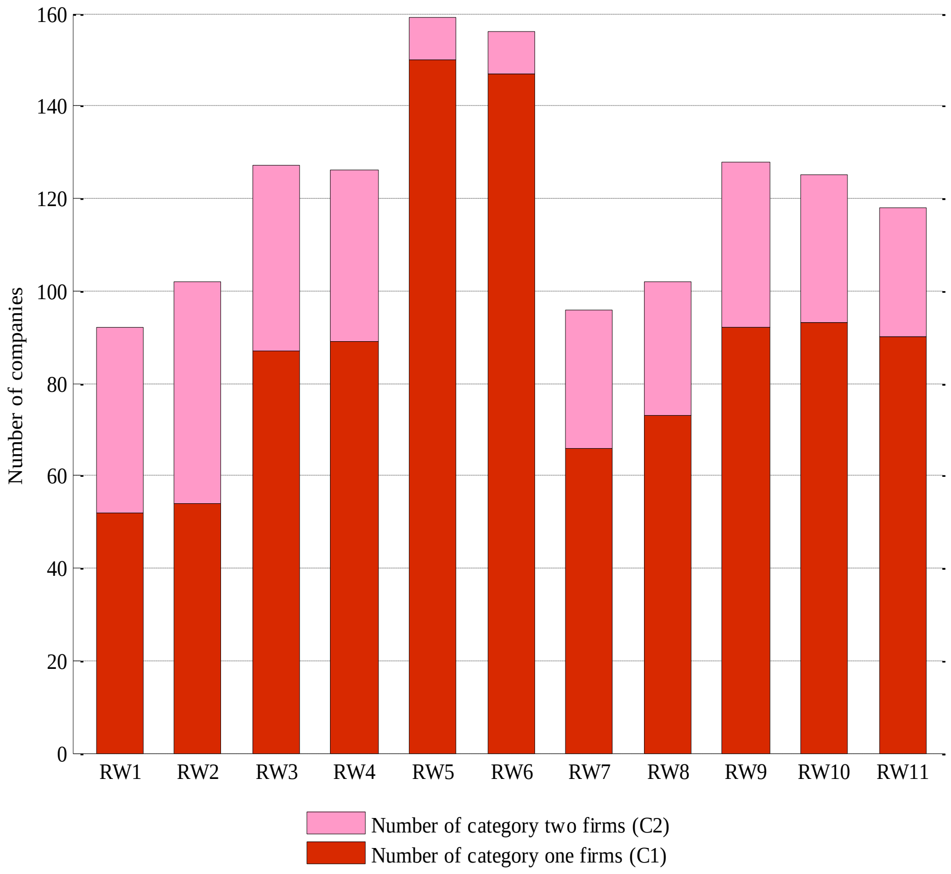

Figure 5.2 plots the number of C1 and C2 firms across {RW1,…,RW11}. The plot shows that the CDS market is gradually taking over price discovery leadership from the equity market as we move towards the GFC. Even as we move away from the

height of the GFC, the heightened awareness of credit risk implies that the number of C1 and C2 firms in RW11 (118 firms) remains high relative to RW 1 (92 firms).

5.4 Portfolio strategies and economic significance

We obtained insights about cross-market credit risk information flows in the preceding section. In this section we implement portfolio strategies to ascertain the economic significance of these information dynamics.

Gonzalo and Granger (1995) and Hasbrouck (1995) both measure the summary informativeness of $CDS_{i,t}$ and $ICDS_{i,t}$. This allows us to determine the direction of credit risk information flows between the two markets for each firm in order to allocate them into price discover categories {C1,…,C5}. For C1 and C2 firms, the CDS market either dominates or leads in the credit risk price discovery mechanism, such that $CDS_{i,t}$ will respond to the credit-related shocks before $ICDS_{i,t}$ due to the delayed response of equity prices. Accordingly, a natural test of the economic significance of the price discovery statistical results is to examine the profitability of trading stocks based on fluctuations in CDS spreads.

The aim of this section is to ascertain the economic significance of i) identifying the direction of credit risk information flow and ii) updating the time-varying nature of credit risk price discovery dynamics between the CDS and equity markets. We implement five portfolio strategies {PS1,…,PS5}, all of which draw trading signals from the CDS market based on changes of $CDS_{i,t}$ to set positions in the corresponding stocks. The key differences among the {PS1,…,PS5} lie in the list of candidate firms that are being considered for trading.

The strategy PS1 is an unconditional strategy that trades from our entire firm sample. To demonstrate the economic significance of information flow from the CDS to the equity market, PS2 considers only 52 C1 and 40 C2 firms in Table 5.5 under RW1, for which the CDS market has price leadership. The firm list for PS2 is static, such that we do not update the list of C1 and C2 firms during the trading period. In contrast, PS3 trades from a list of C1 and C2 firms that is updated on a quarterly basis. Once the list of C1 and C2 firms is updated, it is then used by PS3 in the next quarter. The profit/loss comparison between PS2 and PS3 brings out the incremental value of tracking firm transmigration patterns in and out of C1 and C2. Lastly, PS4 and PS5 trade exclusively in non-C1 and non-C2 firms, i.e. firms that are mutually exclusive to PS2 and PS3 respectively.

The strategies PS4 and PS5 serve three purposes. First, the two pairwise comparisons PS2 versus PS4 and PS3 versus PS5 further bring out the importance of identifying the direction of credit risk information flow. Second, they provide a robustness check. If PS2 and PS3 both outperform PS1 because they trade exclusively in C1 and C2 firms, then PS4 and PS5 should both underperform PS1 since they trade exclusively in non-C1 and non-C2 firms. Third, during part of the test period, the number of C1 and C2 firms increases to nearly 160. This implies the lists of candidate firms for PS1 and PS3 are becoming increasingly similar, at least during part of the test period. The strategy PS5 provides another comparison for PS3.

5.4.1 The portfolio approach

The estimation window runs from 0-January 2005, to June 30, 2007. The remainder of the sample is used for out-of-sample testing. Any categorisation of C1 and C2 firms is based only on past observation, such that anchoring {PS1,…,PS5} on $CDS_{i,t}$ does not evoke a look-ahead bias. All five strategies are designed to share a similar methodology, for example, trading signal, holding period, re-balance frequency etc. This is to ensure that any discrepancy in profit/loss performance is not due to the features of the trading process.

Every Tuesday, we sort candidate firms according to the weekly percentage changes in CDS spreads. We impose a 20% change in the weekly CDS spreads as a signal that the underlying firm's credit risk profile has changed. Next trading day, we form portfolios for {PS1,…,PS5} by buying stocks of the candidate firm if their weekly percentage changes in CDS spreads are less than -20% and by short-selling stocks of candidate firm if their weekly percentage changes in CDS spreads are greater than 20%. A large drop (rise) in CDS spreads suggests a substantial decrease (increase) in perceived credit risk. For companies where the CDS market possesses price leadership, this would translate into higher (lower) subsequent returns. We take $1 long–short equally weighted positions in {PS1,..,PS5} and the portfolio for one week, after which it is liquidated. The portfolio return is calculated as the sum of returns from the long and short positions. For every stock in the portfolio, we deduct 10 bps as a transaction cost.

We address four issues relating to our portfolio approach. First, GG and HAS are measures of summary informativeness. For C1 or C2 firm, the measures indicate, on average, over the estimation window, that the CDS market is more efficient than the equity market in reflecting credit-related information. However, the measures do not explicitly stipulate the extent of delay in the equity market's response relative to the CDS market. Furthermore, such delays are likely to vary across firms. As such, it is an awkward task to set an optimal holding period, if any. To address this issue, we hold portfolios for one week, even though the price discovery measures are based on daily price adjustments. Indeed, if a weekly holding period is deemed too long (short), this simply implies we are too late (early) in closing out stock positions. This can only strengthen our findings of economic significance. Moreover, our main objective is to demonstrate the incremental profits by sequentially moving from PS1 to PS3.

Second, $\pm$20% weekly CDS spread changes as a trigger for credit shocks may seem excessive. However, since CDS spreads are quoted in basis points, a CDS contract trading at 100 bps subject to a 20% change translates to a weekly change of 20 bps. We can confirm that the relative ranking among {PS1,…,PS5} is robust to signal values ranging from5% to 30%. The cross-sectional average CDS spread for our firm sample is around 150 bps. A $\pm$20% change translates to a weekly change of 30 bps. We argue that the value we adopt is more conservative than the 50-bps daily change threshold dummy variable used by Acharya and Johnson (2007).

Third, the number of firms in the long and short positions are not necessarily balanced. However, we maintain a zero-cost portfolio by committing a $1 value exposure to both sides. However, if trading is triggered only at the top (bottom) end of the sorted firm list, our portfolio position would only be short (long). This is designed from the perspective of hedge funds or proprietary trading desks, which are endowed with initial investment capital. The realised annual return is based on the cumulative return of a given portfolio strategy over the trading period.

Fourth, the U.S. Securities and Exchange Commission recommended a short-sale ban list on U.S. equity firms. The ban list was reviewed, revised, and imposed by U.S.

stock exchanges between September 19, 2008, and October 8, 2008. We cross-reference the short-sale ban list and find that 10 firms in our sample are on that list. Since our study is based on high-quality investment-grade firms, the short-sale ban applies to only 5.75% of our firm sample. We mark these 10 firms and impose short-sale constraints on all portfolio strategies during the banned period. Our profit/loss results are adjusted for regulatory short-sale constraints imposed during the GFC.

Table 5.6: Profit/loss results of the threshold portfolio approach

	PS1	PS2	PS3	PS4	PS5
Min	-12.61%	-15.05%	-13.37%	-23.16%	-14.48%
Max	21.18%	23.60%	21.59%	28.07%	20.37%
Median	0.12%	0.31%	0.72%	-0.13%	-0.12%
Mean	0.18%	0.56%	0.52%	-0.12%	0.06%
Standard Deviation	5.26%	6.57%	5.88%	5.8%	4.89%
Percentage of Portfolios Generating Positive Returns	52.94%	52.04%	58.25%	47.41%	47.12%
Cumulative Returns	5.21%	40.10%	43.81%	-28.62%	-5.33%
Annualised Return	2.05%	14.44%	15.64%	-12.61%	-2.17%
Annualised Standard Deviation	37.91%	47.41%	42.41%	41.84%	35.29%
Sharpe Ratio	0.0475	0.2993	0.3629	-0.3074	-0.0686
Number of Portfolios	119	98	103	116	104
Average Number of Stocks Included in the Portfolio	16.62	5.76	10.83	12.19	8.30
Average Number of Long Stocks in the Portfolio	5.01	1.66	2.83	3.72	2.91
Average Number of Short Stocks in the Portfolio	11.61	4.11	8.01	8.5	5.38
Standard Deviation of Number of Stocks Included in the Portfolio	22.22	6.47	15.79	16.56	10.39

We report the profit/loss results in Table 5.6, including the basic statistics of realised returns, portfolio features, and annualised return–risk ratio etc. On average, the ratio of long to short positions across {PS1,…,PS5} is around 3:7. The number of weekly portfolios traded ranges from 98 for PS2 to 119 for PS1. In other words, there are 32 (11) weeks where no trading is warranted for PS2 (PS1), due to the lack of tangible credit signals from the CDS market. Similarly, the average number of firms traded ranges from 5.76 for PS2 to 16.62 for PS1. Even with a dynamically updated list of C1 and C2 firms, PS3 forms 103 weekly portfolios, with an average of 10.83 firms for each traded weekly portfolio.

Only PS1, PS2, and PS3 exhibit positive realised cumulative returns over the 2.5-year trading period. The worst performer is PS4, with an annualised return of -12.61% pa. While PS1 manages a modest return of 2.05% pa, it is clearly overshadowed by the realised returns of PS2 and PS3 at 14.44% pa and 15.64% pa respectively. This clearly brings out the non-trivial economic significance for portfolio strategies that draw trading signals from the CDS market to be conditioned on firms that actually rely on the CDS market for price discovery in the first place. Interestingly, PS3 has both a higher return and lower volatility than PS2, such that it has a more impressive Sharpe Ratio of 0.363 compared to PS2's 0.299. In addition, the proportion of weekly portfolios that generate positive weekly returns is 58.25% for PS3. This is higher than the 52.04% for PS2.

5.4.2 Profit/loss evaluation against proven portfolio strategies

The preceding profit/loss results allow us to ascertain the relative profit rankings among {PS1,…,PS5}. While they confirm the incremental profitability of PS2 and PS3 over PS1, PS4, and PS5, the incremental profits are not formally compared against other proven portfolio strategies. In this section, we evaluate if the profit performance of the five strategies, especially PS2 and PS3, are economically significant when compared against other well-established portfolio strategies. We consider two sets of benchmarks.

A. Jensen's alpha against Fama–French factors

To evaluate the economic significance of risk-adjusted net returns, we compute Jensen's alpha (α_j) by regressing weekly excess returns from $\mathrm{PS_j}$, $\mathrm{j} = 1,2,\ldots,5$, against weekly Fama–French market risk premium (MRP_t), size (SMB_t), and book-to-market (HML_t) factor returns.[29] Panel A of Table 5.7 shows that PS2 and PS3 possess substantially higher (α_j) and lower p-values compared to PS1, PS4, and PS5. However, all (α_j) coefficients are insignificant. In fact, all the coefficient estimates in Panel A are insignificant.

[29] These factor portfolio returns are downloaded from Kenneth French's website.

Table 5.7: Weekly estimation results on Jensen's Alpha

Panel A: Least-Squares Estimation					
Variables	**PS1**	**PS2**	**PS3**	**PS4**	**PS5**
α_i	0.0014	0.0039	0.0038	-0.0012	0.0005
	(0.751)	(0.439)	(0.403)	(0.796)	(0.887)
MRP_{it}	-0.1885	-0.0474	-0.2919	-0.1783	-0.0768
	(0.494)	(0.840)	(0.268)	(0.602)	(0.791)
SMB_{it}	-0.0510	-0.3691	-0.1298	-0.0313	0.2777
	(0.919)	(0.496)	(0.811)	(0.954)	(0.617)
HML_{it}	-0.0528	-0.2341	0.0169	0.0506	-0.1284
	(0.904)	(0.673)	(0.970)	(0.922)	(0.756)

Panel B: GARCH(2,3) Estimation					
Variables	**PS1**	**PS2**	**PS3**	**PS4**	**PS5**
α_i	0.0026	0.0034	0.0041	0.0018	0.0007
	(0.178)	(0.080)*	(0.022)**	(0.539)	(0.759)
MRP_{it}	-0.2823	-0.3635	-0.4380	-0.1608	-0.1512
	(0.154)	(0.001)**	(0.000)**	(0.300)	(0.443)
SMB_{it}	-0.0898	-0.9092	-0.6309	-0.2491	-0.0504
	(0.742)	(0.001)**	(0.012)**	(0.292)	(0.854)
HML_{it}	0.0491	0.8044	0.1977	0.2116	-0.0446
	(0.845)	(0.000)**	(0.375)	(0.412)	(0.850)
ε^2_{it-1}	0.2832	0.3528	0.4439	0.3811	0.5670
	(0.028)**	(0.000)**	(0.000)**	(0.009)**	(0.055)*
ε^2_{it-2}	0.2317	0.1289	-0.1770	-0.4251	-0.5008
	(0.026)**	(0.204)	(0.018)**	(0.002)**	(0.058)*
σ^2_{it-1}	0.1441	0.1773	0.3331	1.1625	1.1292
	(0.206)	(0.022)**	(0.003)**	(0.000)**	(0.000)**
σ^2_{it-2}	-0.4051	-0.2951	-0.2273	0.2511	-0.2318
	(0.000)**	(0.000)**	(0.001)**	(0.310)	(0.438)
σ^2_{it-3}	0.6618	0.6404	0.5698	-0.3747	0.0286
	(0.000)**	(0.000)**	(0.000)**	(0.005)**	(0.834)

The p-values are in parentheses

** indicate 5% or less significance level

* indicates 10% or less significance level

When we plot the weekly residual returns $\varepsilon_{j,t}$ for each of the five portfolio strategies, we observe volatility clustering effect, especially for PS1, PS2, and PS3. Subsequent diagnostic tests using the Godfrey (1978) and Breusch and Pagan (1979) procedures confirm the presence of heteroscedasticity in $\varepsilon_{j,t}$ for all portfolio strategies. The finding suggests that the least-square estimates in Panel A, which ignore GARCH effects, are inefficient. This would explain why all least-square coefficients are statistically insignificant.

