UNIVERSITY OF AMSTERDAM

UvA-DARE (Digital Academic Repository)

Overrated credit risk: three essays on credit risk in turbulent times

Bongaerts, D.G.J.

Link to publication

Citation for published version (APA):
Bongaerts, D. G. J. (2010). *Overrated credit risk: three essays on credit risk in turbulent times*.

General rights
It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other than for strictly personal, individual use, unless the work is under an open content license (like Creative Commons).

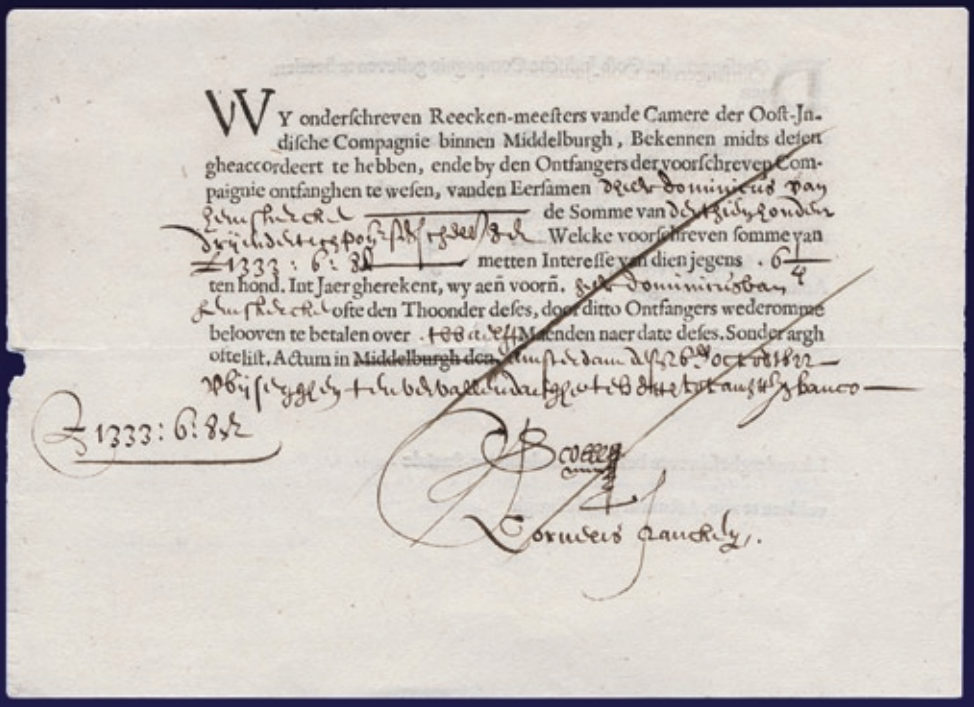
Disclaimer/Complaints regulations
If you believe that digital publication of certain material infringes any of your rights or (privacy) interests, please let the Library know, stating your reasons. In case of a legitimate complaint, the Library will make the material inaccessible and/or remove it from the website. Please Ask the Library: https://uba.uva.nl/en/contact, or a letter to: Library of the University of Amsterdam, Secretariat, Singel 425, 1012 WP Amsterdam, The Netherlands. You will be contacted as soon as possible.

UvA-DARE is a service provided by the library of the University of Amsterdam (http://dare.uva.nl)

Download date: 04 Nov 2020

OVERRATED CREDIT RISK

Three essays on Credit Risk in Turbulent Times


WY onderſchreven Reecken-meeſters vande Camere der Ooſt-Indiſche Compagnie binnen Middelburgh, Bekennen midts deſen gheaccordeert te hebben, ende by den Ontfangers der voorſchreven Compaignie ontfanghen te weſen, vanden Eerſamen
de Somme van
Welcke voorſchreven ſomme van
metten Intereſſe van dien jegens
ten hond. Int Jaer gherekent, wy aeñ voorñ.
ofte den Thoonder deſes, doen ditto Ontfangers wederomme
belooven te betalen over
Maenden naer date deſes. Sonder argh
oftelift. Actum in Middelburgh den
1333: 6: 8 12

Dion Bongaerts

Stellingen

Behorende bij het proefschrift

OVERRATED CREDIT RISK

Three Essays on Credit Risk in Turbulent Times

Dion Bongaerts

Amsterdam, 11 juni 2010

1. With respect to CDSs, there is a trade-off for commercial banks between capital management and liquidity management *(Chapter 2)*

2. In view of the order of magnitude and direction of the expected liquidity effect on the CDS price, the non-default components in Longstaff, Mithal and Neis (2005) for corporate bonds with illiquid CDSs are substantially downward biased *(Chapter 2)*

3. It is impossible to design an incentive compatible business model for credit rating agencies that achieves a socially optimal outcome *(Chapter 3)*

4. The growing body of regulation has led to an increased demand for information insensitive assets, thereby substantially weakening monitoring incentives *(Chapter 3)*

5. The result that a full Campell and Shiller (1988) decomposition is also possible in fixed income markets can help to derive market-implied expected loss rates with a minimum set of assumptions regarding pricing of credit risk *(Chapter 4)*

6. To avoid problems relating to overly persistent variables, the analysis by Campbell and Vuolteenaho (2004) should also have been done on a portfolio of a stock and a short futures contract with relatively short maturity *(Chapter 4)*

7. The fact that AAA securities hardly default is both a blessing and a curse

8. The funding system of Dutch universities has incentives to lower standards that are also found in the credit rating industry

9. Like equity holders, traders benefit from limited liability and large upside whereas risk-managers, like debt holders, suffer from large downside and limited upside

10. Letting politicians decide on financial regulation is likely to create more problems than the implemented regulation can ever solve

11. The relationship between the number of politically incorrect jokes and productivity of PhD students is parabolic and concave in nature

12. An interaction effect between normal finance and real estate finance PhD students increases productivity along the upward sloping part of the parabola in 11. for both groups

Overrated Credit Risk

Three essays on credit risk in turbulent times

ISBN: 978-90-8891-167-5
Published by: Uitgeverij BOXPress, Oisterwijk
Printed by: Proefschriftmaken.nl — Printyourthesis.com

Cover image: The image on the cover is an early corporate bond issued by the Middelburg Chamber of the Dutch East India Trading Company on October 26th 1622. It has a notional value of 1333.33 Flemmish pounds (which is equivalent to 8000 guilders), a coupon of 6.25% per annum and a maturity of 12 months. As such, it is one of the earliest corporate bonds.
Source: Beinecke Rare Book and Manuscript Library, Yale University

Overrated Credit Risk

Three essays on credit risk in turbulent times

ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Universiteit van Amsterdam
op gezag van de Rector Magnificus
mw. prof. dr. D.C. van den Boom
ten overstaan van een door het college van promoties ingestelde commissie, in het openbaar te verdedigen in de Agnietenkapel der Universiteit
op vrijdag 11 juni 2010, te 14:00 uur

door Dion Gert Jos Bongaerts
geboren te Leiderdorp

Promotie commissie:

Promotores:
Prof. dr. J.J.A.G. Driessen
Prof. dr. F.C.J.M. de Jong

Overige leden de commissie:
Dr. A. Beber
Prof. dr. A.W.A. Boot
Dr. K.J.M. Cremers
Prof. dr. A. Lucas

Faculteit der Economie en Bedrijfskunde

Acknowledgements

After slightly more than four years, a memorable period in my life comes to an end with the completion of my dissertation. During this period, a combination of academic research at UvA, applied work at ABN-AMRO, coursework at Tinbergen Institute, a stimulating seminar series, numerous conferences as well as an eight months visit to Yale provided me with the perfect conditions to learn about the mechanics of financial markets and their place in the economy as a whole.