We explore various lag dynamics for the conditional variance equation and find that a GARCH(2,3) specification has the lowest Akaike information criterion (AIC) across portfolio strategies.[30] In equation (5.3), we re-estimate the Fama–French return equation, allowing $\varepsilon_{j,t} \sim N(0, \sigma_{j,t}^2)$ by fitting a GARCH(2,3) specification to $\sigma_{j,t}^2$: We report estimates for both the mean and variance equations in Table 5.7 Panel B. the results show that the majority of AR and MA terms in the conditional variance equation are significant across {PS1,…,PS5}. This reaffirms the presence of GARCH effects in $\varepsilon_{j,t}$.

$$r_{j,t} - r_t^f = \alpha_j + b_j(MRP_t) + s_j(SMB_t) + h_j(HML_t) + \varepsilon_{j,t}$$
$$\sigma_{j,t}^2 = c + \phi_{1,j}\varepsilon_{j,t-1}^2 + \phi_{2,j}\varepsilon_{j,t-2}^2 + \gamma_{1,j}\sigma_{j,t-1}^2 + \gamma_{2,j}\sigma_{j,t-2}^2 + \gamma_{3,j}\sigma_{j,t-3}^2 \tag{5.3}$$

More importantly, the results also show that PS2 and PS3 are the only two strategies that produce a significant weekly alpha against Fama–French factors. For PS3,

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[30] While the Schwartz Information Criterion (SIC) suggests a slight difference in GARCH specifications for each of the five portfolio strategies, the main results are not sensitive to whether we use the AIC or the SIC to specify the GARCH process.

$\alpha_3 = 0.0041$, which is larger than $\alpha_2 = 0.0034$. The p-values indicate that α_2 is significant at the 0.10 level, while α_3 is significant at the 0.05 level. These results support the presence of incremental profits from conditioning and dynamically updating the list of C1 and C2 firms during the course of the trading period.

Interestingly, {PS1,…,PS5} all exhibit negative market beta across Panels A and B. This could be simply due to the overall poor performance of the market during the GFC. Furthermore, while it is standard procedure to evaluate risk-adjusted returns against priced factors, one may question the validity of benchmarking against priced factors for a trading period that encompasses a disequilibrium event such as the GFC.

B. Buy and hold, momentum, and dividend yield

To address the preceding concern, we implement a second set of benchmarks, including buy and hold (B&H), momentum, and dividend yield. Our aim is simple. If we apply the same firms over the same trading period using proven portfolio strategies, can we produce profit results similar to those achieved by PS2 and PS3? We report profit/loss results for the buy and hold strategy in Panel A of Table 5.8, for a six-month rank, one-month hold (6–1) momentum strategy in Panel B, and for two variant dividend yield strategies in Panels C and D. For all strategies, we impose 10 bps per traded stock as a transaction cost, which is consistent with {PS1,…,PS5}.

Table 5.8: Profit/loss results from the second set of bench-marking

	Panel A: Buy and Hold	*Panel B: Momentum*	*Panel C: Dow-Dogs*				*Panel D: CDS-Dogs*			
Rebalancing Frequency	*N.A.*	*Rank 6-Hold 1*	*Yearly*	*Quarterly*	*Monthly*	*Weekly*	*Yearly*	*Quarterly*	*Monthly*	*Weekly*
Cumulative Return	-2.11%	-79.98%	-40.39%	-32.64%	-40.66%	-44.02%	-25.35%	38.12%	11.81%	19.70%
Annualised Return	-0.85%	-31.99%	-22.79%	-14.12%	-18.84%	-20.71%	-13.60%	13.79%	4.57%	7.46%
Annualised Standard Deviation	33.50%	51.68%	3.49%	31.12%	37.21%	38.74%	2.4%	62.29%	49.52%	42.03%
Sharpe Ratio	-0.033	-0.619	-6.601	-0.478	-0.513	-0.541	-5.763	0.217	0.087	0.172
Number of Trading Portfolios	1	30	2	10	30	130	2	10	30	130

First, we analyse the risk–return performance from a B&H strategy in an equally weighted portfolio formed using the entire firm sample. This is a more convincing benchmark than Fama–French priced factors, which plunged during the GFC. On the July 5, 2007, which corresponds to the first Wednesday of the trading period, we form an equally weighted long portfolio in all 174 stocks of our firm sample. We reinvest all dividends back into the portfolio during the holding period, which is liquidated on December 30, 2009. The latter corresponds to the last Wednesday of the trading period. The B&H strategy produces a cumulative net return of -2.11%, or a -0.85%pa annualised return with a Sharpe Ratio (SR) of -0.033.

Second, to ensure that our profit results are not driven by market trend, we implement a 6-1 momentum strategy using our firm sample. Given our earlier concerns on evaluating risk-adjusted return using priced factors, there is limited incremental value in generating Jensen's α_j using Carhart (1997) factors rather than Fama–French factors. Our benchmark is not the momentum factor per se but, rather, momentum as a portfolio strategy.

At the start of the trading period, we sort firms based on their past 6 months' returns. We go long in the bottom (winner) decile portfolio and short-sell the top (loser) decile portfolio. There are 17 stocks in each of the winner and loser portfolios. The momentum profit/loss results correspond to the equally weighted winner-minus-loser (WML) portfolio comprising 34 stocks. The WML portfolio is liquidated at the end of the month, with 10 bps deducted from the realised return for each traded stock. The process is repeated. In Panel B of Table 5.8 the WML portfolio produced an annualised return of -32% pa with an annualised volatility of 51.68% pa. However, there may be an optimal rank–hold configuration for the WML portfolio which corresponds to our firm sample and trading period. We address this issue shortly.

Our last benchmark is a simple but popular strategy on Wall Street. Coined the Dow-Dogs, the strategy goes long in the top 10 dividend-yielding Dow Jones Industrial Average (DJIA) stocks. This strategy is intuitively appealing. It stipulates buying stocks with a high dividend payout that have been potentially oversold relative to other stocks,[31] resulting in excessively high dividend yields. The subsequent price recovery translates into capital gains. In addition, while waiting for the price recovery to eventuate, the investor benefits from generous dividend payments. Dow-Dogs investors argue that the dividend–price ratio is more informative than the earnings–price ratio in reflecting a firm's future earning ability. This is simply because earnings can be 'managed' to a certain extent, but the same cannot be said for dividends.[32]

We implement two similar strategies using the top 10 dividend-yielding stocks from i) the DJIA (Dow-Dogs[33]) and ii) our sample of 174 firms (which we call CDS-Dogs). For each of the two strategies, we consider yearly, quarterly, monthly, and weekly rebalancing intervals, which gives us eight variant portfolios.[34] The profit/loss results

[31] On Wall Street, these stocks are called fallen angels. We believe that a dividend yield strategy is a meaningful benchmark for our paper since it has been proven to outperform the market during times of financial crises. With the associated economic downturn, government stimulus through a loosening monetary policy suppresses Treasury bond yields. This makes a high dividend-yielding portfolio appealing.

[32] If a 50-cent dividend is declared, it has to be paid, whether in cash or new shares.

[33] We match the CRSP dividend announcement data file against the price file for DJIA firms. In addition, we track and update the list of DJIA component stocks during the trading period.

[34] For weekly rebalancing, we sort firms every Tuesday based on dividend yield. The next trading day, we form an equally weighted portfolio of the top 10 dividend yielding firms. This portfolio is liquidated next Tuesday. For monthly rebalancing, we sort firms on the first trading day of each month. The portfolio is formed the next trading day and subsequently liquidated on the last trading day of the month. For quarterly rebalancing, we sort firms on the first trading day of each March, June, September, and December quarter. We form a long portfolio the next trading day, which is subsequently liquidated on the last trading day of each quarter.

for the Dow -Dog and CDS-Dog strategies are reported in Table 5.8 Panels C and D respectively. Panel C shows that none of the four rebalancing intervals for Dow-Dogs manage to produce any profits. In contrast, Panel D shows that three CDS-Dog portfolios are profitable. The weekly CDS-Dog portfolio has a higher return (7.46% pa) and lower volatility (42.03%) compared to the monthly CDS-Dog portfolio. However, it is the CDS-Dog portfolio with quarterly rebalancing that is the best performer, with a 13.79% pa annualised return and a Sharpe ratio of 0.217. All three CDS-Dog portfolios manage to produce Sharpe ratios that are higher than PS1. However, in terms of both annualised returns and Sharpe ratios, the best CDS-Dog portfolio under-performs PS2 (14.44% pa; 0.299) and PS3 (15.64% pa; 0.363).

Our benchmark momentum strategy will be more convincing if we consider more than one rank-hold configuration. In Table 5.9, we present the WML portfolio returns and Sharpe ratios for a six-by-six permutation matrix of momentum strategies, using the same trading procedure as previously described. The results show that 4 out 36 WML portfolios are profitable, with the 1–1 and 1–3 portfolios being the two most outstanding. Both portfolios produce an annualised return of around 11.3% pa. This remains lower than the annualised return of PS2 (14.44% pa) and PS3 (15.64% pa). However, the 1–1 and 1–3 portfolios exhibit impressive Sharpe ratios. The 1–1 WML portfolio has a Sharpe ratio of 0.356. This is higher than PS2 (0.299) but lower than PS3 (0.363). The 1–3 WML portfolio has a Sharpe ratio of 0.516.

Table 5.9: Profit/loss results from a six-by-six month rank-hold permutation matrix of momentum portfolios

We report the annualised returns and Sharpe ratios (in parentheses) for 36 momentum portfolios over a six-month rank–hold permutation matrix. The first column represents the number of ranking months, while the first row represents the number of holding months. We sort firms based on their past k month returns. We go long in the bottom (winner) decile portfolio and short-sell the top (loser) decile portfolio to form our winner-minus-loser portfolio. Accordingly, each momentum portfolio consists of 34 stocks in total. Every momentum portfolio is formed using the same firm sample. The strategies are implemented over the same trading period. Momentum portfolios that generate positive returns are highlighted in bold.

Holding Month Ranking Month	1	2	3	4	5	6
1	**11.34%** **(0.356)**	-3.90% (-0.206)	**11.30%** **(0.516)**	-7.27% (-0.441)	**3.30%** **(0.200)**	-7.91% (-0.823)
2	-0.86% (-0.033)	-1.95% (-0.078)	-1.62% (-0.117)	-9.54% (-0.403)	-6.58% (-0.382)	-9.45% (-0.785)
3	-17.32% (-0.212)	**9.26%** **(0.116)**	-22.55% (-0.401)	-11.08% (-0.218)	-6.96% (-0.218)	-9.93% (-0.201)
4	-9.63% (-0.122)	-13.14% (-0.206)	-12.59% (-0.257)	-19.26% (-0.390)	-21.77% (-0.576)	-11.22% (-0.252)
5	-20.26% (-0.417)	-3.42% (-0.123)	-32.61% (-0.877)	-13.36% (-0.541)	-6.10% (-0.331)	-10.80% (-0.668)
6	-31.99% (-0.619)	-7.30% (-0.286)	-35.02% (-0.846)	-14.97% (-0.724)	-3.78% (-0.210)	-10.57% (-0.766)
Number of Portfolios Traded	30	15	10	7	6	5

In sum, we have considered a total of (1 + 8 + 36) = 45 benchmark portfolio strategies against PS2 and PS3. The best of the 45 strategies is the 1–3 WML portfolio. It possesses a Sharpe ratio higher than both PS2 and PS3. The 1–3 WML portfolio comes from 'cherry-picking' the best benchmark portfolio from Tables 5.8 and 5.9. However, its 11.3% pa return is lower than PS2 and PS3. Furthermore, PS2 and PS3 are evaluated based on weekly returns, while momentum is evaluated based on monthly returns. The difference in return frequency could partially explain a higher annualised volatility, hence lower Sharpe ratio for PS2 and PS3 relative to the 1–3 WML portfolio. Just as importantly, our prime focus is to demonstrate the economic significance from conditioning portfolio strategies, which draw trading signals from the CDS market, on firms that actually depend on the CDS market for credit risk price discovery. Both the conditional PS2 and PS3 strategies substantially outperform the unconditional PS1 strategy, as well as their mutually exclusive counterparts PS4 and PS5, respectively.

5.4.3 Further discussions on the profit/loss results

We design {PS1,…,PS5} to demonstrate that the economic value for portfolio strategies (that draws trading signals from the CDS market) to be conditional on cross-market price discovery dynamics between the CDS and equity markets. The PS1 strategy is the unconditional strategy based on our entire firm sample. The PS2 strategy trades from a conditional but static list of CDS-influenced C2 and C2 firms, while PS3 trades from a conditional and dynamically updated list of CDS-influenced C1 and C2 firms, which incorporates transmigration patterns documented in this paper.

We address four potential issues when interpreting the profit/loss results. First, while {PS1,…,PS5} take advantage of credit signals from the CDS market to set both short and long positions, our documented profit results could be driven simply by short-selling distressed stocks during the GFC. If so, the findings may have limited generalisation to other states of the world. Figure 5.1 shows that during the trading period the cross-sectional average CDS spreads did increase sharply, but it dropped substantially as well. Near the bottom of Table 5.6, we report the average number of stocks traded every week for {PS1,…,PS5}, as well as the proportion of long and short positions. Across the five strategies, the ratio of long to short stock positions is around 3:7. This implies that a reasonable portion of our profit results are driven by long positions. And since the 3:7 long–short ratio is quite stable across {PS1,…,PS5}, the incremental profitability shown by PS2 and PS3 over PS1, PS4, and PS5 cannot be simply explained by the short-selling of financially distressed firms.

Second, our portfolio strategies are executed during a trading period when corporate distress and credit constraints dominated the financial media. As such, a strategy that takes advantage of credit-related information has a natural advantage over other non–credit-risk-driven portfolio strategies. Paradoxically, that is what we set out to demonstrate in terms of ascertaining the economic significance of the heightened importance of the CDS market to credit risk price discovery during a period of heightened sensitivity to credit risk.

Third, our firm sample contains financially distressed firms that survived the GFC. Firm that did not survive would have been excluded from our sample, such that our profit results may be potentially laced with survivorship bias. Our firm sample covers the entire population of investment-grade firms in 2005. These 174 firms are high-quality non-financial companies that survived throughout our sample period. Indeed, that is why we focus on investment-grade firms in the first place. We exclude a small number of firms during the trading period due to the absence of cointegration between $CDS_{i,t}$ and $ICDS_{i,t}$. Furthermore, if survivorship bias exists, this implies our portfolio strategies would only short-sell financially distressed firms that eventually recovered. This can only strengthen the validity of our profit/loss results.

Fourth, if we extend our trading period to include 2010 data, when there is substantial market recovery, the benchmark buy and hold, momentum, and dividend yield strategies are likely to perform better. In addition, the number of C1 and C2 firms may drop further, such that PS2 and PS3 may not be as profitable compared to the results in the current paper. If that is the case, it is entirely consistent with the core implication of our main finding, which is the fact that the CDS market takes over credit risk price discovery when credit risk is a binding concern for firms and investors alike.

5.5 Summary

In this chapter, we analyse cross-market credit risk information flows between the CDS and equity markets for a sample of 174 U.S. investment-grade firms. Our improved calibration of the CreditGrades model, discussed in Chapter 4, allows us to extract $ICDS_{i,t}$, which is a cleaner indicator of the price of credit risk implied by the equity market. $ICDS_{i,t}$ and the CDS market's observable $CDS_{i,t}$ are cointegrated for nearly the entire firm sample and the results are robust across sub-samples. This finding strongly suggests the presence of a prevailing cross-market credit risk pricing equilibrium between the CDS and equity markets. Next, we use Gonzalo–Granger

(1995) and Hasbrouck (1995) measures to sort firms into one of five price discovery categories. When we forward-shift the estimation window on a quarterly basis to update GG and HAS measures, we find strong evidence of a time-varying credit risk price discovery contribution between the CDS and equity markets for the majority of our firm sample.

While we expect to find a time-varying price discovery process for a sample period that encompasses the GFC, it is the direction of the transmigration patterns that constitutes our most interesting finding. One would instinctively expect the price discovery mechanism of any credit-related market to cease functioning properly during a systemic credit-crunch, including, and especially, the U.S. CDS market. This would be manifested in firms migrating out of C1 and other price discovery categories.

What we have documented is the exact opposite. The U.S. CDS market has taken over price discovery leadership from the equity market during the GFC. Between April 2006 and September 2008, the number of CDS influenced C1 and C2 firms constituted nearly the entire firm sample. And as we move away from the height of the GFC, firms gradually migrate out of C1 and C2 into other categories. But the number of C1 and C2 firms remains high compared to the pre-GFC period. Profit/loss evaluation confirms that, using information conveyed by the CDS market, the portfolio strategy conditional on identifying and updating the list of CDS-influenced firms generates a significant alpha against Fama–French factors. It also outperforms other proven portfolio strategies that utilise our firm sample, including buy and hold, momentum, and dividend yield strategies.

Chapter 6: Cross-market credit risk information flows and capital structure arbitrage

6.1 Introduction

Capital structure arbitrage is a convergent-type strategy that explores price discrepancies for various instruments of the firm. Debt and equity, which are the key instruments in capital structure, simultaneously reflect firm value and thus attract the attention of capital structure arbitrageurs. With its recent rapid expansion, the CDS market has taken over the credit risk trading function from the traditional bond market. Accordingly, CDS versus equity opens a new era for the capital structure arbitrageur who triggers trades on the basis of temporary cross-market credit risk mispricing. Indeed, an economic link exists between the CDS and equity markets. While the CDS market provides a price for credit risk directly, the equity market offers an opinion regarding the firm's creditworthiness indirectly through a structural credit risk pricing approach.