Crucial in this whole process has been the excellent guidance I have had over those years from my promotores Joost and Frank, both in academic as well as personal aspects. Their way of providing valuable advice when asked for while leaving much of the initiative to me, stimulated learning while heeding me from large missteps. Thanks also go to my teamheads at ABN-AMRO, Pieter and Erwin for creating the opportunity for a dual track and introducing me to Joost and Frank.

All three places where I spent considerable time during my PhD track provided a stimulating and pleasant working environment. Many thanks to my colleagues, faculty, support staff and PhD students at Finance group of University of Amsterdam, ABN-AMRO enterprise risk modeling and Yale International Center for Finance. Special thanks go to Will and Martijn who, apart from being great co-authors, gave me the opportunity to visit Yale, made me feel very welcome in New Haven and enhanced my understanding of financial markets, research methodologies and the industrial organization of business schools. Special thanks also go to Erwin for our good corporation on our joint research as well as the implementation trajectory of the private equity model at ABN-AMRO.

Besides a good working environment, the finance group at UvA was also a nice environment on a more personal level. Besides my promotores key contributions came from Yolanda for cheering me up and making the bureaucratic chaos easier to digest, Zach for being a good friend and his continuous efforts to engage PhD students and my PhD friends Marcel, T.C., Betty, Razvan, Christel, Mario, Erik, Frans and Xiaolong for all the enlightening discussions about research, fun, random

beer-events, politically incorrect discussions and loads of bad jokes. I am also very much indebted to my close friends that have a long track record of sharing joy, sorrow and advise as well as joining trips, feasts, practical jokes, parties, some time at Yale and discussions about basically everything. Karel, Paul, Afke, Dine, Yvonne, Rik, Ronald, Dennis, Rene, Heleen, Jeroen, Felix, thank you very much!

The final paragraph is reserved for those that provided me with an incredible amount of support during those four years. Of course my lovely girlfriend Jing that gave me so much love and reminded me to care about more than just my dissertation when necessary. And finally the most deserved thanks go to my parents and sister for their continuous and unconditional love and support.

Contents

1 Introduction **1**

1.1 Financial regulation 1

1.2 Credit Derivatives 2

1.2.1 The CDS market 2

1.2.2 The CDO market 4

1.3 Credit Ratings 5

1.4 Fair Value Accounting 6

2 Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market **9**

2.1 Introduction 9

2.2 A model for pricing liquidity in asset and derivative markets 13

2.2.1 Motivation 13

2.2.2 Assumptions and notation 14

2.2.3 Asset pricing implications: Benchmark model 15

2.2.4 Example 18

2.2.5 Model extension I: Long-horizon investors 19

2.2.6 Model extension II: Idiosyncratic background risk and hedging demand 21

2.3 Applying the theory to the CDS market 23

2.3.1 Motivation and theoretical predictions 23

2.3.2 Estimation method 24

2.4 Data and construction of main variables 25

2.4.1 Data description 25

2.4.2 Portfolio construction 26

2.4.3 CDS portfolio return and transaction costs 27

2.4.4 Non-traded credit risk factor and non-hedge asset 29

2.4.5 Time-series model of liquidity 29

2.4.6 Expected CDS returns . . . 30
2.4.7 Alternative CDS liquidity measures . . . 31
2.5 Empirical Results . . . 32
2.5.1 Betas, costs and expected returns . . . 32
2.5.2 Benchmark results . . . 33
2.5.3 Backing out structural parameters . . . 35
2.5.4 Robustness checks . . . 36
2.5.5 Bond liquidity and hedging pressure . . . 38
2.6 Conclusion . . . 40
2.7 Tables . . . 41
2.8 Figures . . . 47
2.9 Appendix . . . 52
2.9.1 Proof of Theorems I to III . . . 52
2.9.2 Taylor approximations . . . 55
2.9.3 GMM standard errors . . . 55
2.9.4 Repeat sales method . . . 56
2.9.5 Risk-free rates and default probabilities . . . 57

3 Tiebreaker: Certification and Multiple Credit Ratings 59
3.1 Introduction . . . 59
3.2 Motivation . . . 63
3.2.1 Credit Rating Agencies and Regulation . . . 63
3.2.2 Why Multiple Ratings Matter . . . 65
3.2.3 Related Research . . . 68
3.3 Sample Construction and Methodology . . . 71
3.3.1 Measures and controls . . . 71
3.3.2 Data and filters . . . 72
3.4 Empirical results . . . 75
3.4.1 Rating Differences and Rating Information . . . 75
3.4.2 Likelihood for Having a Fitch Rating . . . 78
3.4.3 Price Effects of Certification . . . 81
3.4.4 Financials . . . 83
3.5 The nature of certification . . . 84
3.5.1 Information-sensitive versus Information-insensitive securities 84
3.5.2 Empirical implications . . . 85
3.6 Conclusion . . . 88
3.7 Figures . . . 91

3.8 Tables 93

4 Return decompositions: Evidence from the corporate bond market 109

4.1 Introduction 109
4.2 Literature review and contribution 112
4.3 Cash flow and discount rate news in corporate bonds 115
4.3.1 Campbell-Shiller approximation for corporate bonds 115
4.3.2 Unexpected return decomposition 117
4.3.3 Excess returns 118
4.4 Empirical approach 119
4.4.1 Discount rate news 119
4.4.2 Direct cash flow news 121
4.5 Data 122
4.6 Results 123
4.6.1 VAR results 123
4.6.2 Direct cash flow news 126
4.6.3 Accounting for persistent variables 127
4.6.4 The case with a 1 month treasury 128
4.6.5 Alternative variance decomposition 128
4.7 Conclusion 129
4.8 Tables 131
4.9 Appendix 140
4.9.1 Derivation of continuous compounded par coupon duration . 140

5 Conclusion 141

5.1 Summary of the main findings 141
5.2 Implications of the findings 142
5.3 Suggestions for future research 144

6 Samenvatting (Summary in Dutch) 145

Bibliography 146

Chapter 1

Introduction

Despite the long history of debt contracts and their simple structure, debt markets in general do not attract a lot of media attention. Typically, non-professional investors would track the performance of a stock market index, but only few would track the credit spreads on AA rated corporate bonds. However, when debt markets make it to the news headlines, it is usually because of bad news. This is not surprising since debt market instruments usually have only a limited upside and a large potential downside. This was no different when debt markets started to hit the news headlines more regularly from the summer of 2007 on, bringing tidings of the largest financial havoc since the great depression.

Each chapter in this dissertation will be related to trends in credit markets that contributed to the onset of the crisis. To place the chapters in the proper context, I will therefore give a short description of the evolution of credit markets and the associated build-up of the crisis. Throughout I will emphasize how the chapters in this thesis relate to the larger picture described below.

1.1 Financial regulation

As mentioned before, debt markets usually hit the news when they experience problems. Problems in debt markets can very quickly lead to problems affecting the real economy. The reason for this is that banks are major intermediaries in these markets and banks are vital in supplying credit to practically all entities in an economy. However, most banks are privately held and have a for-profit nature. Since shareholders have limited liability and it is hard to coordinate actions for a substantial part of the debtholders (namely depositors), a bank has an incentive to engage in excessive risk taking thereby expropriating debtholders. Moreover, the

excessive risk taking is sub-optimal from a social welfare perspective since bank failures cause negative externalities on the economy as a whole. This insight led to the development of several forms of financial regulation. An important part of the regulation implemented was the institution of the so called Basel accords developed by the Bank for International Settlements. The first Basel accord dates from 1988 and was a first step towards requiring banks to hold capital based on the risk of the asset side of their balance sheet. This accord however suffered from the crudeness of its risk categories. For example, a AAA rated corporate bond would require substantially more capital than a Turkish government bond, whereas the latter is likely to be riskier. The lack of risk-sensitivity of the first Basel accord led to a practice called regulatory arbitrage. This entails selling off safe credit exposure with a relatively high capital consumption while keeping risky debt with a relatively low capital consumption. To fix this loophole, in recent years, a second Basel accord has been developed with more risk sensitive capital charges.