Despite the capital structure arbitrage strategy having been used by hedge funds and the proprietary trading desks of commercial banks since a decade, academic research in this area still remains sparse. To our best knowledge, Yu (2006) and Duarte et al. (2007) are the only published studies in the field. Yu (2006) examines the risk and return of capital structure arbitrage for 261 North American firms at both the individual trade and portfolio levels. Using the same sample, Duarte et al. (2007) include the performance of capital structure arbitrage as part of a fixed-income arbitrage strategy analysis. Both studies utilise the CreditGrades model to estimate the

ICDS from a firm's stock price. An arbitrage opportunity on company i presents on day t when $ICDS_{i,t}$ diverges from observed CDS spreads ($CDS_{i,t}$).

Yu (2006) and Duarte et al. (2007) find that capital structure arbitrage is associated with high levels of risk. While the arbitrageur can easily incur completely drawn down of their entire initial capital, a more pressing concern is that the vast majority of their trades do not converge. For example, more than 90% of trades executed on investment-grade companies fail to converge, even for holding positions for 180 days. This non-convergence result indeed contradicts the basic concept of capital structure arbitrage. As in essence, this strategy is claimed to be a convergent-type strategy that arbitrages from the temporary cross-market mispricing.

The failure of convergence would indicate that the positions are anything other than arbitrage. In stark contrast, the pairs-trading strategy that adopts a similar trading philosophy but focuses entirely within the stock market does not confront this lack of convergence problem (Gatev et al. (2006); Do and Faff (2010)). Indeed, the capital structure arbitrage is a refined pairs-trading strategy. While the pairs-trading strategy requires matching stock partners in the whole universe by some attributes that indicate co-movement, the pairwise stocks may share few economic factors that drive and explain this co-movement. Whereas the capital structure arbitrage successfully circumvents this problem because the firm's credit risk is the common economic factor that drives the co-movement of the pairwise $(CDS_{i,t}, ICDS_{i,t})$. Paradoxically, the convergence for the capital structure arbitrage strategy is reportedly the exception rather than the norm.

Furthermore, setting appropriate positions when a mispricing signal occurs is another challenge for the capital structure arbitrageur, since the divergent $ICDS_{i,t}$ and $CDS_{i,t}$ does not inform the arbitrageur which market is mispriced. For example, when $CDS_{i,t} > (1 + \alpha) \times ICDS_{i,t}$, where α allows mispricing to be sufficient, the arbitrageur cannot ascertain whether this mispricing is caused by an overvalued CDS spread or an undervalued ICDS due to inflated stock price. Confronted with this difficulty, in Yu (2006) and Duarte et al. (2007), the arbitrageur decides to take short positions on both the CDS contract and equity. Unless CDS and ICDS converge in the midway, one position will incur loss and overall profitability will depend on whether the position in one market can is able to yield sufficient profit to cover losses in the other market. Yu (2006) and Duarte et al. (2007) use equity delta to determine the cross-market capital allocation and find that the low correlation between CDS spreads and equity price prevent the delta hedged positions from being effective.

Motivated by the aforementioned difficulties, we propose a novel trading algorithm and re-examine the risk–returns of the capital structure arbitrage strategy. In particular, we address two important issues. First, how can convergence outcome be improved? Second, how can arbitrage positions be formed when the divergent $CDS_{i,t}$ and $ICDS_{i,t}$ do not indicate the mispriced market? When designing our trading algorithm, we incorporate long-run credit risk pricing relation and short-run information dynamics across the CDS and equity markets. The former indicates us whether these two markets are driven by a common credit risk factor and the latter allows us to ascertain the adjustment process when mispricing occurs. We obtain the results of this cross-market information dynamics from the past 12-month period (the formation period) and apply it to trading during the following quarter (the trading period). At the end of the trading period, the results of cross-market information dynamics are updated from the new formation period before being used in the next trading period. In effect, our trading approach involves a quarterly rolling formation period of 12 months and a corresponding trading period of one quarter.

Our trading algorithm consists of a four-step procedure. First, we verify the convergence condition through a cointegration test on $CDS_{i,t}$ and $ICDS_{i,t}$. The firm is eligible for capital structure arbitrage purpose only if the $CDS_{i,t}$ and $ICDS_{i,t}$ are cointegrated. This is to ensure the long-run co-movement of the CDS and equity markets that underpins the foundation for capital structure arbitrage. Because the strategy builds on the premise that the CDS and equity markets are driven by common credit risk factor so that any divergence will be temporary.

In the second step, we search for mispricing (divergent) signal. The presence of cointegration allows us to model cross-market dynamics between $CDS_{i,t}$ and $ICDS_{i,t}$ as a bivariate VECM. The error correction term $\left[CDS_{i,t} - \tau_0 - \tau_1 \times ICDS_{i,t}\right]$ captures the equilibrium relationship between the $CDS_{i,t}$ and $ICDS_{i,t}$. Any departure from this equilibrium relationship i.e. $CDS_{i,t} - \tau_0 - \tau_1 \times ICDS_{i,t} \neq 0$, is indicative of temporary disequilibrium. Unlike existing studies, we let the data speak for themselves regarding the format of the cross-market equilibrium rather than imposing the arbitrary parity condition $CDS_{i,t} = ICDS_{i,t}$. To have sufficient mispricing, we define the divergence signals as either $CDS_{i,t} > \tau_0 + \tau_1 \times ICDS_{i,t} \times (1+\alpha)$ or $CDS_{i,t} \times (1+\alpha) < \tau_0 + \tau_1 \times ICDS_{i,t}$, where α is the trigger for trading.[35]

[35] We consider values of 0.5, 1 and 2 for α in our trading experiments.

Third, we form arbitrage positions once a divergent signal appears presents. We make use of price discovery dynamics between the CDS and equity markets to assist capital allocation. Specifically, we deploy capital across the CDS and equity markets proportionally but inversely to their price discovery contributions. The idea is simple and logical: Suppose there is one-way price discovery process from the CDS to the equity market, i.e. the CDS market performs the entire price discovery function. Once pricing disequilibrium occurs, the equity market is expected to clear this temporary pricing divergence. Accordingly, investing on the stocks would be appropriate to capture the potential once equilibrium (convergence) is re-established.

In the final step, we define conditions to close out the arbitrage positions. Basically, we square the positions at convergence. However, it is rare that the $CDS_{i,t}$ and $ICDS_{i,t}$ would ever reach the equilibrium relation exactly as $CDS_{i,t} - \tau_0 - \tau_1 \times ICDS_{i,t} = 0$. Therefore, we define the closing (convergence) signal as reversion of the initial divergence. For positions entered at $CDS_{i,t} > \tau_0 + \tau_1 \times ICDS_{i,t}(1 + \alpha)$, the convergence occurs when $CDS_{i,t+n} \leq \tau_0 + \tau_1 \times ICDS_{i,t+n}$. Similarly, for positions executed at $CDS_{i,t}(1 + \alpha) < \tau_0 + \tau_1 \times ICDS_{i,t}$, the convergence presents when $CDS_{i,t+n} \geq \tau_0 + \tau_1 \times ICDS_{i,t+n}$.

This chapter proceeds as follows. Section 6.2 describes the data and sample. In Section 6.3, we replicate previous capital structure arbitrage procedures and report the results based on our ICDS estimates as trading input. We describe our trading algorithm and present the result in Section 6.4. Section 6.5 concludes with a summary.

6.2 Data and sample

To implement capital structure arbitrage, we need pairwise $CDS_{i,t}$ and $ICDS_{i,t}$ matched at the firm level. The data source for the input variables that include the CDS spreads and variables to estimate $ICDS_{i,t}$ are discussed in Chapter 3. Table 6.1 summarises the data and variables.

Table 6.1: Data description

Data	Description	Source
CDS spread: $CDS_{i,t}$	Five-year USD 10 million CDS contracts written on senior unsecured debt issued by U.S. firms.	Provided by CMA, downloaded from Bloomberg and Datastream.
Stock price: $S_{i,t}$	Daily closing price.	CRSP daily file.
Stock return volatility: $\sigma_{i,t}$	One-year historical volatility using CRSP adjusted daily returns.	CRSP daily file.
Debt-per-share: $D_{i,t}$	Total liabilities divided by common shares outstanding. We use the quarterly figure of total liabilities and daily observations of common shares outstanding.	We download quarterly total liabilities figures from the Compustat North America file. Daily observations on common shares outstanding are accessed from the CRSP daily file.
Risk-free rate: r_t^f	We use the five-year swap rate as a proxy for the risk-free rate.	Datastream.

As discussed in Chapter 4, our sample consists of 174 U.S. investment-grade firms and covers a five-year period between January 3, 2005, and December 31, 2009. Our capital structure arbitrage algorithm requires observations from the prior 12 months (the formation period) to verify the co-movement condition and ascertain the price discovery dynamics before implementing trading over the following quarter (the trading period). Accordingly, we need to set the first 12-month period as the initial formation period. Therefore, our trading period covers four years, from January 3, 2006, to December 31, 2009.

6.3 Replicating the existing capital structure arbitrage algorithm

In this section, we start our analysis by replicating the existing capital structure arbitrage algorithm. We use Yu (2006) as well as our proposed CreditGrades model calibration approach to extract ICDS from firm stock prices. Our objective is to examine whether the documented unsatisfactory results, such as non-convergence, severe loss, and excessive risk, are caused by inaccurate ICDS estimates.

6.3.1 Existing capital structure arbitrage algorithm

Following Yu (2006) and Duarte et al. (2007), we start with estimating the time series of $ICDS^{*}_{i,t}$ for each firm in our sample.[36] To have consistent trading period, we replicate the existing trading algorithm between January 3, 2006, and December 31, 2009.

Yu (2006) and Duarte et al. (2007) define a divergence signal as either

$$CDS_{i,t} > (1+\alpha)ICDS^{*}_{i,t} \qquad (6.1)$$

or

$$ICDS^{*}_{i,t} > (1+\alpha)CDS_{i,t} \qquad (6.2)$$

[36] The calibration procedures of the CreditGrades model to estimate $ICDS^{*}_{i,t}$ are described in Chapter 4. The $ICDS^{*}_{i,t}$ are obtained using the existing calibration procedures, which differ from our calibration approach. The details of the existing calibration approach and ours are discussed in Chapter 4.

where α is trading trigger that ensures sufficient divergence. Following prior studies, we consider different values for the trigger (α = 0.5, 1.0, and 2.0). The divergent signal indicates violation of the law of one price across the CDS and equity markets. However, it does not suggest which market is being mispriced. For the case of (6.1), the divergence could be due to either overvalued CDS spreads ($CDS_{i,t}$) or undervalued $ICDS^*_{i,t}$ as a result of stock price being overvalued. Finding it difficult to ascertain the cause of mispricing, the arbitrageur decides to take short positions on both the CDS and the stock. For similar reasons, long positions are created in the case of (6.2). In effect, the position on the stock is a hedge for the position on the CDS contract and vice versa. In that regard, the concept of delta hedging is utilised to determine the combination of CDS contract and stocks. The calculation of equity delta (Δ) is provided in Appendix 1.

The trading algorithm adopted by Yu (2006) and Duarte et al. (2007) is as follows. First, we search for the divergence signal of (6.1) and (6.2) on a daily basis. For scenario (6.1), a unit CDS contract with a corresponding number $-\Delta_t$ of shares is shorted. For scenario (6.2), long positions are taken on one CDS contract and a number $-\Delta_t$ of shares. Second, the positions are held till the end of the holding period or whenever convergence occurs, where convergence is defined as $CDS_{i,t} = ICDS^*_{i,t}$. Third, daily marking-to-market process is assumed so that the positions are liquidated immediately once the total value becomes negative. The calculation of the value of the CDS position, $\pi(t)$, on day t is provided in Appendix 1. Fourth, 5 percent bid–ask spreads are imposed on the CDS contract for transaction cost. i.e. the buyer (seller) pays (receives) 2.5 percent more (less) than the closing price. Finally, initial capital is required to implement trading. As explained by Yu (2006), the initial capital is deposited in a margin account and used to finance the delta hedging. Any inflow or outflow from the trade will be debited or credited to the account accordingly.

Similar to Yu (2006) Table 3, we report the following results, where N is the total number of trades executed, N_1 is the number of trades closing at convergence, N_2 is the number of trades with loss greater than 20 percent and N_3 is the number of trades with negative holding period returns. We execute trading simulations with various holding periods (HP = 30 days and 180 days) and trading triggers (α = 0.1, 1.0, and 2.0) and an initial capital of $0.50 per $1.00 of CDS notional amount. The results are provided in Table 6.2.

Table 6.2: Summary statistics for various holding-period returns: based on the trading algorithm of Yu (2006)

							Holding-Period Returns		
HP	Alpha	N	N_1	N_2	N_3	Convergence Ratio	Mean	Minimum	Maximum
30	0.5	129878	6	71	85087	0.00%	-0.03%	-449.50%	116.40%
	1.0	116334	0	59	76559	0.00%	-0.03%	-449.50%	100.00%
	2.0	100522	0	48	66407	0.00%	-0.03%	-449.50%	100.00%
180	0.5	105796	130	234	70332	0.12%	-0.10%	-1052.47%	1368.59%
	1.0	92654	105	192	62155	0.11%	-0.10%	-1052.47%	296.63%
	2.0	78127	49	157	53070	0.06%	-0.12%	-1052.74%	296.63%

As shown in Table 6.2, using the previous trading algorithm, strategies with different holding periods and trading triggers all generate losses, on average. During the trading period, arbitrageurs inevitably experiences a completely drawdown of their entire initial capital as the minimum returns may reach -450 percent and -1052 percent for holding periods of 30 days and 180 days, respectively. The riskiness of the strategy is also demonstrated by the fact that many of the trades incur losses of more than 20 percent ($\mathrm{N_2}$) and more than half the trades produce negative holding period returns ($\mathrm{N_3}$). Moreover, consistent with the results reported by Yu (2006), convergence ($\mathrm{N_1}$) barely exists. The convergence ratios ($\mathrm{N_3/N_1}$) are less than 0.12% across various combinations of holding periods and trading triggers. However, the capital structure arbitrage strategy is built on the premise of the law of one price and is designed to profit from the convergence of temporary mispricing. The scarcity of the convergence clearly contradicts this strategy's basic concept. Consequently, the above results do not indicate the risk–return profile of capital structure arbitrage.

What actually causes convergence failure? The strategy utilises ICDS estimates as input throughout the entire trading process; thus the accuracy of the ICDSs would certainly have an impact on trading performance, including convergence outcomes. As demonstrated in Chapter 4, our calibration procedure provides a cleaner measure of the ICDS estimate. Accordingly, we substitute $ICDS_{i,t}$, obtained using our calibration procedure, for $ICDS^{*}_{i,t}$ and re-apply the existing trading algorithm. Our aim is to ascertain whether the poor performance is due to inaccurate ICDS estimates. The results are reported in Table 6.3.

Table 6.3: Summary statistics for various holding period returns for the existing trading algorithm with a new ICDS

							Holding-Period Returns		
HP	Alpha	N	N_1	N_2	N_3	Convergence Ratio	Mean	Minimum	Maximum
30	0.5	18949	8	17	11974	0.04%	-0.03%	-434.10%	100.00%
	1.0	5090	0	3	3289	0.00%	-0.05%	-434.10%	100.00%
	2.0	1514	0	0	1032	0.00%	-0.02%	-10.81%	100.00%
180	0.5	13037	80	63	8823	0.61%	-0.31%	-1025.15%	544.95%
	1.0	2923	7	20	2071	0.24%	-0.37%	-459.22%	544.95%
	2.0	786	0	6	608	0.00%	-0.55%	-51.63%	100.00%

Even with more accurate $ICDS_{i,t}$, the results do not improve from those reported in Table 6.2. It is noted that the convergence rate still remains exceptionally low. While the highest convergence ratio is at 0.61%, three out of six strategies do not produce any convergence at all. All strategies produce negative mean holding-period returns. In particular, implementing strategies with a trading trigger of 0.5 and 1.0 will result in severe loss, at least four times as large as the initial capital.

The above results demonstrate that $ICDS^*_{i,t}$ is not the cause of convergence failure. Furthermore, using $ICDS_{i,t}$ obtained from our calibration approach, we have document strong evidence of a cross-market credit risk pricing equilibrium in the Chapter 5. The prevailing cross-market pricing equilibrium should have established necessary conditions for mispricing convergence. Therefore, it becomes evident that the documented problem may be attributed to the trading algorithm itself.

6.4 A new algorithm of capital structure arbitrage

In view of the above, we propose a new approach to implement capital structure arbitrage. Our trading algorithm incorporates both long-run credit risk pricing relation and short-run credit risk price discovery process across the CDS and equity markets. The long-run credit risk pricing relation enforces co-movement of the two markets so that any divergence is temporary and expected to revert. The short-run price discovery process reveals adjustment mechanism of the two markets that allows us to ascertain how correction of mispricing is will take place. Specifically, the algorithm consists of four sequential steps. Each step addresses one issue that did not receive adequate consideration in the prior trading algorithm.