1.2 Credit Derivatives

Since profit for a bank originates to a large extent from fees, most banks would be happy to engage in large volumes of loan-making but afterward get rid of the loans on the balance sheet to free up capital for new loans, especially for the loans that require much capital relative to their expected return. To this extent, credit derivatives have been developed, which have been explicitly accommodated within existing regulation by an amendment to the first Basel accord. The two most popular credit derivatives are Credit Default Swaps (CDSs) and Collateralized Debt Obligations (CDOs). Both are used to transfer credit risk. Below I will discuss the workings of these credit derivatives.

1.2.1 The CDS market

The CDS is the simplest of the two. It is basically an insurance against losses due to default on a loan or bond. In ideal conditions a CDS can be replicated with a credit risky bond and a floating rate treasury. Since a CDS is a derivative, it is relatively easy to short credit risk by buying a CDS, something that is rather difficult and costly in the corporate bond market and impossible with bank loans. This is exactly what one wants to do to get rid of credit risk on the balance sheet. Therefore the CDS market expanded quickly and attracted many participants. Another benefit of this market that is often referred to is its liquidity. Illiquidity

has always been a feature of the corporate bond market (see for example Chen, Lesmond and Wei (2007) and De Jong and Driessen (2005)). However, the relatively standardized CDS contracts with equal access for short and long investors to the market led in general to more liquidity than in the corporate bond market. Consequently, several studies, like for example Blanco, Brennan and Marsh (2005) and Longstaff, Mithal and Neis (2005) have ignored liquidity effects in CDS markets and have used CDS spreads as pure measures of (priced) credit risk. Still, liquidity has always been orders of magnitude smaller than in the equity market. Therefore, liquidity in the CDS market might still be an important factor for pricing, as it also is in the more liquid equity market (see for example Amihud and Mendelson (1986) and Acharya and Pedersen (2005)). In contrast to the stock and bond markets which are in positive net supply, the CDS market is a derivative market which is in zero net supply. Consequently, a liquidity effect on pricing in this market should be the result of the tolerance towards liquidity of the one side of the market relative to the other, rather than the average tolerance towards liquidity of the whole market. Chapter 2 develops theory for the pricing of expected liquidity and exposure to liquidity risk in markets with substantial short selling, thus including derivatives markets. The pricing of liquidity depends crucially on the wealth, risk aversion and investment horizon of long versus short investors, whereas for the pricing of liquidity risk also the exposure to non-tradable background risk is important. While the asset pricing equilibrium model is applicable to all assets with substantial short-selling, the impact of liquidity on pricing differs between positive net supply assets like stocks and bonds on the one hand and zero net supply assets like derivative contracts on the other. The model is also taken to the data in the CDS markets and indeed finds a strong effect of liquidity on pricing. In particular, higher expected liquidity costs lead to a higher spread to be pocketed by the protection seller.

1.2.2 The CDO market

An important motivation for analysis done in Chapter 3 is the recent discussion about credit ratings in the market for CDOs and other similar products. Therefore, I will discuss the working of CDOs here as well. The CDO is a more complex credit derivative and can either be synthetically constructed from CDSs or be set up as a separate operating entity. The increased focus on credit risk regulation had led to increased research, both in academia as well as within financial institutions. Meanwhile, increased regulation and sophistication of bilateral corporate financial contracts had generated a high demand for high quality assets, because they could for example easily be pledged as collateral in a repo. To this end, a CDO was invented. The basic idea is very simple. A pool of loans, bonds or other credit risky instruments are selected. These form the asset side of the CDO. Next, investors can purchase tranches in the CDO with different seniority. During the life of the CDO, coupon income from the asset side is used to pay interest to the tranche holders in order of their seniority. If losses occur, they first accrue to the tranche with lowest seniority (equity tranche) and then move up the capital structure. Consequently, the tranche with the highest seniority (super senior tranche) is much safer than the underlying pool of assets. The whole process of slicing and dicing a portfolio of mainly illiquid loans is called securitization. In recent years, these securities have become increasingly popular. Not only regular loans were securitized this way, but also residential mortgages (a CDO on a pool of residential mortgages is called a Residential Mortgage Backed Security or RMBS), commercial mortgages (CMBS) and other tranches of CDOs (CDO squared) or even tranches of CDO squared (CDO cubed). Officially, the claim was that by selling off CDO tranches, risk was transferred out of the banking system, leading to a better diversification of risk across the society. In practice however, banks were trading these securities also amongst themselves or holding on to certain tranches. An important reason was that the total capital to be held for all tranches together was typically lower than the capital to be held for the original portfolio. Thus, there was another opportunity for regulatory arbitrage. This effectively led banks to engage in more risk taking by levering up, which in the boom time from 2004 up to 2007 has led to exceptionally high profits for banks. However, when markets collapsed afterwards, the lack of capital within banks contributed severely to the gravity of the crisis.

1.3 Credit Ratings

Credit ratings have been used for a long time in debt markets. After having emerged as independent evaluators for credit quality of railway bonds around the start of the twentieth century, credit rating agencies (CRAs) have started to cover the whole spectrum of corporate as well as sovereign debt. Whereas initially investors generated the demand for ratings, around the great depression, it was the Office of the Comptroller of the Currency (OCC) that spurred the development of rating agencies by making credit ratings input for regulation about investment restrictions. Up to the seventies, the rating agencies made money by selling books containing credit ratings to investors. Whereas initially investors demand created incentives for accuracy, the regulatory need for ratings reduced these incentives already somewhat. In the seventies, when the photocopiers became widely available and affordable, the business model of credit rating agencies changed to an issuer-pays-model. This means that debt issuers pay to have their debt rated. Although figures about rating fees are not freely available, anecdotal evidence reports fees of between 2 and 4 bps of notional issued. As around the great depression, the increase in regulation by the Basel accords as well as the sophistication of corporate credit and collateral arrangements has made credit ratings more and more important (see for example Partnoy (2001)). Also the capital to be held against CDO tranches was largely based on credit ratings. Since these products were substantially harder to evaluate, rating agencies charged substantially higher fees for rating CDOs, anecdotal evidence reports figures ranging between 13 to 16 bps of notional. The cutoff points in the capital structure of the CDOs became extremely important for the profitability of the CDO for the issuing bank and the CRAs were often actively involved in this process by giving advise rather than only doing the rating exercise at the end of the process. When the crisis hit and many highly rated CDO tranches suffered losses, issuing banks were accused of shopping for the best ratings while credit rating agencies were accused of competing on standards rather than price (see Skreta and Veldkamp (2009) for a theoretical motivation for excessive rating shopping in markets for structured products). However, due to the lack of data and the complexity of the products, these claims and accusations are hard to certify empirically. However, in the corporate bond market which is simpler in structure and for which more data is available, not all bonds are rated by the same credit rating agency, while corporate bonds are also subject to many regulations. This led to the natural question to explain the difference in CRA coverage of corporate bonds. Chapter 3 of this thesis investigates this

question. Several academic studies provide motivations for applying for an extra rating. For example Guntay and Hackbarth (2006) show that uncertainty about firm fundamentals leads to higher credit spreads, indicating a possible role for an extra rating agency to reduce uncertainty. Existing literature on unsolicited ratings like Bannier, Behr and Güttler (2009) and Poon and Firth (2005) finds that lower unsolicited than solicited ratings are due to rating shopping, suggesting that this could be going on for multiple ratings. Finally, Kisgen and Strahan (2009) show the importance of ratings related regulation by investigating the natural experiment when the rating agency Dominion was granted an official status. Chapter 3 first derives empirical predictions for the three motivations for acquiring extra ratings mentioned above. Empirically, almost all corporate bonds receive a rating from both Moody's and S&P, while only 40% to 60% of the bonds are rated by Fitch. When testing the empirical predictions, the main driver for getting an extra rating turns out to be compliance by regulation, in particular to qualify as investment grade or to limit the possibility of losing this qualification. Evidence is found against hypotheses bringing forward information production or market-wide rating shopping as motives for obtaining extra ratings. Despite suggesting inefficiencies, these and additional findings are consistent with a framework in which the extra rating provides extra information about the information-sensitiveness of the bond rather than the credit quality and thereby resolves a partial market breakdown.