In the first step, we select firms in which $CDS_{i,t}$ and $ICDS_{i,t}$ are expected to converge. This is achieved by applying cointegration test on the pairwise $(CDS_{i,t}, ICDS_{i,t})$. The presence of cointegration indicates the long-term co-movement of the two markets such that any disturbance from the cointegration relation lasts only temporarily. For arbitrage trading purposes, a firm is shortlisted only if it passes the cointegration test. Specifically, we perform Johansen's cointegration test for each firm's $(CDS_{i,t}, ICDS_{i,t})$ using the prior 12 months' observations (formation period). The selected firms are then saved for trading in the following quarter (trading period). At the end of the trading period, the firm list is updated based on the past adjacent 12 months' formation period before it is applied in the new trading period. In effect, we have a quarterly-rolling formation period of 12 months followed by corresponding trading periods of one quarter.

In the second step, we search for an arbitrage (divergence) signal. Since capital structure arbitrage is designed to exploit divergent prices, how to define divergence becomes a vital and challenging issue. The cointegration between $CDS_{i,t}$ and $ICDS_{i,t}$ implies that a credit risk pricing equilibrium exists across the CDS and equity markets. Any disequilibrium is akin to a divergence that would revert back to equilibrium (convergence) over time. We estimate a bivariate VECM over the formation period to model cross-market dynamics between $CDS_{i,t}$ and $ICDS_{i,t}$ for each selected firm.[37] At the firm level, the VECM is written as

$$\begin{aligned} \Delta CDS_t &= \sum_{s=1}^{S}(\alpha_{1,s}\,\Delta CDS_{t-s} + \beta_{1,s}\Delta ICDS_{t-s}) + \lambda_1(CDS_{t-1} - \tau_0 - \tau_1 ICDS_{t-1}) + \varepsilon_{1,t} \\ \Delta ICDS_t &= \sum_{s=1}^{S}(\alpha_{2,s}\,\Delta CDS_{t-s} + \beta_{2,s}\Delta ICDS_{t-s}) + \lambda_2(CDS_{t-1} - \tau_0 - \tau_1 ICDS_{t-1}) + \varepsilon_{2,t} \end{aligned} \tag{6.3}$$

In equation (6.3), the long-run credit risk pricing equilibrium is manifested in the error correction term $(CDS_{\mathrm{t}-1} - \tau_0 - \tau_1 ICDS_{\mathrm{t}-1})$, implying the equilibrium relation is held at $CDS_{\mathrm{t}} = \tau_0 + \tau_1 ICDS_{\mathrm{t}}$. Any departure from this equilibrium relation would be temporary and bounded and hence could be utilised to signal divergence. Imposing restrictions $\tau_0 = 0$ and $\tau_1 = 1$, we reduce the equilibrium relationship reduces to $CDS_{\mathrm{t}-1} = ICDS_{\mathrm{t}-1}$, which is the case used by the prior trading algorithm. However, it is not adequate to enforce this parity relation for the cross-market equilibrium for at least two reasons. First, despite $CDS_{i,t}$ and $ICDS_{i,t}$ both measuring credit risk, the former is an observed price whereas the latter is an implied measure using the CreditGrades model. The imperfection of the model may result in two spreads $CDS_{i,t}$

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[37] We use the Schwarz Information Criterion (SIC) to determine the VECM's optimal lag specifications S on a firm-by-firm basis.

and $ICDS_{i,t}$ not having a parity relation. Second, the CDS spreads may contain a non-default component. Tang and Yan (2008) document a non-trivial liquidity component and Blanco et al. (2005) point out the cheapest-to-deliver option and counter-party risk factor in the CDS spreads. Consequently, we do not impose restrictions regarding the credit risk equilibrium relation between the CDS and equity markets.

During the trading periods, we monitor the pairwise ($CDS_{i,t}, ICDS_{i,t}$) of the selected firm on a daily basis. A divergence signal presents if either of the following cases (6.4) or (6.5) occurs:

$$CDS_{i,t} > \tau_0 + \tau_1 ICDS_t(1+\alpha) \tag{6.4}$$

or

$$(1+\alpha)CDS_t < \tau_0 + \tau_1 ICDS_t \tag{6.5}$$

where α is a trading trigger that allows divergence to be sufficient and is similar to that of Yu (2006) and Duarte et al.(2007).

In step three, we form arbitrage positions after receiving a divergence signal. As mentioned in the previous section, the trading signal (6.4) or (6.5) does not suggest which market is being mispriced. The situation (6.4) could be due to either overvalued CDS spreads (CDS_{t}) or inflated stock price (S_{t}), while situation (6.5) may link the divergence to either undervalued CDS_{t} or depressed S_{t}.

We analyse the short-run price discovery process between $CDS_{i,t}$ and $ICDS_{i,t}$ to ascertain the adjustment mechanism on the path to re-establish equilibrium (convergence). If the price discovery process is dominated by one market, then the other market will be forced to clear pricing disequilibrium. If a bi-directional price discovery process exists, the price adjustments will take place in both markets but inversely proportional to their relative price discovery contributions.

Using the procedures described in Chapter 5, we classify firms into five mutually exclusive price discovery categories, {C1,…,C5}. The categorisation is updated before each trading period based on the parameters of the VECM model (6.3).[38] Table 6.4 summarises the categorisation criteria as well as the price discovery process characteristics for {C1,…,C5}.

Table 6.4: Price discovery categorisation criteria and price discovery process characteristics

	Categorisation criteria	Price discovery process characteristics.
C1	$\lambda_1 < 0$ is not significant; $\lambda_2 > 0$ is significant.	One-way price discovery process dominated by the CDS market.
C2	$\lambda_1 < 0$ and $\lambda_2 > 0$ are significant; HAS > 0.5 and GG > 0.5.	Bi-directional price discovery process. The CDS market makes a greater contribution than the equity market.
C3	$\lambda_1 < 0$ and $\lambda_2 > 0$ are significant; Either HAS > 0.5 or GG > 0.5.	Bidirectional price discovery process. The CDS and equity markets make similar contributions.
C4	$\lambda_1 < 0$ and $\lambda_2 > 0$ are significant; HAS < 0.5 and GG < 0.5.	Bi-directional price discovery process. The CDS market makes less contribution than the equity market.
C5	$\lambda_1 < 0$ is significant; $\lambda_2 > 0$ is not significant.	One-way price discovery process dominated by the equity market.

[38] The key parameters are λ_1 and λ_2, as well as the elements of the covariance matrix of $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$. We calculate Gonzalo–Granger (1995) and Hasbrouck's (1995) measure to determine the price discovery contribution of the CDS market. HAS is average of the upper and lower bound of the Hasbrouck (1995) measure and GG is the Gonzalo–Granger measure (see Chapter 5 for detailed calculations).

For C1 firms, the price discovery process is dominated by the CDS market, indicating $ICDS_{\mathrm{t}}$ would adjust to clear the temporary pricing divergence. Accordingly, we only take the stock position. More specifically, if the divergence signal is triggered by $CDS_{\mathrm{t}} > \tau_0 + \tau_1 ICDS_{\mathrm{t}}(1 + \alpha)$ as (6.4), $ICDS_{\mathrm{t}}$ is expected to increase towards CDS_{t}. Therefore, we short-sell only the stocks. Conversely, if the mispricing occurs at $(1 + \alpha)CDS_{\mathrm{t}} < \tau_0 + \tau_1 ICDS_{\mathrm{t}}$, as in (6.5), subsequent convergence should be initiated by $ICDS_{\mathrm{t}}$, decreasing towards CDS_{t}. Therefore, we take a long position only on the stocks. The procedure is applied analogously to the C5 firms. The only difference is that we take positions on the CDS contracts only. This is because for the C5 firms, the price discovery process is dominated by the stock market and the subsequent convergence should be initiated by the CDS_{t} that moves towards $ICDS_{\mathrm{t}}$.

For C2, C3, and C4 firms, the bi-directional price discovery process exists. This suggests that while both markets contribute to the price discovery process, they also respond to the disequilibrium event and make corresponding price adjustments till convergence is reached. Therefore, if the trading signal is triggered by $CDS_{\mathrm{t}} > \tau_0 + \tau_1 ICDS_{\mathrm{t}}(1 + \alpha)$, we expect CDS_{t} to fall and $ICDS_{\mathrm{t}}$ to rise. Accordingly, we would take short positions on the CDS contract and the stock jointly. Similarly, when divergence occurs at $(1 + \alpha)CDS_{\mathrm{t}} < \tau_0 + \tau_1 ICDS_{\mathrm{t}}$, we go long on the CDS contract and underlying stocks. To determine capital allocation across the CDS contract and stocks, we utilise the relative price discovery contributions performed by the two markets. The market that contributes less price discovery is expected to experience greater price adjustments. Therefore, capital allocation should be inversely related to the proportional price discovery contribution performed by each market. For C2 and C4 firms, we use the average of HAS and GG to measure the relative price discovery contribution of the CDS market. For example, if the average of HAS and GG measures is 70%, this implies 70% of the price adjustment will take place in the equity market, leaving 30% of the price adjustment happening in the CDS market. As a result, we allocate 30% of the capital to the CDS contract and 70% to the stocks. For C3 firms, HAS and GG do not share a consensus as to which market performs more price discovery. Hence an equally-weighted pairwise position is created across the CDS contract and stocks.

Each trade consists of a unit-sized CDS contract and a corresponding number of shares. The cost of a CDS contract with USD 10 million notional amount equals $\$10\mathrm{M} \times CDS_{\mathrm{t}}$. The relative capital allocation across the CDS contract and stocks is determined using the procedures described above. Then the amount allocated to the stock position can be identified. We only trade stocks (the CDS contract) for C1 (C5) firms; to be consistent with C2, C3, and C4 firms, we determine the amount of invested capital with respect to a unit-sized CDS contract. Accordingly, $\$10\mathrm{M} \times CDS_{\mathrm{t}}$ represents total capital employed to trade the stocks (the CDS contract) for C1 (C5) firms.

In the final step, we define the conditions to square the position. The strategy is designed to exploit temporary cross-market pricing divergence; we unwind the position when the divergent prices are reverted (convergence). For the positions that are triggered at $CDS_{\mathrm{t}} > \tau_0 + \tau_1 ICDS_{\mathrm{t}}(1+\alpha)$, the convergence signal would occur at first time $CDS_{\mathrm{t}} \leq \tau_0 + \tau_1 ICDS_{\mathrm{t}}$. Similarly, for the positions created at $(1+\alpha)CDS_{\mathrm{t}} < \tau_0 + \tau_1 ICDS_{\mathrm{t}}$, the convergence signal is received the first time $CDS_{\mathrm{t}} \geq \tau_0 + \tau_1 ICDS_{\mathrm{t}}$. However, if the divergent prices do not converge, the position is liquidated at the end of the holding period. Following Yu (2005), we also monitor fluctuations of the trading account on a daily basis and decide to liquidate the position immediately once the total value becomes negative. To avoid trading on the same divergent event, we do not create a new position until the existing position is unwound.

We execute the strategies with the same trading parameters as in Section 6.3 so that any difference in the results is entirely driven by differences in the trading algorithm. Recall from Section 6.3 that we simulate the trading strategies with various holding periods (HP = 30 days and 180 days) and trading triggers (α = 0.1, 1.0, and 2.0) and an initial capital of \$0.50 per \$1.00 of CDS notional amount. In addition, we impose 5 percent bid–ask spreads on the CDS contract as the transaction cost. For the results, we report the total number of trades (N) executed, the number of trades closing at convergence (N_1), the number of trades with losses greater than 20 percent (N_2), and the number of trades generating negative holding period returns (N_3). The results are provided in Table 6.5.

Table 6.5: Summary statistics for various holding-period returns: our trading algorithm

							Holding-Period Returns		
HP	Alpha	N	N1	N2	N3	Convergence Ratio	Mean	Minimum	Maximum
30	0.5	2395	932	4	1424	38.91%	-0.33%	-37.64%	35.79%
	1.0	1701	818	1	1173	48.09%	-0.35%	-22.65%	21.50%
	2.0	1522	967	1	1144	63.53%	-0.33%	-94.72%	46.27%
180	0.5	1232	1037	11	672	84.17%	-0.41%	-38.17%	39.28%
	1.0	987	826	8	668	83.69%	-0.40%	-43.20%	41.40%
	2.0	1024	912	4	778	89.06%	-0.39%	-56.87%	16.62%

First, there is substantial improvement in the convergence ratio. For the strategies with a 30-days holding period, the convergence ratios are in the range from 39% to 64%; when the holding period is extended to 180 days, the convergence prevails even more, with convergence ratios all above 84%. As a stark contrast, recall the results reported in Table 6.2, where convergence barely exists with a 30-days holding period and the highest convergence ratio is only at 0.12% for strategies with a 180-day holding period.

Second, the downside risk is also significantly reduced. It is evident that only a few trades incur losses greater than 20 percent (N2). More importantly, the risk of complete drawdown of the initial capital has been eliminated. The worst holding period loss is 94.72 percent when implementing a strategy with a 30-day holding period and an alpha (trading trigger) of 2.0, whereas, as reported in Table 6.2, the previous trading algorithm would easily result in a complete drawdown of the entire initial capital and losses may even reach -449.50 percent and -1052.47 percent for holding periods of 30 days and 180 days, respectively.

Third, all strategies are associated with negative mean holding period returns. For the strategy with a 30-day (180-day) holding period and a trading trigger of 0.5, the mean holding period loss is -0.33 (-0.41) percent. We confirm that the loss is partially due to the 5 percent transaction cost assumption. Without this arbitrary transaction cost assumption, the loss could be mitigated to -0.15 (-0.18) percent.[39]

The above trading simulations adopt the same trading parameters as Yu (2006). However, the trading triggers may not be appropriate because our $ICDS_{i,t}$ estimates track $CDS_{i,t}$ more closely than$ICDS_{i,t}^{*}$ of Yu (2006).[40] When the trading trigger (alpha) is set at 0.5, the divergence signal will not be considered unless $CDS_{i,t}$ is underpriced or overpriced by more than 50 percent relative to $ICDS_{i,t}$. As a result, many opportunities have been missed due to this excessive trading trigger. We analyse trading performance across a lower range of trading triggers. The results are reported in Table 6.6.

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[39] Following Yu (2006), we assume 2.5% higher (lower) than the closing price to buy (sell) the CDS contract. The author examines trading performance from 2001 through 2004, during which the CDS market is tranquil, whereas our trading period covers the entire period as the credit crunch finally became the global GFC, since mid-2007. During our trading period, the CDS spreads became substantially higher and more volatile. It may not be appropriate to follow the same assumption regarding the bid–ask spreads, as the fixed percentage assumption would translate into expensive and unrealistic transaction costs. Indeed, we find in 13 (40) firms the CDS spreads exceeded 1000 bps (500 bps), which implies more than 50 bps (25 bps) is assumed for a transaction cost. For a CDS contract with USD 10 million notional value, this is equivalent to USD 500,000 (USD 250,000). Accordingly, we remove the transaction cost assumption from the trading simulations. We find that with a 30-day holding period, the mean holding-period returns are -0.15 percent, -0.18 percent and -0.15 percent if the trigger trades are equal to 0.5, 1 and 2 respectively; for strategies with a 180-day holding period, the mean holding-period returns are -0.23 percent, -0.21 percent and -0.18 percent, respectively.

[40] See Chapter 4 for a detailed discussion on the differences between $ICDS_{i,t}$ and $ICDS_{i,t}^{*}$.

Table 6.6: Summary statistics for various holding-period returns: our trading algorithm with lower trading triggers

							Holding-Period Returns		
HP	Alpha	N	N1	N2	N3	Convergence Ratio	Mean	Minimum	Maximum
30	0	7364	4777	12	3805	64.87%	-0.20%	-90.15%	188.54%
	0.1	5315	2834	10	2643	53.32%	-0.21%	-90.15%	200.00%
	0.2	4045	1804	5	2097	44.60%	-0.25%	-53.75%	135.14%
	0.3	3271	1331	7	1800	40.69%	-0.33%	-37.36%	54.35%
	0.4	2730	1052	3	1547	38.53%	-0.32%	-44.67%	49.69%
180	0	3841	3618	19	1781	94.19%	-0.22%	-80.05%	161.15%
	0.1	2607	2383	18	1092	91.41%	-0.25%	-80.05%	161.15%
	0.2	1934	1719	14	825	88.88%	-0.28%	-80.46%	115.85%
	0.3	1633	1425	14	781	87.26%	-0.35%	-82.50%	100.60%
	0.4	1373	1170	12	693	85.21%	-0.35%	-38.17%	82.39%

Compared with the results reported in Table 6.5, the lower trading triggers indeed improve trading performance. For a strategy with a 30-days holding period, the mean holding period loss could be reduced to -0.20 percent whereas the lowest loss was found at -0.33 percent in Table 6.5. For a strategy with a 180-days holding period, the lower trading triggers also result in a smaller mean holding-period loss as well as a higher convergence ratio. For example, reducing trading triggers from 2 to 0.1, the convergence ratio rises from 89.06 percent to 91.41 percent and the mean holding-period loss decreases from -0.39 percent to -0.25 percent.