1.4 Fair Value Accounting

Another factor that has often been referred to as a factor that aggravated the crisis is the fair value accounting practice introduced in recent years as laid out in IFRS and FASB rule 157. Since especially financial institutions are rather intransparent, recent investor protection oriented legislation aimed to improve transparency of balance sheets by showing assets at market-equivalent prices rather than historical cost. The degree to which this was required depended among others on the intended holding period of the asset. Typically, assets intended to be held to maturity could be held at historical cost, whereas trading assets and assets labeled as "available-for-sale" would be reported at market value. The difference between trading assets and available-for-sale assets is that value changes in trading assets directly flow through the profit and loss statement whereas value changes for "available-for-sale" assets are accumulated in a separate account on the balance sheet that is deducted from shareholders' capital, but these value changes do not show up in the profit and loss statement. Typically, CDO tranches were labeled

available-for-sale, even though many of them were intended to be held till maturity, but the hold-to-maturity label would limit the use and flexibility of these assets. When the crisis hit, mainly the CDO tranches decreased in value significantly. Consequently shareholders' equity shrunk substantially leading to immediate capital shortages for many banks. This drop of available capital would be justified if the drop in market valuation of these securities was purely based on news about default and recovery rates (that is, cash flow news). However, when a substantial part of the drop in market value was due to risk aversion going up or outright panic (that is, discount rate news), bank capital may have suffered more than necessary since these factors do not immediately affect the long term solvency of the bank. Earlier work by Collin-Dufresne, Goldstein and Martin (2001) indeed shows that for corporate bonds, only a small fraction of the changes in credit spreads can be explained by changes in fundamentals. In equity markets, there is a large body of academic literature decomposing stock returns into cash-flow and discount rate news, starting from Campbell and Shiller (1988). These decompositions typically depending on predictive regressions in a VAR setup (see for example Campbell and Vuolteenaho (2004)) have recently been criticized by Chen and Zhao (2009), for example because persistent variables can lead to spurious results. Meanwhile, several contributions have been made to the estimation of the related so called fair value models (see for example Van Binsbergen and Koijen (Forthcoming)) that also originate from the results in Campbell and Shiller (1988). Chapter 4 builds up a framework to explore how unexpected corporate bond returns can be decomposed into a cash flow news and discount rate news part to shed more light on how both components affect debt markets. Theoretically, the influence of persistent variables should be substantially smaller due to the limited maturity of these securities. The approach developed works well for corporate bonds compared to the stock market, but in some cases still suffers from the disruptive effects of overly persistent state variables. Nevertheless, the limited maturity of corporate bonds reduces the impact of overly persistent state variables substantially. A variance decomposition shows that in general, a large part of corporate bond returns is due to discount rate news. A theoretical side result of this chapter allows a whole range of tools developed to estimate present value models for the stock market to be applied on the corporate bond market.

Chapter 2

Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market

This chapter is based on Bongaerts, De Jong and Driessen (2010).

2.1 Introduction

The relation between liquidity and asset prices has received considerable attention recently. Much less is known about liquidity effects in derivative markets. This chapter provides a theoretical asset pricing model of liquidity effects in both primary asset markets and derivative markets, incorporating short selling and non-traded risk exposure. We derive new and testable implications for the pricing of liquidity and test these for one of the key derivative markets, the credit default swap market.

This chapter has two main contributions. The first contribution is a new equilibrium pricing model for assets and derivatives that incorporates liquidity risk and short-selling due to hedging of non-traded risk. This model builds on the 'Liquidity-CAPM' of Acharya and Pedersen (2005), who only consider investors with long positions in assets that are in positive net supply, in which case illiquidity always leads to lower asset prices and higher expected returns. We show that, if some investors optimally short assets, the effects of liquidity are more complicated and can be zero, positive or negative. Obviously, allowing for short positions is essential for derivative assets, but our framework is also relevant for positive-net-supply assets with considerable short-selling activity. Our theory thus also adds

to the literature on asset pricing and liquidity.[1]

In the equilibrium framework heterogenous investors use some assets to hedge exposure to a non-traded risk factor. We derive that the expected return on these 'hedge assets' can be decomposed into priced exposure to non-hedge asset returns, hedging demand effects, an expected liquidity component, and several liquidity risk premia. The first main theoretical result is that the sign of these liquidity effects depends on heterogeneity in investors' non-traded risk exposure, risk aversion, horizon and wealth. For example, if the investors who are long in the hedge assets are more aggressive (due to either higher aggregate wealth or lower risk-aversion) or have a shorter horizon than the 'short' investors, the effect of expected liquidity on expected returns is positive. The intuition for this result is that the aggressive investors are most sensitive to transaction costs and thus need to be compensated for these costs in equilibrium. This result holds for both positive-net-supply assets and derivatives. Our second main theoretical result is that, if the hedge assets are derivatives in zero net supply, some of the liquidity risk covariances have a zero premium. Specifically, the covariance between the return on a derivative (net of transaction costs) and the return on the total derivative market return (net of market-wide transaction costs) has a zero premium in case of zero-net-supply assets. Another liquidity risk covariance, the covariance between transaction costs on a given derivative and the return on the non-traded risk factor, does carry a risk premium however, whose sign depends on the investors' non-traded risk exposures.

Our model also generates interaction effects between hedging demand and liquidity premia. We show that increased hedging demand on the one hand implies that some investors will short hedge assets to hedge, but that on the other hand this hedging pressure pushes up expected returns which increases the speculative demand of investors. The net effect can either be an increase or decrease in the net aggressiveness of the 'long' versus 'short' investors and the premium on expected liquidity. If hedging demand varies across assets, the model thus generates cross-sectional effects in the pricing of liquidity and we test for such effects empirically. Of course, we also get a standard hedge pressure effect in our model because the covariance of an asset's return with the non-traded risk factor is priced. We thus add to existing work on hedging pressures in derivative markets (see, for example, De Roon, Nijman and Veld (2000) and Gârleanu, Pedersen and Poteshman (2009))

[1]For the equity market, the pricing of liquidity risk has been studied by Amihud (2002), Acharya and Pedersen (2005), Pastor and Stambaugh (2003), Bekaert, Harvey and Lundblad (2007), and Korajczyk and Sadka (2008), amongst others. De Jong and Driessen (2007), Downing, Underwood and Xing (2005) and Nashikkar and Subrahmanyam (2006) study on the pricing of liquidity in corporate bond markets, amongst others.

by incorporating liquidity effects.

Our second main contribution is an empirical test of this theoretical framework for an important class of derivative assets, credit default swaps (CDS). By now, the CDS market is one of the largest derivative markets with a total notional amount of approximately 31 trillion USD around August 2009 according to the Depository Trust & Clearing Corporation. This has induced researchers and practitioners to use CDS spreads as pure measures of default risk (for example, Longstaff et al. (2005) and Blanco et al. (2005)). However, as discussed below, we find that part of the CDS spread reflects liquidity effects.