We also observe some patterns in the results. First, a lower trading trigger loosens the criteria for the divergent signal, which in turn results in a larger number of trades executed (N). It is noted that as trading become more frequent, the convergence ratio increases. This implies the marginal convergence ratio rises at an increasing rate as we turn down the trading trigger. If we use 0 trading trigger, i.e. we include those signals for which relative divergence is less than 0.1, the convergence ratio could be as high as 94.19 percent for a strategy with a 180-days holding period. Second, despite all strategies producing an average holding period loss, the magnitude of the loss is inversely related to the level of the trading trigger. When we adjust the trading trigger from 0.4 to 0.1, the mean holding-period loss reduces from -0.32 percent to -0.21 percent and from -0.35 percent to -0.25 percent for the strategies with a 30-days and a 180-days holding periods, respectively. Third, the longer holding period is associated with greater convergence. For example, extending the holding period from 30 to 180 days, we can improve the convergence ratio from 53.32% to 91.41%, from 44.60% to 88.88%, and from 40.69% to 87.26% for the strategy with trading triggers of 0.1, 0.2, and 0.3, respectively. This finding suggests that while our trading algorithm can capture significant amounts of convergence within a short time period (30 days), a significant proportion of the divergence does require a longer time (up to 180 days) to revert.

Base on the results discussed above, strategies with a lower trading trigger and longer holding periods seem to outperform. Therefore, we decide to set the trading trigger at 0.1 and to allow 180 days for the maximum holding period. We also implement a strategy with trading trigger of 0 and 0.2 as a robustness check.

6.4.1 Trading performance decomposition by price discovery categorisation

Our trading algorithm utilises short-run price discovery mechanism to inform the adjustment process on the path of convergence. A firm is classified into five price discovery categories, {C1,…,C5} and each category is associated with a unique approach to allocate capital across the CDS and equity markets. In this section, we decompose the results of capital structure arbitrage and examine the trading performance based on the price discovery categorisation results {C1,…,C5}. The results are reported in Table 6.7.

Table 6.7: Trading performance decomposition

	Overall	C1	C2	C3	C4	C5
Panel A: Trading Trigger at 0.1						
Number of Trades (N)	2607	944	170	153	480	860
Number of Convergent Trades (N1)	2383	880	160	150	456	737
Convergence rate	91.41%	93.22%	94.12%	98.04%	95.00%	85.70%
Observation with Return < 0	41.89%	46.19%	47.06%	38.56%	31.46%	42.56%
Average Round-Trip Length	42	36	44	41	37	54
Average Holding-Period Return	-0.0025	0.0015	-0.0084	-0.0009	-0.0003	-0.0073
Median	0.0002	0.0001	0.0001	0.0008	0.0007	0.0005
Standard Deviation	0.0519	0.0559	0.0374	0.0175	0.0110	0.0655
Minimum Holding-Period Return	-0.8005	-0.0956	-0.2807	-0.1390	-0.1074	-0.8005
Maximum Holding-Period Return	1.6115	1.6115	0.1203	0.0390	0.0439	0.4533
Panel B: Trading Trigger at 0						
Number of Trades (N)	3841	1473	266	218	715	1169
Number of Convergent Trades (N1)	3618	1410	256	215	691	1046
Convergence Rate	94.19%	95.72%	96.24%	98.62%	96.64%	89.48%
Observation with Return < 0	46.37%	43.31%	57.52%	50.00%	43.92%	48.50%
Average Round-Trip Length	35	30	38	33	30	45
Average Holding-Period Return	-0.0022	0.0010	-0.0059	-0.0013	-0.0006	-0.0065
Median	0.0001	0.0001	-0.0003	-0.0000	0.0001	0.0000
Standard Deviation	0.0540	0.0459	0.0291	0.0152	0.0091	0.0584
Minimum	-0.8005	-0.0956	-0.2807	-0.1518	-0.1074	-0.8005
Maximum	1.6115	1.6115	0.1077	0.0390	0.0439	0.4533
Panel C: Trading Trigger at 0.2						
Number of Trades (N)	1934	672	116	99	336	711
Number of Convergent Trades (N1)	1719	611	106	96	315	591
Convergence Rates	88.88%	90.92%	91.38%	96.97%	93.75%	83.12%
Observation with Return < 0	42.66%	45.39%	47.41%	34.34%	31.25%	45.85%
Average Round-Trip Length	48	40	49	47	43	61
Average Holding-Period Return	-0.0028	0.0013	-0.0001	-0.0002	-0.0004	-0.0068
Median	0.0003	0.0001	0.0002	0.0013	0.0009	0.0003
Standard Deviation	0.0501	0.0500	0.0438	0.0193	0.0129	0.0630
Minimum	-0.8046	-0.1723	-0.2807	-0.1193	-0.1074	-0.8046
Maximum	1.1585	1.1585	0.1065	0.0390	0.0439	0.3928

Table 6.7 summarises trading statistics for the overall strategy and decomposes the results according to the price discovery categorisation {C1,…,C5}. Panel A reports results for the strategy with a 0.1 trading trigger. The results demonstrate that the trading opportunities are concentrated towards the categorisation tails, that is, i.e. C1 and C5 firms. There are 944 and 860 trades that belong to C1 and C5 firms, respectively. In terms of percentages, 36% and 33% of trades are executed on C1 and C5 firms, respectively, which leaves only 31% of trades belonging to C2, C3, and C4 firms collectively. This implies that the mispricing more likely occurs when there is one-way directional cross-market information flows i.e. one market dominates the other another in the price discovery process.

It is also noted that the convergence prevails reasonably well across {C1,…,C5} firms. In particular, 93.22% (85.7%) of trades on C1 (C5) firms close at convergence and the outcomes for C2, C3, and C4 firms are slightly higher. On average, we expect 42 days for the divergent prices to revert. But for C1 firms, the mispricing requires only 36 days to converge. In contrast, it takes 54 days for price divergence on C5 firms to revert. The outperformance of trading C1 firms is more evident in terms of profitability. While the overall strategy generates a mean holding period loss of -0.25 percent, this loss is indeed caused by trading {C2,…,C5} firms. Only applying strategy on C1 firms is profitable and the mean holding period return is 0.15 percent. We also observe that fewer than half of the trades across all {C1,…,C5} firms incur negative holding-period returns and the median figure is indeed close to zero.

Panels B and C report the results for strategies with trading triggers of 0 and 0.2 respectively. The results remain consistent. First, the trading opportunities are heavily distributed over C1 and C5 firms and are jointly responsible for 69% and 72% of total trades when the trading trigger is set at 0 and 0.2, respectively. Second, trading on C1 firms outperforms the other categories. The average length of convergence is shortest for the C1 firms. Executing strategy with 0 (0.2) trading trigger, it takes 30 (40) days for mispricing on C1 firms to converge, whereas it takes 45 (61) days for C5 firms. Moreover, only C1 firms deliver positive mean holding-period returns. The average holding period return is 0.1 percent and 0.13 percent for strategies with a trading trigger of 0 and 0.2, respectively, whereas the overall strategy and trading {C2,…,C5} firms all incur a mean holding-period loss.

6.4.2 Capital structure arbitrage portfolio performance

The preceding section reveals the performance of a capital structure arbitrage strategy at the individual trade level. In this section, we construct capital structure arbitrage portfolio to track strategy performance at the aggregate level. We have two related objectives. First, we examine the risk–return profile for the capital structure arbitrage portfolio. Second, we test whether the strategy at the portfolio level constitutes the concept of statistical arbitrage introduced by Hogan et al. (2004).

Because the capital strategy arbitrage individual trades have randomly distributed opening and closing signals throughout the trading period, the holding period returns cannot be aggregated for the portfolio return. To construct a portfolio, we monitor the outstanding trades on a daily basis so that the portfolio is rebalanced immediately once a new position is opened or an existing position is closed. Then the positions are marked-to-market on a daily basis. Accordingly, the capital structure arbitrage portfolio returns are calculated as the equally weighted average of the marked-to-market returns from the outstanding positions. The daily portfolio returns are then compounded to obtain monthly capital structure arbitrage portfolio returns. Analogously, we also form conditional portfolios that only include firms in each price discovery category {C1,…,C5}.

Table 6.8 reports the results for the capital structure arbitrage portfolio. We form an overall portfolio that consists of all individual trades as well as conditional portfolios that only include firms in one of the price discovery categorisations {C1,…,C5}. As a further analysis from the previous section, we implement the trading algorithm with a 180 days holding period and initial capital of $0.50 per $1.00 of CDS notional amount. In Panel A, positions are executed with a trading trigger of 0.1. We also implement trading with trigger 0 and 0.2 and report the results in Panels B and C, respectively.

Table 6.8: Trading statistics of monthly capital structure arbitrage portfolios

Panel A: Trading Trigger at 0.1	Overall	C1	C2	C3	C4	C5
Average Monthly Excess Return	0.0002	0.0056	-0.0038	-0.0001	0.0002	-0.0008
t-Statistic	0.1257	0.8890	-1.8434**	-0.0453	0.1032	-0.3448
Median	0.0005	0.0000	-0.0006	0.0004	0.0007	0.0005
Minimum	-0.0320	-0.1293	-0.0458	-0.0459	-0.0834	-0.0567
Maximum	0.0723	0.2487	0.0406	0.0496	0.0217	0.0510
Standard Deviation	0.0127	0.0431	0.0140	0.0133	0.0135	0.0163
Sharpe Ratio	-0.1634	0.3963	-1.1184	-0.2392	-0.1614	-0.3505
Value at Risk (VaR)						
1%	-0.0320	-0.1293	-0.0458	-0.0459	-0.0834	-0.0567
5%	-0.0145	-0.0031	-0.0283	-0.0345	-0.0097	-0.0322
10%	-0.0087	-0.0018	-0.0261	-0.0091	-0.0024	-0.0190
Panel B: Trading Trigger at 0	**Overall**	**C1**	**C2**	**C3**	**C4**	**C5**
Average Monthly Excess Return	0.0004	0.0059	-0.0036	0.0001	0.0004	-0.0008
t-Statistic	0.1754	0.8918	-1.8813**	0.0385	0.2042	-0.3499
Median	0.0006	0.0001	-0.0009	0.0005	0.0006	0.0006
Minimum	-0.0342	-0.1308	-0.0460	-0.0433	-0.0834	-0.0560
Maximum	0.0809	0.2665	0.0329	0.0494	0.0248	0.0485
Standard Deviation	0.0138	0.0454	0.0131	0.0130	0.0137	0.0159
Sharpe Ratio	-0.1204	0.4019	-1.1521	-0.2022	-0.1073	-0.3574
Value at Risk (VaR)						
1%	-0.0342	-0.1308	-0.0460	-0.0433	-0.0834	-0.0560
5%	-0.0137	-0.0043	-0.0281	-0.0345	-0.0097	-0.0304
10%	-0.0092	-0.0018	-0.0244	-0.0075	-0.0023	-0.0184
Panel C: Trading Trigger at 0.2	**Overall**	**C1**	**C2**	**C3**	**C4**	**C5**
Average Monthly Excess Return	-0.0005	0.0028	-0.0038	-0.0004	0.0001	-0.0008
t-Statistic	-0.3948	0.7283	-1.7254**	-0.1813	0.0533	-0.3518
Median	0.0007	0.0000	-0.0003	0.0008	0.0004	0.0005
Minimum	-0.0307	-0.1013	-0.0458	-0.0497	-0.0834	-0.0487
Maximum	0.0383	0.1269	0.0406	0.0499	0.0200	0.0529
Standard Deviation	0.0091	0.0262	0.0149	0.0148	0.0135	0.0160
Sharpe Ratio	-0.5161	0.2634	-1.0472	-0.2866	-0.1874	-0.3573
Value at Risk (VaR)						
1%	-0.0307	-0.1013	-0.0458	-0.0497	-0.0834	-0.0487
5%	-0.0147	-0.0042	-0.0310	-0.0395	-0.0095	-0.0321
10%	-0.0110	-0.0016	-0.0265	-0.0119	-0.0027	-0.0189

Note: ** indicates significance at the 5 percent level.

As reported in Panel A of Table 6.8, the overall strategy that includes all individual trades can deliver an average monthly return of 0.02 percent during the trading period between January 2006 and December 2009. However, the return is statistically insignificant. Despite the trading period encompassing the entire GFC, the worst monthly loss is limited to -3.2 percent. The empirical value at risk (VaR) reveals that there is a 5 percent (10 percent) chance the portfolio loses more than -1.45 percent (-0.87 percent) in one month. We also note that the overall portfolio fails to produce a positive Sharpe ratio.

If there is any economic profit in the capital structure arbitrage portfolio, it could be almost entirely brought about by the C1 firms. The conditional portfolio that only includes C1 firms has an average monthly return at 0.56 percent with a t-statistic of 0.8890. The lack of statistical significance could be partially due to the fact that we only cover 48 months in the trading period. The C1 portfolio has a median monthly return close to zero, indicating that at least half of the monthly portfolio returns are positive. Furthermore, applying this strategy to C1 firms results in an impressive annualised Sharpe ratio of 0.3963, which is the only positive ratio across the five conditional strategies. Although confronted with the GFC, the magnitude of the Sharpe ratio is still comparable to those in the fixed-income arbitrage strategies examined by Duarte et al. (2005). The VaR analysis suggests that there is a 5 percent (10 percent) chance the C1 portfolio could incur a loss greater than -0.31 percent (-0.18 percent) over a one-month period.

Other conditional strategies on the {C2,…,C5} firms have inferior results to those of the C1 portfolio. The portfolios that include C2, C3, and C5 firms have average monthly losses of -0.38 percent, -0.01 percent and -0.08 percent respectively, and the loss for the C2 portfolio is significant at the 0.05 level. The C4 portfolio has an average monthly return but it is only 0.02 percent. For the risk-adjusted return, the {C2,…,C5} firms all produce negative annualised Sharpe ratios. Switching the strategy from C1 to C4 firms significantly reduces the Sharpe ratio from 0.3963 to -0.1614 and it could further deteriorate to -1.1184 if the strategies are applied to C2 firms.

The superior performance of the C1 portfolio is robust in Panels B and C of Table 6.8. With trading triggers 0 and 0.2, the C1 portfolio has average monthly returns of 0.59 percent and 0.28 percent respectively. In contrast, with the same trading triggers, the average monthly portfolio returns for the overall strategy are at 0.04 percent and -0.05 percent. Again, only the C1 portfolio is able to generate positive Sharpe ratios, whereas the overall strategy and other conditional strategies on {C2,…,C5} firms all produce negative Sharpe ratios.

We confirm that the C1 portfolio is able to generate robust profits and positive Sharpe ratios. Finally, we use the methodology proposed by Hogan et al. (2004) to check whether a capital structure arbitrage strategy on C1 firms constitutes statistical arbitrage. The authors define statistical arbitrage as a zero-initial-cost, self-financing trading strategy that generates positive expected discounted profits while having a probability of loss converging to zero or a time-averaged variance converging to zero. If the trading strategy constitutes statistical arbitrage opportunities, the trading profit would be driven by persistent anomalies. In our case, the confirmation of statistical arbitrage opportunities would suggest that the profits from the C1 portfolio are largely driven by the informational efficiency gap across the CDS and equity markets.

To empirically test for statistical arbitrage, we need to calculate the cumulative profit V_t for the C1 portfolio at each month *t*. Following Hogan et al. (2004), V_t is described as

$$V_t = R_t - r_t^f + V_{t-1}\left(1 + r_{t-1}^f\right) \tag{6.6}$$

where $\mathrm{R_t}$ is the portfolio return realised at month *t* and $\mathrm{r_t^f}$ is the risk-free rate at month *t*. The cumulative profit has two components: First, to comply with the zero initial capital and self-financing requirements, we invest \$1 at $\mathrm{R_t}$ financed by borrowing at $\mathrm{r_t^f}$. Second, the previous month's cumulative profit is reinvested at $\mathrm{r_{t-1}^f}$. The monthly cumulative profit ($\mathrm{V_t}$) is then discounted back to the starting point, denoted $\mathrm{v_t}$. The incremental discounted profit, $\Delta\mathrm{v_t}$, is tested for statistical arbitrage. Under statistical arbitrage, the incremental discounted profit is normally distributed with mean μ and variance $\sigma^2 t^{2\lambda}$. The parameters values are obtained by maximising the log-likelihood function for $\Delta\mathrm{v_t}$ as

$$log\, L(\mu, \sigma^2, \lambda | \Delta v) = -\frac{1}{2}\sum_{t=1}^{48} log(\,\sigma^2 i^{2\lambda}) - \frac{1}{2\sigma^2}\sum_{t=1}^{48}\frac{1}{i^{2\lambda}}(\Delta v_t - \mu)^2 \tag{6.7}$$

To comply with the statistical arbitrage concept, $\mu > 0$ and $\lambda < 0$ must be satisfied.

Table 6.9: Tests of statistical arbitrage

Trading trigger	M	σ	λ
0.1	0.005	0.0339	0.1229
	0.9503	0.8948	2.7839***
0	0.0052	0.0421	0.1259
	0.7624	0.6936	2.3697***
0.2	0.0021	0.0304	0.9823
	0.7169	0.8026	1.4697*

The t-statistics are in parentheses

*Significant at the 0.1 level, ***Significant at 0.01 level

Table 6.9 reports the results of statistical arbitrage tests for the C1 portfolio. The point estimates for the mean (μ) are positive, indicating the C1 portfolio can deliver positive discounted incremental profits over our test periods. However, the time-averaged variance of the incremental profits (λ) is greater than zero and statistically significant. This suggests that the time-averaged variance is not declining over time. Therefore the trading profits from the C1 portfolio do not constitute the statistical arbitrage opportunities. Our test period lasts only 48 months, from January 2006 to December 2009, during which time the credit crunch was exacerbated and finally became the unprecedented GFC. While the heightened volatility during this period increases the chances of cross-market mispricing and offers more opportunities to arbitrageurs, it also causes the trading returns to be more volatile. Consequently, we observe an increasing time-averaged variance of the incremental profits.

6.5 Summary

In this chapter, we examines the profitability of capital structure arbitrage, a convergent-type strategy that exploits mispricing across the CDS and equity markets. While the CDS spread ($CDS_{i,t}$) provides an observable price of a firm's credit risk, the structural credit risk pricing approach allows us to extract an ICDS ($ICDS_{i,t}$) from the firm's stock price. An arbitrage opportunity presents when $CDS_{i,t}$ and $ICDS_{i,t}$ deviate from each other. Using our calibration approach of the CreditGrades model, we obtain a cleaner measure of $ICDS_{i,t}$.

We propose a novel approach to implement capital structure arbitrage strategy. Our trading algorithm involves a four-step procedure. First, we include only firms in which cointegration exists between $CDS_{i,t}$ and $ICDS_{i,t}$. This is to verify the co-movement between the CDS and equity markets, such that the divergence between $CDS_{i,t}$ and $ICDS_{i,t}$ will revert back to equilibrium. Second, we specify a condition for mispricing that initiates the capital structure arbitrage position. As we only include firms that have cointegrated pairwise ($CDS_{i,t}$,$ICDS_{i,t}$), we are able to estimate the cross-market credit risk pricing dynamics as a bivariate VECM. The error correction term describes the empirical equilibrium relation between $CDS_{i,t}$ and $ICDS_{i,t}$. Any departure from the equilibrium relation is expected to converge back eventually, thus signalling a capital structure arbitrage opportunity whenever there is a divergence between $CDS_{i,t}$ and $ICDS_{i,t}$. Third, the VECM model further allows us to compute Gonzalo–Granger (1995) and Hasbrouck (1995) measures of the cross-market price discovery contribution, based on which we sort firms into one of the five categories of cross-market price discovery, {C1,…,C5}. The categorisation of firms and the price discovery weights are used to set capital allocation across the CDS and stock position. Fourth, we define the conditions to unwind the position. When the initial divergent prices are reversed, the position is closed at convergence. If the divergent prices do not converge, the position will be liquidated at the end of the holding period.

Meanwhile, we unwind the position immediately as the total value of the position becomes negative for risk management purposes.

We begin our analysis by replicating the existing trading algorithm. The results show that the arbitrageur is confronted with the risk of incurring substantial losses and convergence has barely occurred across the various holding periods and trading triggers. Further analysis confirms that with our improved $ICDS_{i,t}$, the results remain unchanged. Therefore, we suspect it could be the trading algorithm itself that causes the poor results.

Our trading algorithm significantly improves trading performance. First, the convergence prevails and becomes robust across the various holding periods and trading triggers. For strategies with a 180-day holding period, the proportion of convergent trades is greater than 83 percent. The strong convergence results suggest our trading algorithm complies with the concept of convergence trading.

Second, our trading algorithm does not expose the arbitrageur to severe losses. Compared with the results of the existing strategy, our results show that arbitrageurs avoid the risk of losing their entire initial capital and incur losses greater than -20 percent in only a few occasions. Furthermore, trading opportunities often cluster in C1 or C5 firms, in which the CDS or equity market dominates in the signal directional price discovery process. If there is any profit in capital structure arbitrage trading, it would have been driven by the C1 firms. Despite the convergence rates being similar among {C1,…,C5} firms, the C1 firms are associated with the shortest period for the reversion of divergent prices. These results are robust for different trading triggers.

Third, we form monthly capital structure arbitrage portfolios. The results confirm the superior performance of the C1 portfolio. Even though we witness a credit crunch gradually evolving into the GFC during our trading period, the C1 portfolio is still able to generate a positive average monthly return and a comparable Sharpe ratio, as reported in studies of fixed-income arbitrage strategies during normal market conditions. Using procedures introduced by Hogan et al. (2004), we find that the profits from the C1 portfolio do not constitute statistical arbitrage opportunities. While the discounted incremental profits are positive, the strategy's time-averaged variance does not fall over time.

Chapter 7: Summary and concluding remarks

7.1 Summary

With remarkable growth in the past decade, the CDS market has become a major credit derivative market that facilitates credit risk trading and hedging. While the CDS spreads provide observable prices of credit risk for the underlying firms, the stock prices react to and reveal credit risk-related information as well. The structural credit risk pricing approach, pioneered by Merton (1974), indeed establishes an economic link between firm equity price and default risk measured by the probability of default. This implies that, utilising the structural credit risk pricing theory, we can extract an ICDS from a firm's stock price. The pairwise CDS spreads and ICDSs thus represent the prices of credit risk from the CDS and equity markets, respectively. This thesis undertakes a comprehensive empirical analysis to examine the cross-market credit risk information dynamics across these two markets and discusses its application to capital structure arbitrage strategy.

Specifically, we have five related objectives. First, we propose a new method to calibrate the CreditGrades model when extracting the ICDS from the firm's stock price. Our calibration approach provides more accurate ICDS estimates, which facilitates a cleaner study of cross-market credit risk information flows between the CDS and equity markets. Second, we analyse the long-run credit risk pricing relation and short-run credit risk price discovery mechanism across the CDS and equity markets. The results allow us to ascertain i) whether the two markets have credit risk pricing equilibrium in the long run and ii) which market is more efficient in reflecting credit risk information in the short run and thus leads in the credit risk price discovery process. Third, we examine the impact of the credit risk-induced GFC on this cross-market information linkage between the CDS and equity markets. During the GFC, credit risk became a binding concern among market participants. Does the credit risk pricing equilibrium still prevail? How does the price discovery function performed by the two markets evolve as we are approaching to and moving away from the midst of the GFC Fourth, we implement portfolio strategies to ascertain the economic significance of these cross-market credit risk information dynamics. We compare the portfolio performance against proven benchmarks, including buy-and-hold, momentum, and dividend yield. Finally, we propose a novel approach of capital structure arbitrage trading algorithm and examine the strategy's profitability. Unlike the trading algorithm employed by the prior studies, our strategy formulation incorporates cross-market credit risk pricing.

In Chapter 2, we review the literature that is relevant to the studies in this thesis. The gaps in the literature are identified and provide motivation for this research. The chapter commences with an introduction to CDS pricing, in which the probability of default is the key parameter. To model the probability of default, two well-established approaches are used, namely, the structural credit risk pricing approach and the reduced form approach. Unlike the reduced form approach that treats default as an exogenous random event with a certain distribution, the structural credit risk pricing approach models the default event as the asset value falling under a certain threshold. Accordingly, the structural approach links the probability of default with a firm's fundamentals, for example, asset value and equity value.

While empirical studies document that the variables suggested by the structural credit risk pricing approach are significant in explaining CDS spread variation, some models tend to underestimate credit spreads for short-term maturity. Motivated by this underpricing issue, the CreditGrades model proposed by leading credit institutions in the credit market, adjusts the default barrier to follow a stochastic process. By introducing uncertainty to the default barrier, the chances of the stochastic asset value process hitting the default barrier become greater. As a result, the short-term probability of default and credit spread becomes more reasonable. Furthermore, the CreditGrades model establishes a robust framework linking credit and equity markets and provides a closed-form solution for the equity price implied credit default spread (ICDS). For these reasons, it has become the benchmark model for both practitioners and researchers examining the linkage between the CDS and equity markets.

Chapter 2 also provides a comprehensive review of the literature that empirically examines the relationship between the CDS and other financial markets. Using a reduced form model, Duffie (1999) derives a parity relation between the CDS and bond yield spreads. The empirical studies document strong cointegration between the CDS and bond yield spreads, corroborating the parity relation in the long run. Having confirmed a long-run credit risk pricing equilibrium, these studies further investigate short-run credit risk pricing dynamics between the CDS and bond markets. The results collectively show that the CDS market dominates the bond market in performing its credit risk price discovery function, indicating the CDS market is more informational efficient in processing credit risk-related information.

In stark contrast, the long-run credit risk pricing equilibrium and short-run price discovery between the CDS and equity markets remain under-researched. Several studies employ a VAR model to examine the lead–lag relation between the changes of CDS spreads and stock returns. While these studies document inconclusive results, their modelling approach offers little economic insight with respect to the information linkage across the CDS and equity markets for at least two reasons. First, the CDS spreads and stock returns have different information contents. The CDS spreads represent the price of credit risk, yet this cannot be said for the stock returns. Second, significant non-linearity exists between the CDS spreads and stock returns based on the structural credit risk pricing approach and this non-linearity effect is ignored by the VAR model.

Other studies utilise event study methodology to compare the informational efficiency between the CDS and equity markets for events that release credit risk-sensitive information, such as credit rating and earnings announcements. However, no evident results are documented regarding the relative informational efficiency between these two markets. The review in Chapter 2 also reveals that insider trading activity may cause the information flow from the CDS and equity markets. However, this incremental information revelation from the CDS market is only found before negative credit risk shocks.

To undertake a comprehensive analysis of the credit risk information dynamics between the CDS and equity markets, we need to match and compare observable CDS spreads with corresponding credit risk measures implied by the stock market. We implement the CreditGrades model under the structural credit risk pricing approach to extract ICDSs embedded in the firm stock price. In Chapter 3, we describe data and variables to construct pairwise credit risk measures $(CDS_{i,t}, ICDS_{i,t})$. The daily CDS spreads data are provided by CMA, a leading data provider in the credit derivatives market. Following previous studies in the CDS market, we focus on five-year USD 10 million CDS contracts written on senior debt issued by U.S. firms. To extract

$ICDS_{i,t}$, the CreditGrades model requires the following model inputs: stock price, stock return volatility, debt per share, and the risk-free rate. The daily closing price and return are downloaded from the CRSP, based on which we compute one-year historical return volatility. The debt per share is calculated as total liabilities divided by common shares outstanding. We download quarterly total liabilities from the Compustat North American files and daily common shares outstanding from the CRSP. Finally, we use a five-year swap rate as a proxy for the risk-free rate, downloaded from Datastream.

To avoid anomalous results due to the GFC, our firm sample includes only investment-grade firms with S&P long-term debt ratings above BBB-. After matching data and variables from different sources, our sample contains 174 firms over a five-year period from January 3, 2005 to December 31, 2009, or 1,259 daily observations per firm. Compared with previous studies, our sample has wider cross-sectional coverage and a longer sample period. We further split our sample into a pre-GFC sub-sample period from January 2005 to June 2007 and a GFC sub-sample period from July 2007 to December 2009. The unique event of GFC allows us to study the impact of a credit risk-induced crisis on the cross-market credit risk information linkage across the CDS and equity markets.

In Chapter 4, we propose a novel calibration approach for the CreditGrades model to extract the ICDS from the firm stock price. The chapter commences by elaborating the procedures in the CreditGrades model to derive the probability of default and ICDS. The CreditGrades model defines a default event as the first time the stochastic asset value process hits the stochastic default barrier, which is the recovery amount at default. The model assumes recovery process follows a log-normal distribution with expected recovery rate $\bar{L}$ and variance λ^2. Since these two parameters are non-observable, the CreditGrades model needs to be calibrated before it is used to calculate the probability of default and the ICDS.

Our calibration approach differs from the previous approach in three regards. First, we calibrate both $(\bar{L}, \lambda^2)$, whereas the previous calibration approach assumes $\lambda^2 = 0.3$ and calibrates the model with respect to $\bar{L}$. In this regard, our ICDS contains less bias associated with the ad hoc setting of λ^2. Second, we adopt a frequent calibration approach to update the value of $(\bar{L}, \lambda^2)$ in a timely manner. The previous approach calibrates the value of $\bar{L}$ once, using the first 10 observations, and then applies the calibrated parameter for the rest of the sample period. In contrast, we re-calibrate $(\bar{L}, \lambda^2)$ every 30 days based on the prior 30 days' observations. In effect, the calibrated parameters $(\bar{L}, \lambda^2)$ are only utilised to estimate the ICDS during the extraction window of 30 days. Third, our calibration approach takes into account the fact that capital structure fundamentals have impact on the recovery process. Accordingly, we re-calibrate the parameters $(\bar{L}, \lambda^2)$ immediately when new accounting information arrives during the extraction window. The newly update recovery rate variables are then used to estimate the ICDS during the rest of that extraction window.

To demonstrate the claimed advantage, we compare the $ICDS_{i,t}$ estimate using our calibration approach with $ICDS_{i,t}^*$ obtained using the previous model calibration procedure. We provide both graphical and statistical evaluations utilising the CDS spread $(CDS_{i,t})$ as the benchmark. The time-series plot demonstrates that $ICDS_{i,t}$ is better able to track $CDS_{i,t}$ than $ICDS_{i,t}^*$. Especially during the GFC sub-sample period, while the gap between $CDS_{i,t}$ and $ICDS^*_{i,t}$ widens, $ICDS_{i,t}$ still maintains its tracking ability and is able to capture variations in$CDS_{i,t}$. The statistical evaluation based on Average Absolute Pricing Error (AAPEs) further confirms that the $ICDS_{i,t}$ obtained using our calibration approach is more accurate than the $ICDS^*_{i,t}$ of previous calibration approach. For example, 90% of firms have an AAPE less than 31.59 bps using $ICDS_{i,t}$. In stark contrast, only less than 10% of firms have an AAPE of 31.86 bps or less based on $ICDS^*_{i,t}$. Hence, our calibration approach provides more accurate ICDS estimates, which in turn facilitates a cleaner study of cross-market credit risk dynamics between the CDS and equity markets.

In Chapter 5, we undertake a comprehensive analysis of the credit risk information dynamics across these two markets. Our main findings are generated from a four-stage empirical analysis. First, we examine the long-run credit risk pricing relation between the CDS and equity markets. The pairwise measure $(CDS_{i,t}, ICDS_{i,t})$ is matched at the firm level such that $CDS_{i,t}$ and $ICDS_{i,t}$ represent the prices of credit risk from the CDS and equity markets, respectively. The unit root test suggests that both $CDS_{i,t}$ and $ICDS_{i,t}$ have one unit root. Using the Johansen cointegration test, we document strong cointegration between $CDS_{i,t}$ and $ICDS_{i,t}$ for 173 out of 174 firms based on the full sample period. This indicates long-run credit risk equilibrium across the CDS and equity markets. The perceived long-run credit risk pricing equilibrium is robust in the pre-GFC and GFC sub-samples. During the GFC sub-sample, cointegration between $CDS_{i,t}$ and $ICDS_{i,t}$ is found in 165 firms. This result strongly suggests that, despite the heightened credit risk during the GFC, the cross-market credit risk information linkage still prevails and drives the co-movement of the CDS and equity markets.

Second, we examine the short-run credit risk pricing dynamics across the CDS and equity markets. The presence of cointegration allows us to model the dynamics between $CDS_{i,t}$ and $ICDS_{i,t}$ in a VECM setting. While the error-correction term captures the long-run equilibrium relation, the error-correction coefficients indicate the short-run adjustment process between $CDS_{i,t}$ and $ICDS_{i,t}$ when deviation from equilibrium occurs. If a bi-directional price discovery process exists, we further apply the Gonzalo–Granger (1995) common factor weight (GG) and Hasbrouck (1995) information share measures to determine the credit risk price discovery contributions from the CDS and equity markets. We sort firms into five price discovery categories, {C1,…,C5}. The latter represent a spectrum of cross-market price discovery status. As we move from C1 to C5, the price discovery contribution shifts from the CDS market to the equity market.