Empirical work on liquidity and derivative assets is scarce. Two recent papers empirically assess the impact of liquidity on CDS spreads, Tang and Yan (2007) and Chen, Cheng and Wu (2005). Tang and Yan (2007) regress CDS spreads on variables that capture expected liquidity and liquidity risk, and find that illiquidity leads to higher spreads. Chen et al. (2005) estimate the impact of liquidity and other factors on CDS spreads using a term structure approach. They find that premia for liquidity risk and the expected liquidity premium are earned by the CDS buyer. The identification of the liquidity risk premium comes from the term structure of CDS spreads, whereas our method follows the standard procedure of identifying risk premia from expected excess returns. Another recent paper by Das and Hanouna (2009) develops a framework in which lower equity market liquidity leads to higher CDS prices and confirms this mechanism empirically. Bühler and Trapp (2009) estimate a reduced-form CDS pricing model that allows for an interaction of CDS and bond liquidity effects. Turning to other derivative markets, Çetin, Jarrow, Protter and Warachka (2006) add illiquidity to the standard Black-Scholes framework and Brenner, Eldor and Hauser (2001) investigate the effect of non-tradability on currency derivatives. Deuskar, Gupta and Subrahmanyam (2009) find empirically that illiquid interest rate options trade at higher prices than liquid options, and also find evidence for commonality in liquidity of different options. this chapter contributes to this literature by developing an equilibrium pricing model and testing this structural asset pricing model for the CDS market. Our use of an asset pricing model allows for an immediate interpretation of our results in terms of hedging pressure effects, liquidity and liquidity risk premia.

In addition to our two main contributions, the empirical analysis makes several methodological contributions. We derive expressions for realized and expected excess returns on CDS positions. In particular, we show how to construct expected excess returns from the CDS spread level, corrected for the expected loss where we use Moody's-KMV Expected Default Frequencies (EDFs) to assess default

probabilities. As argued by Campello, Chen and Zhang (2008) and De Jong and Driessen (2007), this procedure gives more precise estimates of expected returns than averaged realized returns. On the econometric side, we use a repeat sales method to construct unbiased and efficient estimates of portfolio CDS returns from the unbalanced panel of individual CDS quotes.

We use a representative dataset of CDS bid and ask quotes for U.S. firms and banks over a relatively long period (2004-2008). We only rely on the most standard 5-year contracts. Applying the repeat sales method to these data, we construct CDS returns and bid-ask spreads for portfolios sorted on a range of variables capturing default risk and liquidity. The level and innovations of the bid-ask spreads are used to construct measures of expected liquidity and liquidity risk. We estimate our asset pricing model using the Generalized Method of Moments and find significant exposure to expected liquidity and liquidity risk. Our key empirical finding is that sellers of credit protection receive an illiquidity compensation on top of the compensation for default risk. Most of the liquidity effect comes from the expected liquidity component, and the effect of expected liquidity implies that credit protection sellers are more aggressive than protection buyers, either due to more wealth, lower risk-aversion, or shorter horizons. The theoretical model can fully explain the empirical effect of expected liquidity provided that holding periods are not too long. We also confirm that several parameter restrictions imposed by the theory are not violated by our empirical estimates. For example, the theory predicts that the covariance between derivative transaction costs and derivative-market-wide transaction costs carries a zero premium, and we cannot reject this empirically.

We perform an extensive series of robustness checks that support our results. Our benchmark results imply that the expected liquidity effect on expected returns is 0.175% per quarter on average, while across all robustness checks the lowest expected liquidity effect is 0.060% per quarter and still strongly statistically significant. We also control for corporate bond market liquidity and find evidence of hedging demand effects that are in line with our theory, with some evidence for interaction between hedging demand and liquidity effects as discussed above.

Our results are robust to inclusion of the two last quarters of 2008. In this economic crisis period, CDS spreads and bid-ask spreads increase dramatically, amongst others due to a strong increase in counterparty risk and deleveraging of many financial institutions. The liquidity effects remain statistically significant and even become larger in some cases.

The remainder of this chapter is structured as follows. Section 2.2 introduces our theoretical model. Section 2.3 discusses in detail how the model can be applied and estimated for the CDS market. Section 2.4 discusses the data and construction of CDS returns and liquidity measures. Section 2.5 presents the results of the empirical analysis and Section 2.6 concludes.

2.2 A model for pricing liquidity in asset and derivative markets

2.2.1 Motivation

In this section we derive an asset pricing model in a setting with transaction costs, heterogeneous agents and multiple assets. The model has two key ingredients that differentiate it from the liquidity CAPM of Acharya and Pedersen (2005) (henceforth AP). First of all, some of the assets can be derivative assets in zero net supply. Second, agents have exposure to a non-traded risk factor. We introduce this non-traded risk factor so that, in equilibrium, a fraction of the agents optimally hold short positions in some assets in order to hedge the non-traded risk exposure. This contrasts with AP whose assumptions imply that all agents hold long positions in equilibrium.

After deriving the implications of this benchmark setup, we study two extensions. First, we incorporate long-horizon investors who are not exposed to transaction costs. Second, we allow part of the non-traded risk to be idiosyncratic.

In the empirical analysis we apply our model to a setting where agents have a non-traded exposure to credit risk. For example, commercial banks have exposure to non-traded bank loans and illiquid corporate bonds, which they can partially hedge using credit default swaps. Other agents, such as hedge funds or insurance companies, have little or zero exposure to non-traded credit risk and may sell credit default swaps to commercial banks, thus earning a credit risk premium.

Even though we test our model empirically on a derivative market, the theory applies more generally to asset markets with positive supply, but where some agents short assets to hedge their non-traded risk exposure. A pricing model similar to the liquidity CAPM of AP is a special case of our model, since in AP all assets are in positive net supply and agents have no non-traded risk exposure.

2.2.2 Assumptions and notation

1. *AGENTS.* The economy has N agents with CRRA preferences. Agents live for one period, invest at time $t-1$ and consume at t (this assumption will be relaxed in one of the model extensions). We allow for heterogeneity in relative risk aversion γ_i and initial wealth w_i.

2. *TRADED ASSETS.* There are K traded assets, divided into two subsets without loss of generality. For the first subset of K_b assets, all agents optimally hold long positions in equilibrium. We refer to these assets as basic assets or non-hedge assets. The second subset has K_h assets, and some agents optimally hold short positions in these assets. We refer to these assets as hedge assets. For simplicity, each investor can be either optimally long in all hedge assets or short in all hedge assets.[2] Again, this assumption will be relaxed in one of the model extensions. Using δ_i to denote a diagonal matrix with the sign of the hedge asset positions of investor i on the diagonal, we thus have either $\delta_i = I$ or $\delta_i = -I$.[3] Aggregate supply is denoted by S_b for non-hedge assets and S_h for hedge assets. Obviously, for non-hedge assets supply has to be positive. For hedge assets, aggregate supply could be zero, in which case these are derivative assets, but it can also be nonzero. To maintain tractability, we assume that all asset returns are jointly lognormally distributed.[4]

3. *NON-TRADED RISK EXPOSURE.* Agent i has an exposure of q_i to non-traded background risk with log-return equal to $r_{n,t}$, where $r_{n,t}$ is the return on a single non-traded risk factor. This assumption is necessary to generate nonzero positions in hedge assets. If the exposure q_i varies across agents or if agents have different risk aversion, their hedging demands will differ and they will hold different hedge asset positions if the hedge asset returns correlate with $r_{n,t}$. For example, agents with large positive q_i may hold short positions in hedge assets, while agents with zero or negative non-traded exposure take long positions in the hedge assets. We think of $r_{n,t}$ as the return on a diversified portfolio of very illiquid assets that

[2]This assumption is made only to generate tractable expressions that allow for a simple empirical test of liquidity effects. It is straightforward to include more than two groups in the theory.

[3]Of course, the sign of the optimal portfolio weights is determined in equilibrium. In Appendix 2.9.1 we show the necessary conditions (equation (2.29)). Essentially, the 'long' group of investor should have zero or small hedging demand while the 'short' group needs to have sufficient hedging demand to ensure that they always short derivatives.

[4]In this one-period setup, similar asset pricing implications are obtained without distributional assumptions if we assume mean-variance investors. The assumption of CRRA investors and lognormal returns allows us to extend the model to a setting with long-horizon investors in a simple way.

are not traded in equilibrium. For our credit risk application, these can be bank loans or illiquid corporate bonds.

4. *TRANSACTION COSTS.* Following Acharya and Pedersen (2005), the one-period investors investing at $t-1$ pay transaction costs proportional to the current price when closing the position at time t. Transaction costs are stochastic. The percentage costs are denoted by the K_b-dimensional vector $C_{b,t}$ for non-hedge assets and K_h-dimensional vector $C_{h,t}$ for hedge assets. Transaction costs represent both the bid-ask spread and search costs, which are relevant in over-the-counter markets (see Duffie, Gârleanu and Pedersen (2005)). Both long and short holders pay transaction costs. This can be motivated by the existence of (implicit) market makers who only play a role as intermediary, i.e. they earn the bid-ask spread and hold zero net positions in the hedge assets. Alternatively, our assumption that both long and short investors pay transaction costs is appropriate in a setting without market makers if transaction costs fully represent search costs. The net log-returns of the agents (in excess of the risk-free rate) are then given by the vectors $r_{b,t} - c_{b,t}$ for the basic assets and $r_{h,t} - c_{h,t}$ for the investors who are long in the hedge assets, and $-r_{h,t} - c_{h,t}$ for the investors who are short in the hedge assets, with log-transaction costs defined as $c_{h,t} = -\ln(1 - C_{h,t})$.

2.2.3 Asset pricing implications: Benchmark model

We now derive the main asset pricing implications for this benchmark economy. We focus on the implications for the hedge asset returns, since these are the relevant assets for our empirical analysis. Using the standard approximation of log-portfolio returns (Campbell and Viceira (2002), page 29), investor i with CRRA preferences and relative risk aversion γ_i trades off the mean and variance of the log portfolio return. As shown in Appendix 2.9.1, investor i thus maximizes

$$x_i' E(r_b - c_b + \tfrac{1}{2}\sigma_b^2) + y_i' E(r_h - \delta_i c_h + \tfrac{1}{2}\sigma_{i,h}^2) - \tfrac{1}{2}\gamma_i Var(x_i'(r_b - c_b) + y_i'(r_h - \delta_i c_h) + q_i r_n) \tag{2.1}$$

over positions x_i in non-hedge assets and positions y_i in hedge assets, where σ_b^2 is the diagonal of $Var(r_b - c_b)$ and $\sigma_{i,h}^2$ the diagonal of $Var(r_h - \delta_i c_h)$. To simplify notation, we drop all time subscripts. In particular, note that the expectation and variance in (2.1) are conditional on the information set at time $t-1$.

Imposing the market clearing condition and the optimality conditions for each investor, we can derive the asset pricing equation for the hedge assets.

Theorem I. *Given assumptions 1 to 4, investors maximizing the function in*

(2.1) and using a Taylor-expansion of $Var(\widehat{r}_h - \widehat{c}_h)\, Var(\widehat{r}_h - \delta_i \widehat{c}_h)^{-1}$ around $\widehat{c}_h = 0$, *the vector with expected excess log-returns on the hedge assets,* $E(r_h)$, *satisfies in equilibrium*

$$\begin{aligned} E\left(\widehat{r}_h\right) + \tfrac{1}{2}\sigma^2_{\widehat{r}_h} + F_h - AE(\widehat{c}_h) \;=\; & \lambda\left[Cov(\widehat{r}_h, r_n) - ACov(\widehat{c}_h, r_n)\right] + \\ & \zeta_0\left[E(\widehat{c}_h) - AE(\widehat{r}_h + \tfrac{1}{2}\sigma^2_{\widehat{r}_h})\right] + \\ & \kappa_0\left[Cov(\widehat{c}_h, r_n) - ACov(\widehat{r}_h, r_n)\right] + \\ & \phi(I - H_1)^{-1} Cov(\widehat{r}_h - \widehat{c}_h, \widehat{r}_m - \widehat{c}_m) \end{aligned} \tag{2.2}$$

where F_h *is a vector of convexity corrections (see Appendix 2.9.1) and*

$$\widehat{r}_h = r_h - \beta_{r_h, r_b}(r_b - c_b),\ \widehat{c}_h = c_h - \beta_{c_h, r_b}(r_b - c_b) \tag{2.3}$$

where $\beta_{r_h, r_b} = Var(r_b - c_b)^{-1} Cov(r_h, r_b - c_b)$ *and* $\beta_{c_h, r_b} = Var(r_b - c_b)^{-1} Cov(c_h, r_b - c_b)$. *The market-wide hedge asset return and transaction costs are defined as* $\widehat{r}_m = S_h{}'\widehat{r}_h / \iota' S_h$ *and* $\widehat{c}_m = S_h'\widehat{c}_h / \iota' S_h$ *if* $S_h \neq 0$ *and equal to zero otherwise. The following asset pricing parameters are scalars, and defined as*

$$\begin{aligned} \lambda &= \frac{1}{\eta}\sum_{i=1}^{N} w_i q_i \\ \zeta_0 &= \frac{1}{\eta}\left(\sum_{i:\delta_i = I} w_i \gamma_i^{-1} - \sum_{i:\delta_i = -I} w_i \gamma_i^{-1}\right) \\ \kappa_0 &= \frac{1}{\eta}\left(\sum_{i:\delta_i = -I} w_i q_i - \sum_{i:\delta_i = I} w_i q_i\right) \\ \phi &= \frac{1}{\eta}\iota' S_h \geq 0 \\ \eta &= \sum_{i=1}^{N} w_i \gamma_i^{-1} > 0 \end{aligned} \tag{2.4}$$

and with $A = (I - H_1)^{-1} H_1$, $H_1 = (C + C')Var(\widehat{r}_h)^{-1}$, *and* $C = Cov(\widehat{c}_h, \widehat{r}_h)$.

Proof: Appendix 2.9.1.

Note that the expected return on the hedge assets also enters on the right hand side of (2.2), hence the expected returns are implicitly defined in (2.2).[5]

This theorem shows that expected returns on the hedge assets are determined

[5]It is straightforward to show that equation (2.2) reduces to a model similar to AP's Liquidity CAPM if $S_h > 0$, $K_b = 0$, $q_i = 0$ and $\delta_i = I$ for all agents. In this case λ and κ_0 are equal to zero and all the liquidity risk premia are in the term $\phi(I - H_1)^{-1} Cov(\widehat{r}_h - \widehat{c}_h, \widehat{r}_m - \widehat{c}_m)$.

by five terms. First of all, from the definition of $\widehat{r}_h$ in (2.3) we obtain the standard result that covariance with the non-hedge asset returns is priced if these non-hedge assets carry a risk premium ($E(r_b - c_b) > 0$).

The second term concerns the covariance of hedge asset returns (orthogonalized for non-hedge asset returns) with the non-traded risk factor returns r_n. Given that $\eta > 0$, the sign of the coefficient λ on this covariance depends on the sign of $\sum_i w_i q_i$. For example, if aggregate exposure to non-traded risk is positive we obtain the intuitive result that assets that have positive covariance with the non-traded risk factor have high expected returns, in a similar way as in De Roon et al. (2000).

The third term captures expected liquidity. The sign of this effect depends on ζ_0. The model implies that if the more wealthy or less risk averse investors have long positions in the assets, the coefficient on expected transaction costs is positive and the 'long' holders earn an expected liquidity premium. In the next subsection we illustrate this in a simple example.