We find that 131 firms, or 76% of the firm sample, are categorised as C1 or C2, where the CDS market either solely dominates or leads the stock market in the credit risk price discovery process. However, the equity market is not entirely irrelevant, with 28 C4 and C5 firms, which constitutes around 17% of the firm sample. These results suggest that the CDS market is more informational efficient than the equity market in reflecting credit risk information. In contrast, prior studies by Norden and Weber (2004, 2009) and Bystrom (2006) offer inconclusive findings on this issue.

Further comparison of the categorisation results between the pre-GFC and GFC sub-sample periods reveals that the number of firms in each category {C1,…,C5} is unstable. This implies the short-run credit risk price discovery process that depicts the direction of cross-market information flow is time-varying. When tracking the migration of firms from one category to another, from the pre-GFC to the GFC sub-sample, we find evident evidence that the CDS market absorbs the price discovery function from the equity markets. For example, 77.78% of pre-GFC C3 firms, 63.83% of pre-GFC C4 firms, and 66.67% of pre-GFC C5 firms migrated to either GFC C1 or C2.

Third, we forward-shift the estimation window over the pre-GFC sub-sample on a quarterly basis to re-compute the GG and HAS measures. This allows us to re-categorise firms across {C1,…,C5} over 11 rolling-window estimations during the GFC sub-sample. Accordingly, we are able to track the transmigration patterns of firms across {C1,...,C5} as we approach and move past the height of the GFC. Doing so, we offer a better understanding of the time-varying nature of cross-market credit risk information flows between the CDS and equity markets before, during, and after the GFC. Thus our study does not merely test whether the GFC imposed some structural break on cross-market credit risk price discovery but, rather, offers insight into the nature of the structural break itself.

We uncover an interesting transmigration pattern of price discovery categories. During the initial estimation window from January 2005 to June 2007, 92 firms are categorised as C1 and C2, in which CDS market has credit risk price leadership. This number increases to 158 during the estimation window from April 2006 to September 2008 characterised as the onset of the GFC. This documented transmigration pattern strongly suggests that the CDS market gradually took over the price discovery leadership from the underlying equity market for nearly all our 174 firms as we moved towards the GFC. When we moved past the height of the GFC, despite the relative contribution of the CDS market to the price discovery process being reduced, it remains high compared to the pre-GFC period. In the final estimation window, from July 2007 to December 2009, 118 firms are classified as C1 and C2, whereas the number was 92 in the first estimation window.

Fourth, we ascertain economic significance with five portfolio strategies {PS1,…,PS5}, all of which draw trading signals from the CDS market to trade corresponding stocks. The PS1 strategy considers the entire firm sample. The PS2 strategy is based on a static list of firms for which the CDS market processes the price discovery leadership, i.e. C1 and C2 firms. The PS3 strategy is similar to PS2, except that its firm list is updated every quarter. PS4 and PS5 are control strategies that trade in firms that are mutually exclusive to PS2 and PS3, respectively. These five strategies are designed to analyse the incremental profit/loss from identifying and updating the list of CDS-influenced firms during the trading period, net of transaction costs.

We implement {PS1,…,PS5} as follows. Every Wednesday, we set a long (short) position in firm *i* if on Tuesday we observe that the weekly $\Delta CDS_{i,t} < -20\%$ ($> 20\%$). The portfolio is liquidated next Wednesday and a new portfolio is formed. A non-trivial drop (rise) in $CDS_{i,t}$ suggests a substantial decrease (increase) in the firm's credit profile. For C1 and C2 firms, for which the CDS has price leadership, this would translate into higher (lower) subsequent stock returns.

The PS2 and PS3 strategies are the only two strategies that display substantial profitability, with returns (Sharpe ratios) of 14.44% pa (0.299) and 15.64% (0.363), respectively. Compared to PS2, PS3 has a higher return and lower volatility, which accounts for its higher Sharpe ratio. The PS1 strategy generates a 2.05% pa return and a Sharpe ratio of 0.048. In terms of risk-adjusted net realised returns against Fama–French factors, PS2 and PS3 are the only two strategies that produce a significant alpha, with p-values of 0.08 and 0.022, respectively.

From the second set of bench-marking, the buy-and-hold strategy leads to a realised loss of 0.85% pa. The six-month rank and one-month hold, or 6-1, momentum portfolio produces an even greater loss, at 32% pa. We expand the momentum benchmark to a 6 x 6 rank-hold permutation matrix of 36 momentum strategies. Only four momentum portfolios generate positive returns. The two largest realised returns of 11.34% pa and 11.30% pa come from the 1–1 and 1–3 strategies, which are lower than the returns of PS2 and PS3. We implement two dividend-yield strategies: i) Dow-Dogs, which ranks Dow-Jones stocks, and ii) CDS-Dogs, which ranks our entire firm sample. We consider annual, quarterly, monthly, and weekly re-balancing, which gives eight variant dividend-yield strategies. All Dow-Dogs produce negative returns. In contrast, three CDS-Dogs produce positive returns. The quarterly CDS-Dog strategy exhibits the highest Sharpe ratio, at 0.217. While it manages to outperform PS1, the best CDS-Dog's Sharpe ratio is still lower than those of PS2 (0.299) and PS3 (0.363).

In Chapter 6, we examine the profitability of a capital structure arbitrage strategy. The strategy is designed to exploit divergent prices across the CDS and equity markets. We propose a novel trading algorithm that incorporates the credit risk information dynamics between these two markets. Utilising our trading algorithm, the arbitrageur is able to avoid the risks of non-convergence and severe loss that contradict the basic concept of capital structure arbitrage.

The chapter commences by replicating the trading algorithm employed by previous studies. Not surprisingly, we document analogous results. Despite the strategy being claimed a convergent-type strategy, actual convergence is indeed the exception rather than the norm. The arbitrageurs frequently incur substantial losses, even their entire initial capital.

Since the strategy utilises opening and closing signals that are based on the relative value between $CDS_{i,t}$ and $ICDS_{i,t}$, a biased $ICDS_{i,t}$ estimate would result in an incorrect trading signal. Thus this will have a significant impact on trading performance. Accordingly, we re-implement the previous trading algorithm, but using our improved CreditGrades model calibration approach to extract $ICDS_{i,t}$ estimates. Despite the more accurate $ICDS_{i,t}$, the non-convergence risk and substantial loss prevail in the trading book. This result implies that the real cause of the problem stems from the trading algorithm itself.

We identify several issues in the trading algorithm adopted by previous studies. First, the divergent $CDS_{i,t}$ and $ICDS_{i,t}$ does not necessarily converge unless a strong cross-market equilibrium exists. The cross-market equilibrium condition enforces the long-run co-movement of $CDS_{i,t}$ and $ICDS_{i,t}$, but this is an empirical issue that needs verification. Second, the existing trading algorithm assumes a parity relation between $CDS_{i,t}$ and $ICDS_{i,t}$ such that a trading opportunity presents if i) $CDS_{i,t} > (1+\alpha)ICDS_{i,t}$ or ii) $ICDS_{i,t} > (1+\alpha)CDS_{i,t}$, where α is a trading trigger to ensure sufficient mispricing, and convergence occurs at $CDS_{i,t} = ICDS_{i,t}$. However, the equilibrium relation between $CDS_{i,t}$ and $ICDS_{i,t}$ may not be necessarily confined to parity due to microstructure issues across the two markets. We should let the data speak for itself regarding the true equilibrium relation, based on which we draw signals of divergence and convergence. Third, without knowledge of the short-run price discovery dynamics, the arbitrageur cannot identify which market is providing the more efficient price and thus has difficulty in clarifying the adjustment process between $CDS_{i,t}$ and $ICDS_{i,t}$ towards convergence. As a result, the arbitrageur has to bet on both markets and utilise the delta hedging concept to match the equity and CDS positions. However, the substantial loss results suggest that the entire process is inappropriate.

By taking into account these issues, we propose a novel approach to implement capital structure arbitrage trading. Our trading algorithm involves a four-step procedure that incorporates both long-run credit risk pricing relation and short-run credit risk price discovery dynamics across the CDS and equity markets. First, we include only candidate firms for which cointegration exists between $CDS_{i,t}$ and $ICDS_{i,t}$. This is to ensure that long-run credit risk pricing equilibrium prevails across the CDS and equity markets. Second, we utilise the equilibrium relation between $CDS_{i,t}$ and $ICDS_{i,t}$ to determine signals of divergence. Because of cointegration, we are able to estimate the cross-market dynamics of $CDS_{i,t}$ and $ICDS_{i,t}$ in a bivariate VECM setting. The error correction term captures the empirical equilibrium relation between $CDS_{i,t}$ and $ICDS_{i,t}$.

Third, we set arbitrage positions based on the short-run price discovery mechanism that informs the adjustment process between $CDS_{i,t}$ and $ICDS_{i,t}$ on the path to convergence. The VECM model parameters allows us to compute the Gonzalo–Granger (GG, 1995) and Hasbrouck (HAS, 1995) measures of cross-market price discovery contributions, based on which we sort firms into one of five price discovery categories, {C1,…,C5}. For C1 (C5) firms, the CDS (equity) market dominates one-way price discovery process, implying the price adjustment takes place in the equity (CDS) market. Accordingly, we invest only in the equity (CDS) market when price divergence occurs in C1 (C5) firms. For C2, C3, and C4 firms, bi-directional price discovery process exists. We deploy capital in both markets. Intuitively, the market that performs less price discovery is likely to experience greater short-run price adjustments. This would suggest that capital allocation should be inversely related to the proportion of price discovery contributions. For example, if the average of GG and HAS is 70% and 30% of the price discovery contributions performed by the CDS and equity market, respectively, then we allocate 30% of our capital to the CDS market and 70% to the stock market. For C3 firms, the GG and HAS measures do not share a consensus as to which market performs more price discovery. Hence we deploy an equally weighted pairwise position across both CDS and stocks.

Fourth, we close the position when convergence occurs. If the prices do not converge, the position is unwound at the end of the holding period. We mark-to-market the trading account on a daily basis and liquidate the position immediately whenever the total value becomes negative. The long-run cointegration test and short-run price discovery categorisation are performed on a quarterly basis based on the prior 12 months' estimation window and the estimation results are applied to the trading period in the following quarter.

Our trading algorithm significantly improves trading performance. Convergence prevails and becomes robust, indicating the trading strategy is indeed a convergent-type strategy that complies with the underlying concept of capital structure arbitrage. With a 180-days holding period, the convergence ratio is above 83%, whereas it was only 0.12% using the previous trading algorithm. Furthermore, the arbitrageur avoids the risk of substantial loss. Unlike the results of using the previous trading algorithm, the risk of complete drawdown of one's entire initial capital is eliminated. Also, there is a large drop in the number of cases incurring losses worse than -20 percent. Further analysis reveals that the trading trigger adopted by the previous study seems excessive. Smaller trading triggers further improve trading performance, for example, with a higher convergence ratio and smaller holding period loss.

Our trading algorithm utilises price discovery categorisation results to deploy capital across the CDS and equity markets, we implement conditional strategies for each price discovery category in {C1,…,C5}. The results demonstrate that the trading opportunities tilt toward C1 and C5 firms, for which one-way price discovery process exists. The C1 and C5 firms account for 36% and 33% of trading opportunities, respectively, leaving only 31% of trades belonging to the C2, C3, and C4 firms collectively. While all conditional strategies have comparable convergence ratios, it is evident that C1 firms are associated with the fastest convergence speed. The divergent prices takes 36 days to revert for C1 firms, whereas convergence requires 54 (42) days for C5 firms (overall strategy). It is also noted that only the conditional strategy on C1 firms has a positive mean holding period return and this result is robust across various trading triggers.

At the portfolio level, trading on C1 firms also outperforms the overall strategy and other conditional strategies on C2, C3, C4, and C5 firms. The capital structure arbitrage portfolio that includes C1 firms provides higher average monthly returns and lower VaR measures. More importantly, only the C1 portfolio produces positive risk-adjusted returns. The annual Sharpe ratio remains positive and robust across different trading triggers. Despite our trading encompassing the entire GFC period, the Sharpe ratio for the C1 portfolio is still comparable with those documented in the fixed-income arbitrage strategies during normal market conditions. Finally, using procedures proposed by Hogan et al. (2004), we examine whether the C1 portfolio gives rise to statistical arbitrage, a self-financing strategy with a positive expected discounted profit, a probability of loss converging to zero and a time-averaged variance converging to zero. The results, however, demonstrate that the C1 portfolio does not give rise to statistical arbitrage. While it generates positive discounted incremental profits, the time-averaged variance of incremental profits is greater than zero, suggesting the time-averaged variance does not decline over time.

7.2 Implications for future research

This study leaves several paths open for future research. First, we analyse the credit risk information linkage between the CDS and equity markets. A similar information linkage exists between the CDS and bond market. This implies that credit risk information may also link the equity market with the bond market as well. Thus future research could examine the credit risk information dynamics between the equity and bond markets. Alternatively, it could analyse the dynamics relationship between these related markets in a triangular setting for the CDS, equity, and bond markets together.

Second, cross-market relationship could be further extended to include the option market. While there is a general consensus that the derivatives market is more efficient than the spot market, the relative informational efficiency between related derivatives markets still remains under-researched. Indeed, the CDS contract is analogous to the put option contract, since both provide protection against downside risk. Future research could examine the cross-market relationship between the CDS and put option markets and focus on the relative informational efficiency between these two derivatives markets.

Third, cross-market trading strategies may further illuminate relative informational efficiency between related markets. We only implement trading strategies based on information transmission between the CDS and equity markets. A similar strategy would apply to other related pairwise markets, including CDS–bond, CDS–option, and equity–bond. The strategy can be designed by anchoring to the price discovery mechanism across related markets. Shocks in the market that has price leadership will signal possible future price adjustments in the other market.

Fourth, our analysis is based on a comprehensive sample of investment-grade firms and the results do not necessarily represent those of non-investment-grade firms. The credit risk dynamics of lower-rated firms are more complex and thus require an advanced model to extract appropriate ICDS measures embedded in firm stock prices. The interactions between CDS spreads and ICDSs would provide new evidence regarding the cross-market credit risk information flows for a lower-rated sector. The results may further be combined with the findings in this research to draw a complete conclusion.

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Appendices

Appendix 1. Computation of the equity hedge ratio and value of the CDS

Following Yu (2006), the equity hedge ratio or equity delta is defined as

$$\delta = \frac{\partial \pi_{(0.T)}}{\partial S_t} \tag{A.1}$$

where $\pi_{(0.T)}$ denotes the change of CDS contract value and S_t denotes the change of equity price. The equity delta measures the sensitivity of the CDS contract value to equity price changes. On day t, for the CDS contract initiated on day 0, the value of a long position, becomes

$$\pi_{(0.T)} = [CDS_t - CDS_0] \int_0^t P_{(s)} e^{-rs} ds \tag{A.2}$$

where CDS_t is the CDS spread observed on day t, CDS_0 is the CDS spread of the contract when it was first initiated, and $P_{(s)}$ is the risk natural survival probability of the firm. Defining the default density function as $f(t) = -\frac{dP_{(t)}}{dt}$. The integral part in (A.2), $\int_0^t P_{(s)} e^{-rs} ds$, equals

$$\int_0^t P_{(s)} e^{-rs} ds = \frac{1}{r}\left(P_{(0)} - P_{(t)} e^{-rt}\right) - \frac{1}{r}\int_0^t f(s) e^{-rs} ds \tag{A.3}$$

The CreditGrades model provides closed-form solutions for $P_{(0)}$, $P_{(t)}$, and $\int_0^t f(s) e^{-rs} ds$. Using equations (4.4), (4.9), and (4.10) in Chapter 4, we can express the value of the contract (A.2) as

$$\pi_{(0.T)} = \frac{[CDS_t - CDS_0]}{r}\{P_{(0)} - P_{(t)} e^{-rt} - e^{r\xi}[G(t+\xi) - G(\xi)]\} \tag{A.4}$$

The hedge ratio or equity delta of (A.1) can be calculated as

$$\delta = \frac{1}{r}\frac{\partial CDS_t}{\partial S_t}\{P_{(0)} - P_{(t)}e^{-rt} - e^{r\xi}[G(t+\xi) - G(\xi)]\} \tag{A.5}$$

To calculate $\frac{\partial \mathrm{CDS_t}}{\partial \mathrm{S_t}}$, we differentiate the CDS spread $\mathrm{CDS_t}$ numerically with respect to the equity price $\mathrm{S_t}$.