The fourth term contains a coefficient κ_0 on the covariance of hedge asset transaction costs (orthogonalized for non-hedge asset returns) with r_n, which depends on the non-traded risk exposure of the short versus long agents. If, for example, the 'short' agents have positive non-traded risk exposure while the 'long' agents have zero non-traded risk exposure, κ_0 is positive. In this case, only the 'short' agents care about covariance with r_n. If the covariance between costs c_h and r_n is negative, the non-traded risk is amplified by the costs because the return on their short position equals $-r_h - c_h$. This weakens the hedge quality of the hedge asset, thus decreasing the demand for hedge assets by the 'short' agents which in turn lowers the expected return. This is the effect that we find empirically.

The final term in (2.2) only enters if aggregate supply S_h is positive. In this case, the covariance with the net market-wide return of hedge assets is priced since the agents have to hold the positive supply in equilibrium. This term is equal to zero if the hedge assets are in zero net supply ($S_h = 0$).

All expectations and covariances in (2.2) are 'corrected' for the covariance matrix between the hedge asset returns and costs through the matrix A. In the example below we provide more intuition for the presence of this correction term A. If the matrix $Cov(\widehat{c}_h, \widehat{r}_h)$ is equal to zero, we have $A = 0$ and (2.2) simplifies to a linear asset pricing equation

$$E\left(\widehat{r}_h\right) + \tfrac{1}{2}\sigma^2_{\widehat{r}_h} + F_h = \zeta_0 E(\widehat{c}_h) + \lambda Cov(\widehat{r}_h, r_n) + \kappa_0 Cov(\widehat{c}_h, r_n) + \phi Cov(\widehat{r}_h - \widehat{c}_h, \widehat{r}_m - \widehat{c}_m) \tag{2.5}$$

In Section 2.3.2.3.2 we discuss in detail how the general model in (2.2) can be estimated using the Generalized Method of Moments (GMM).

2.2.4 Example

We provide more intuition for the expected liquidity effect by a simple example with constant transaction costs c. Let there be one hedge asset with return r with $\sigma^2 = Var(r)$ and two investors. One investor (agent 1) has a positive exposure to the non-traded risk factor r_n and the other investor (agent 2) none, hence $q_1 > 0$ and $q_2 = 0$. There are no other assets. If agent 1 is short an agent 2 long, the asset demands (as a fraction of wealth) of the investors are

$$\begin{aligned} y_1 &= \frac{E(r) + \frac{1}{2}\sigma^2 + c}{\gamma_1 \sigma^2} - Cov(r, r_n) q_1 / \sigma^2 \\ y_2 &= \frac{E(r) + \frac{1}{2}\sigma^2 - c}{\gamma_2 \sigma^2} \end{aligned} \tag{2.6}$$

In a zero net supply market, the wealth-weighted demands have to add up to zero, $w_1 y_1 + w_2 y_2 = 0$, which gives the equilibrium expected returns

$$E(r) + \tfrac{1}{2}\sigma^2 = \frac{cov(r, r_n) w_1 q_1}{w_1 \gamma_1^{-1} + w_2 \gamma_2^{-1}} + \left(\frac{w_2 \gamma_2^{-1} - w_1 \gamma_1^{-1}}{w_1 \gamma_1^{-1} + w_2 \gamma_2^{-1}} \right) c = \rho + \zeta_0 c \tag{2.7}$$

with the compensation for transaction costs determined by the coefficient ζ_0. For this equilibrium to hold, we need to make sure that $y_1 < 0$ and $y_2 > 0$ in equilibrium. These inequalities are satisfied if $Cov(r, r_n) q_1 \gamma_1 > 2c$, requiring that the hedge demand has to be sufficiently large relative to the costs c and the speculative demand (which depends on γ_1). In Appendix 2.9.1 we show the restrictions needed in the general setting.

Figure 2.1 illustrates the equilibrium for two cases, $c = 0$ and $c > 0$. It shows minus the asset demand of agent 1 ($-w_1 y_1$) and the asset demand of agent 2 ($w_2 y_2$), and is drawn such that agent 2 is more aggressive (i.e. less risk averse or more wealthy, $w_2 \gamma_2^{-1} > w_1 \gamma_1^{-1}$), hence her speculative asset demand is steeper than that of agent 1. The equilibrium expected return is obtained at the point where the two lines cross, i.e. $-w_1 y_1 = w_2 y_2$ or $w_1 y_1 + w_2 y_2 = 0$. For $c > 0$, both lines shift downward as transaction costs make the investors want to invest less (in absolute value). The lines now cross at a different point, where the expected return is higher by $\zeta_0 c$. Due to higher wealth and/or lower risk aversion, the demand of the 'aggressive' agent 2 is more sensitive to transaction costs than agent 1. Therefore,

when transaction costs increase, the asset demand of agent 2 reduces more strongly than the asset demand of agent 1. Then, to persuade agent 2 to invest a sufficient amount in the risky asset, the expected return needs to increase so that $\zeta_0 c$ must be positive.

Allowing for stochastic transaction costs, this two-investor example can be used to understand the role of the "correction term" A for expected returns and costs in (2.2). It is straightforward to show that in this simple example we have

$$\frac{\partial E(r)}{\partial E(c)} = \frac{\zeta_0 + 1}{1 + 2(\zeta_0 - 1)Cov(c, r)/V(r)} - 1 \tag{2.8}$$

and that this term has a positive dependence on $Cov(c, r)$ since $|\zeta_0| \leq 1$. For example, empirically we typically have $Cov(c, r) < 0$. Such negative covariance lowers the speculative demand of agent 2, since it increases the variance of her net return $r - c$. The speculative demand of agent 1 increases, since the return on her short position is $-r - c$. In the context of Figure 2.1, negative covariance thus flattens the demand of agent 2 and steepens the demand of agent 1, leading to a lower coefficient on $E(c)$ and a lower expected return for agent 2. This effect occurs even when both agents have the same wealth and risk aversion (i.e. if $\zeta_0 = 0$).

2.2.5 Model extension I: Long-horizon investors

We extend the model presented above in two directions. Our first extension is that we allow some investors to have a long horizon. Specifically, we add M investors with CRRA preferences and investment horizon till the expiration of the contract, so that they are not exposed to the transaction costs. For simplicity, we assume that any intertemporal rebalancing is costless for these investors.[6] In addition, each period N one-period investors enter the market and close their positions at the end of the period, incurring transaction costs at that moment. In order to generate a stationary equilibrium, we assume that all returns and costs are independent and identically distributed (IID) over time and that the characteristics of the one-period investors are the same each period.

This setup captures in a simple way that some investors essentially hold buy-and-hold portfolios and thus incur no transaction costs, while other investors trade frequently in financial markets, either due to external constraints, liquidity shocks, investor-specific preferences or beliefs.

[6] As shown below, these investors have constant portfolio weights in equilibrium. We thus neglect the transaction costs needed to maintain constant portfolio weights.