Appendix 2. List of sample firms

Company Name	Rating	Industry
ABBOTT LABORATORIES	AA	Consumer Noncyclical
AETNA INC NEW	BBB	Consumer Noncyclical
AIR PRODUCTS & CHEMICALS INC	A	Basic Materials
HONEYWELL INTERNATIONAL INC	A	Consumer, Cyclical
ALCOA INC	A-	Basic Materials
HESS CORP	BBB	Energy
AMGEN INC	A+	Consumer Noncyclical
NABORS INDUSTRIES LTD	A-	Energy
APACHE CORP	A-	Energy
ARCHER DANIELS MIDLAND CO	A+	Consumer Noncyclical
ARROW ELECTRONICS INC	BBB-	Industrial
ASHLAND INC NEW	BBB	Basic Materials
AVNET INC	BBB-	Industrial
AVON PRODUCTS INC	A	Consumer Noncyclical
BARRICK GOLD CORP	A	Basic Materials
BAXTER INTERNATIONAL INC	A-	Consumer Noncyclical
VERIZON COMMUNICATIONS INC	A+	Communications
BLACK & DECKER CORP	BBB	Industrial
BOEING CO	A	Industrial
BRISTOL MYERS SQUIBB CO	AA-	Consumer Noncyclical
BURLINGTON NORTHERN SANTA FE CP	BBB+	Industrial
C S X CORP	BBB	Industrial
CAMPBELL SOUP CO	A	Consumer Noncyclical
NEXEN INC	BBB	Energy
CARDINAL HEALTH INC	A	Consumer Noncyclical
CATERPILLAR INC	A	Industrial
CENTURYTEL INC	BBB+	Communications
CHEVRON CORP NEW	AA	Energy
CLOROX CO	A+	Consumer Noncyclical
COCA COLA CO	A+	Consumer Noncyclical
COLGATE PALMOLIVE CO	AA-	Consumer Noncyclical
COMMERCIAL METALS CO	BBB	Industrial

Company Name	Rating	Industry
AVIS BUDGET GROUP INC	BBB	Consumer Noncyclical
C A INC	BBB+	Technology
COMPUTER SCIENCES CORP	A	Technology
CONAGRA INC	BBB+	Consumer Noncyclical
CON WAY INC	BBB-	Industrial
COOPER TIRE & RUBBER CO	BBB	Consumer, Cyclical
MOLSON COORS BREWING CO	BBB+	Consumer Noncyclical
TARGET CORP	A+	Consumer, Cyclical
DEERE & CO	A-	Industrial
DISNEY WALT CO	BBB+	Communications
DOVER CORP	A+	Industrial
DOW CHEMICAL CO	A-	Basic Materials
OMNICOM GROUP INC	A-	Communications
DU PONT E I DE NEMOURS & CO	AA-	Basic Materials
EASTMAN KODAK CO	BBB-	Industrial
EATON CORP	A-	Industrial
EMERSON ELECTRIC CO	A	Industrial
WEATHERFORD INTL LTD NEW	BBB+	Energy
EXXON MOBIL CORP	AAA	Energy
FEDEX CORP	BBB	Industrial
MACYS INC	BBB+	Consumer, Cyclical
G A T X CORP	BBB-	Industrial
GANNETT INC	A	Communications
GENERAL DYNAMICS CORP	A	Industrial
GENERAL MILLS INC	BBB+	Consumer Noncyclical
GOODRICH CORP	BBB-	Industrial
HALLIBURTON COMPANY	BBB	Energy
HEINZ H J CO	A	Consumer Noncyclical
HERSHEY CO	A+	Consumer Noncyclical
HEWLETT PACKARD CO	A-	Technology
HOME DEPOT INC	AA	Consumer, Cyclical
CENTERPOINT ENERGY INC	BBB	Energy
INGERSOLL RAND PLC	BBB+	Industrial
INTERNATIONAL BUSINESS MACHS COR	A+	Technology

Company Name	Rating	Industry
INTERNATIONAL GAME TECHNOLOGY	BBB	Consumer, Cyclical
INTERNATIONAL PAPER CO	BBB	Basic Materials
ENBRIDGE INC	A-	Energy
JOHNSON & JOHNSON	AAA	Consumer Noncyclical
JOHNSON CONTROLS INC	A	Consumer, Cyclical
KELLOGG CO	BBB	Consumer Noncyclical
KIMBERLY CLARK CORP	AA-	Consumer Noncyclical
KROGER COMPANY	BBB	Consumer Noncyclical
LENNAR CORP	BBB-	Consumer, Cyclical
LILLY ELI & CO	AA	Consumer Noncyclical
LIMITED BRANDS INC	BBB+	Consumer, Cyclical
LIZ CLAIBORNE INC	BBB	Consumer, Cyclical
LOCKHEED MARTIN CORP	BBB	Industrial
LOWES COMPANIES INC	A	Consumer, Cyclical
M D C HOLDINGS INC	BBB-	Consumer, Cyclical
MARATHON OIL CORP	BBB+	Energy
MASCO CORP	BBB+	Industrial
MATTEL INC	BBB	Consumer, Cyclical
MCDONALDS CORP	A	Consumer, Cyclical
MCKESSON H B O C INC	BBB	Consumer Noncyclical
MEDCO HEALTH SOLUTIONS INC	BBB	Consumer Noncyclical
MEDTRONIC INC	AA-	Consumer Noncyclical
C V S CAREMARK CORP	A	Consumer, Cyclical
MERCK & CO INC NEW	AAA	Consumer Noncyclical
3M CO	AA	Industrial
MOTOROLA INC	BBB	Communications
NEWELL RUBBERMAID INC	BBB+	Consumer, Cyclical
NEWMONT MINING CORP	BBB	Basic Materials
NORDSTROM INC	A-	Consumer, Cyclical
NORFOLK SOUTHERN CORP	BBB	Industrial
NUCOR CORP	A+	Basic Materials
OCCIDENTAL PETROLEUM CORP	BBB+	Energy
OLIN CORP	BBB-	Basic Materials
P P G INDUSTRIES INC	A	Basic Materials

Company Name	Rating	Industry
PEPSICO INC	A+	Consumer Noncyclical
PFIZER INC	AAA	Consumer Noncyclical
ALTRIA GROUP INC	BBB+	Consumer Noncyclical
CONOCOPHILLIPS	A-	Energy
PITNEY BOWES INC	AA	Technology
PROCTER & GAMBLE CO	AA-	Consumer Noncyclical
PULTE HOMES INC	BBB-	Consumer, Cyclical
R P M INTERNATIONAL INC	BBB	Basic Materials
RAYTHEON CO	BBB-	Industrial
RYDER SYSTEMS INC	BBB	Industrial
RYLAND GROUP INC	BBB-	Consumer, Cyclical
SAFEWAY INC	BBB	Consumer Noncyclical
SARA LEE CORP	A+	Consumer Noncyclical
SCHLUMBERGER LTD	A+	Energy
SEALED AIR CORP NEW	BBB	Industrial
SHERWIN WILLIAMS CO	A	Basic Materials
SOUTHWEST AIRLINES CO	A	Consumer, Cyclical
SUNOCO INC	BBB	Energy
RADIOSHACK CORP	A-	Consumer, Cyclical
TEMPLE INLAND INC	BBB	Basic Materials
TEXTRON INC	A-	Industrial
TYCO INTERNATIONAL LTD SWTZLND	BBB-	Industrial
TYSON FOODS INC	BBB	Consumer Noncyclical
UNION PACIFIC CORP	BBB	Industrial
UNITEDHEALTH GROUP INC	A	Consumer Noncyclical
UNITED PARCEL SERVICE INC	AAA	Industrial
UNITED TECHNOLOGIES CORP	A	Industrial
UNIVERSAL HEALTH SERVICES INC	BBB	Consumer Noncyclical
V F CORP	A-	Consumer, Cyclical
WAL MART STORES INC	AA	Consumer, Cyclical
MEADWESTVACO CORP	BBB	Basic Materials
WEYERHAEUSER CO	BBB	Basic Materials
WHIRLPOOL CORP	BBB+	Consumer, Cyclical
T J X COMPANIES INC NEW	A	Consumer, Cyclical

Company Name	Rating	Industry
ENCANA CORP	A-	Energy
ANADARKO PETROLEUM CORP	BBB+	Energy
TOLL BROTHERS INC	BBB-	Consumer, Cyclical
COCA COLA ENTERPRISES INC	A	Consumer Noncyclical
B H P LTD	A+	Basic Materials
CARNIVAL CORP	A-	Consumer, Cyclical
TALISMAN ENERGY INC	BBB+	Energy
WASTE MANAGEMENT INC DEL	BBB	Industrial
DELL INC	A-	Technology
OFFICE DEPOT INC	BBB-	Consumer, Cyclical
DEVON ENERGY CORP NEW	BBB	Energy
CANADIAN NATURAL RESOURCES LTD	BBB+	Energy
SUNCOR ENERGY INC NEW	A-	Energy
VALERO ENERGY CORP NEW	BBB	Energy
STAPLES INC	BBB-	Consumer, Cyclical
ALLERGAN INC	A	Consumer Noncyclical
POTASH CORP SASKATCHEWAN INC	BBB+	Basic Materials
AUTOZONE INC	BBB+	Consumer, Cyclical
JONES APPAREL GROUP INC	BBB	Consumer, Cyclical
ENBRIDGE ENERGY PARTNERS LP	BBB+	Energy
TIME WARNER INC NEW	BBB+	Communications
PRAXAIR INC	A-	Basic Materials
BOSTON SCIENTIFIC CORP	A-	Consumer Noncyclical
KOHLS CORP	A-	Consumer, Cyclical
KINDER MORGAN ENERGY PARTNERS LP	BBB+	Energy
HUMANA INC	BBB	Consumer Noncyclical
AGRIUM INC	BBB	Basic Materials
X T O ENERGY INC	BBB-	Energy
TRANSOCEAN LTD	A-	Energy
BORGWARNER INC	BBB+	Consumer, Cyclical
MARRIOTT INTERNATIONAL INC NEW	BBB+	Consumer, Cyclical
EASTMAN CHEMICAL CO	BBB	Basic Materials
CYTEC INDUSTRIES INC	BBB	Basic Materials
DARDEN RESTAURANTS INC	BBB+	Consumer, Cyclical

Company Name	Rating	Industry
QUEST DIAGNOSTICS INC	BBB	Consumer Noncyclical
PLAINS ALL AMERN PIPELINE L P	BBB-	Energy
PEPSI BOTTLING GROUP INC	A	Consumer Noncyclical
PACKAGING CORP AMERICA	BBB	Industrial
MONSANTO CO NEW	A	Consumer Noncyclical
KRAFT FOODS INC	A-	Consumer Noncyclical

Amendments and responses to examiners' comments on my PhD thesis

I would like to sincerely thank both examiners: Professor Richard Heaney of University of Western Australia and Dr Wai-Man Liu of the Australian National University for their comments and suggestions on my thesis.

The suggested amendments by both examiners are addressed in the ADDENDUM section. Dr Wai-Man Liu stated in his examiner's report that I am not required to incorporate all his suggestions for thesis submission purpose. Therefore only selected comments from Dr Wai-Man Liu are addressed. I will certainly incorporate all his comments when this thesis is converted into papers for journals submission in the future. In ERRATA section, gramma and other typographical errors are corrected. These two sections will be inserted into the thesis once the Head of Department approves.

ADDENDUM

Responses to comments from Professor Richard Heaney

1. The main theme of the thesis is to investigate the credit risk information dynamics across the CDS and equity market. We noticed that the ICDS estimated from CreditGrades model exhibits different tracking ability to the CDS spreads between the pre-GFC and GFC period. I decide to investigate the stability of CreditGrades model parameter in a future follow up research.
2. P44: add as a separate paragraph after para 3:
   The choice of data follows Blanco et al (2005) and Acharya and Johnson (2007).

   The exact timing for the daily closing CDS spreads and share prices are not reported by the database. Acharya and Johnson (2007) point out that the U.S CDS market closes no later than 4:15 p.m. New York time, which closely matches 4 p.m. closing time of New York stock exchange. If this timing gap matters, the results should be more biased towards information flow from the equity to CDS market. However, we document strikingly different results that the CDS market dominates the equity market for price discovery.

3. The structural and reduced form models are common names for the two well accepted credit risk modelling approaches. The discussion on these two classes of models is provided on pages 16 to 19.
4. P33: add as a separate paragraph after para 2:
   We are aware of that historical volatility may not be an efficient measure of volatility for CDS pricing. However, our main objective in this thesis is to ascertain the credit risk information dynamics between the equity and CDS markets. By using option-implied volatility, the information content of spans both the equity and option markets. This would contaminate the interpretation of our main results.
5. P42: add at the end of para1:
   CMA's daily closing CDS spreads can be accessed from either the Datastream or Bloomberg terminals. However, two issues are noticed and force us to merge these two databases. First, the CDS spreads from Datastream remain constant during two weeks period between 6 June to 17 June 2005 for the whole market. Second, the Bloomberg only has a limited cross-sectional coverage at beginning of 2005, and full cross-sectional coverage starts from June 2005. We further notice that the valid observations are consistent across these two databases.
6. We follow literatures in credit risk pricing area to choose proxy for risk-free rate, e.g. Blanco et al. (2005). I will further explore the impact of different alternative of risk-free rate on trading performance during GFC period in a future research project.
7. To the best of my knowledge, there is limited statistical evidence on the accuracy of previous CreditGrades model calibration result. Therefore, to compare the

performance between my proposed calibration procedure and the previous approach, I have to replicate the previous CreditGrades calibration procedure and compare the accuracy of ICDS using CDS spreads as a benchmark.

8. P64: add as a separate paragraph after para 1:
The examiner made a mistake (typo) in this comment. The Wall Street Crash was in 1987, not in 1929. We use 1987 Wall Street Crash as one of the motivations to investigate derivative-spot market linkage during recent GFC period. During the Wall Street crash of October 1987, the price discovery function of index futures market was severely impaired by the lack of liquidity and market making to facilitate the trading process. During the recent global financial crisis (GFC) that stemmed from the U.S. credit market in mid-2007, the CDS market was heavily criticised for its lack of regulation and transparency. However, to my best knowledge, no study has yet examined the price discovery function performed by the CDS market and its dynamic relation with the stock market during the course of the GFC.
9. Here is the correction: P67 para 2 second sentence: First, we test the significance of each strategy's risk-adjusted realised returns using Jensen's alpha estimated from Fama–French three factors model.
10. The non-synchronous data is trivial issue here. We use daily closing share price and CDS spreads. Acharya and Johnson (2007) point out that the U.S CDS market closes no later than 4:15 p.m. New York time, which closely matches 4 p.m. closing time of New York stock exchange. If this timing gap matters, the results should be more biased towards information flow from the equity to CDS market. However, we document strikingly different results that the CDS market dominates the equity market for price discovery.
11. The portfolio strategy we examined is indeed zero net investment. The number of stocks in the long and short positions may not equal. We overcome this issue by incurring $1 dollar exposure to each long and short position. Within the long and short positions, the stocks are equally weighted.
12. I will further explore this comment in my future work.
13. In this thesis, we investigate cross-markets information flow between the CDS and equity market. If we use implied volatility to estimate ICDS, then the interaction between the pairwise CDS and ICDS also involve information in the

option market. However, I will use this superior implied volatility when I convert this chapter into a research paper.

Responses to comments from Dr Wai-Man Liu

1. We do not observe large gap between the upper and lower bound of Hasbrouck's information share measure. We will include the actual number when it is converted into a research paper.
2. In the example of page 116, we trade stock only for a C1 firm; we trade CDS only for a C5 firm. The rationale behind this is to utilise the price discovery process to guide the capital allocation. For C1 firms, for which the CDS market dominates the stock market for price discovery, the mispricing correction is expected to take place in the stock market. Therefore, we trade the stocks only.
3. The structural credit risk pricing is also derived from arbitrage free and risk-neutral assumption. The CreditGrades model is further extension from the Merton (1974) model.
4. I will include bond recovery rate R into the calibration procedure in future work and compare the accuracy of ICDS estimates.
5. Our calibration only utilises past observation in the CDS market to determine $\bar{L}$ and λ. At time t, which corresponds to the last day of each calendar month, we calibrate $\bar{L}$ and λ to minimize the sum of squared difference between CDS_{it} and $ICDS_{it}$ over the past 30 days. We use the calibrated $\bar{L}$ and λ over the next 30 days to extract ICDS. As such, $ICDS_{it}$ does not contain any information from CDS_{it} and therefore the cointegration should not be driven by our calibration.

ERRATA

p 9, line 5: "dynamics" not "dynamics".
p 9, line 12: "informationally" not "informational"
p 11, line 9: "algorithms" not "algorithm"
p 17, line 1: "concern" not "concerns"
p 20, line 1, last para: add "the" before Merton.
p 42, line1: "swap" not "swaps"
p 46, line 2: the Mean CDS spread is "89.4561" not "89.4661"
p 49, 5th last line, "existing" not "exist"
p 71, 5th line from the last para: include "in" to give "…systematic patterns in cointegration…"
p 71, last line: "lag" not "leg"
p 74, first line to p 75, line 1, delete "are" to give "…with 28 firms indeed categorised…"
p78, line 4: use "attracted" to give "…C2 have jointly attracted…"
p 82, last para: "01-January-2005" not "0-January-2005"
p 83, 5th last line: use "C2 firms" not "C2 firm"
p 97, line 6: use "spread" and not "spreads"
p 97, 3rd line: use "Firms" not "Firm".
P 101, 3rd last line: "pair" not "pairwise"
P 102, 1st para, 4th line: delete "can"