Given these assumptions, the optimal portfolio choice of the long-horizon investors is constant over time and equal to the myopic portfolio rule. Then, the equilibrium generates the following asset pricing implications:

Theorem II. *Given assumptions 1 to 4, N investors maximizing the function in (2.1), M long-horizon investors, and using a Taylor-expansion of* $Var(\widehat{r}_h - \widehat{c}_h)\,Var(\widehat{r}_h - \delta_i \widehat{c}_h)^{-1}$ around $c_h = 0$, *the* K_h-*dimensional vector with expected excess log-returns on the hedge assets,* $E(r_h)$, *satisfies in equilibrium*

$$E(\widehat{r}_h) + \tfrac{1}{2}\sigma^2_{\widehat{r}_h} + F_h = \frac{1}{1+\mu_0}\left(E_{BM}(\widehat{r}_h + \tfrac{1}{2}\sigma^2_{\widehat{r}_h}) + F_h\right) + \frac{\mu_1}{1+\mu_0} Cov(\widehat{r}_h, r_n) \quad (2.9)$$

where $E_{BM}(\widehat{r}_h)$ *denotes the expected returns that hold in the benchmark model (Theorem I), and*

$$\begin{aligned} \mu_0 &= \frac{1}{\eta}\sum_{i=N+1}^{N+M} w_i \gamma_i^{-1} \\ \mu_1 &= \frac{1}{\eta}\sum_{i=N+1}^{N+M} w_i q_i \end{aligned} \quad (2.10)$$

and, as before, $\eta = \sum_{i=1}^{N} w_i \gamma_i^{-1}$.

Proof: Appendix 2.9.1.

The effect of the presence of long-term investors is twofold. First of all, given that the long-term investors do not care about transaction costs, all terms involving expected transaction costs and covariation with costs (liquidity risk) are depreciated by the term $\frac{1}{1+\mu_0}$, with μ_0 capturing the aggressiveness of the long-term investors relative to all short-term investors. Second, the risk premium on the non-traded risk factor r_n is adjusted to reflect the exposure of long-term investors.

An interesting feature of this extension is that it can generate liquidity effects even if investors are identical in terms of wealth and risk aversion. The coefficient on expected liquidity is

$$\zeta_0 = \frac{\sum_{i:T_i=1,\delta_i=I} w_i \gamma_i^{-1} - \sum_{i:T_i=1,\delta_i=-I} w_i \gamma_i^{-1}}{\sum_{i:T_i=1} w_i \gamma_i^{-1} + \sum_{i:T_i=L} w_i \gamma_i^{-1}} \quad (2.11)$$

where $T_i = 1$ denotes one-period investors and $T_i = L$ long-horizon investors. In the model with only short-term investors the expected liquidity coefficient ζ_0 is zero if buyers and sellers have the same aggregate wealth-weighted risk aversion.

However, if the sellers are long-term investors and buyers short-term, the expected liquidity effect is positive. In this case, only the short-term buyers care about transaction costs and need to be compensated for this by the long-term sellers.

2.2.6 Model extension II: Idiosyncratic background risk and hedging demand

The second extension incorporates that (part of) the non-traded background risk is idiosyncratic, by assuming that each investor i has exposure of q_i to background risk with log-return equal to $r_{n,t} + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ is independent from $r_{n,t}$ and independent across investors but potentially correlated with the asset returns. In addition, we introduce a third group of investors to generate heterogeneity in hedging demand across hedge assets. This group of investors is long for a fixed subset of the hedge assets and short in the other hedge assets. For this 'long/short' group we then have $\delta_i = D$, where D is a diagonal matrix with diagonal elements equal to 1 or -1. This will lead to an interaction effect between hedging demand and liquidity effects as discussed below.

Theorem III. *Given assumptions 1 to 4, the presence of idiosyncratic background risk, and the presence of 'long/short' investors, all investors maximizing the function in (2.1) and using a Taylor-expansion of* $Var(\widehat{r}_h - \widehat{c}_h)\, Var(\widehat{r}_h - \delta_i \widehat{c}_h)^{-1}$ around $\widehat{c}_h = 0$, *the* K_h-*dimensional vector with expected excess log-returns on the hedge assets,* $E(r_h)$, *satisfies in equilibrium*

$$\begin{aligned} E(\widehat{r}_h) &= E_{BM}(\widehat{r}_h) \\ &+ \zeta_1[B_1 E(\widehat{c}_h) - B_2 E(\widehat{r}_h + \tfrac{1}{2}\sigma^2_{\widehat{r}_h})] + \kappa_1[B_1 Cov(\widehat{c}_h, r_n) - B_2 Cov(\widehat{r}_h, r_n)] \\ &+ \frac{1}{\eta}(I - H_1)^{-1}\left[\sum_i w_i q_i \left(I - 2H_1 1_{\delta_i = -I} + (H_2 - H_1)1_{\delta_i = D}\right) Cov(\widehat{r}_h - \widehat{c}_h, \varepsilon_i)\right] \end{aligned} \tag{2.12}$$

where $E_{BM}(\widehat{r}_h)$ *denotes the expected returns that hold in the benchmark model (Theorem I),* 1 *is the indicator function,*

$$\begin{aligned} \zeta_1 &= \frac{1}{\eta}\sum_{i:\delta_i = D} w_i \gamma_i^{-1} \geq 0 \\ \kappa_1 &= -\frac{1}{\eta}\sum_{i:\delta_i = D} w_i q_i \end{aligned} \tag{2.13}$$

and with the following matrix definitions: $H_2 = (DC + C'D)Var(\widehat{r}_h)^{-1}$, $B_1 = (I - H_1)^{-1}(D + H_2 D - H_1 - H_1 D)$, and $B_2 = (I - H_1)^{-1} H_2$. *If* $C = Cov(\widehat{c}_h, \widehat{r}_h) = 0$,

(2.12) *simplifies to*

$$E(\widehat{r}_h) = E_{BM}(\widehat{r}_h) + \zeta_1 DE(\widehat{c}_h) + \kappa_1 DCov(\widehat{c}_h, r_n) + \frac{1}{\eta}\left[\sum_i w_i q_i Cov(\widehat{r}_h - \widehat{c}_h, \varepsilon_i)\right] \tag{2.14}$$

Proof: Appendix 2.9.1.

Theorem III adds three new terms to the model. First of all, the final term in (2.12) and (2.14) shows how the presence of idiosyncratic background risk generates asset-specific and investor-specific hedging pressures. For example, if a wealthy investor has large and positive $q_i Cov(\widehat{r}_{jh} - \widehat{c}_{jh}, \varepsilon_i)$ for asset j, this investor will likely short this asset, paying a premium to those willing to buy the asset and thus increasing the expected return.

The second key implication of Theorem III is that the introduction of 'long/short' investors generates additional effects for expected liquidity and liquidity risk. There are several reasons why some investors are optimally long in some hedge assets and short in the other. For example, if they only have moderate non-traded risk exposure they may only short those hedge assets that covary most strongly with the non-traded risk factor. In addition, the investor-specific hedging effects in Theorem III can also generate strong hedging demand for only a subset of hedge assets.

The effect of this on liquidity premia can be seen most easily when $C = 0$. In this case, assets for which the long/short investors are long have a coefficient on expected costs equal to $\zeta_0 + \zeta_1 = (\sum_{i:\delta_i=I \vee \delta_i=D} w_i \gamma_i^{-1} - \sum_{i:\delta_i=-I} w_i \gamma_i^{-1})/\eta$. For the remaining hedge assets, the long/short investors have a short position, and the expected liquidity coefficient is $\zeta_0 - \zeta_1 = (\sum_{i:\delta_i=I} w_i \gamma_i^{-1} - \sum_{i:\delta_i=-I \vee \delta_i=D} w_i \gamma_i^{-1})/\eta$. In both cases the coefficient captures the net aggressiveness of long versus short investors. A similar effect occurs for liquidity risk.

In which assets the long/short investors are long or short depends on a complex interaction between hedging demands and expected returns. A high hedging demand for an asset on the one hand implies that some investors will short hedge assets to hedge, but on the other hand this hedging pressure pushes up expected returns which increases the speculative demand of other investors. The net effect in equilibrium can be either a long or a short position. For example, if high hedging demand for an asset is caused by only a few agents who have large idiosyncratic background risk covarying with this hedge asset, the net effect will be that most other investors will be long in this hedge asset to exploit the higher expected return (pushed up by hedging demand). In this case we expect that the long/short

investors are long in the assets with high hedging demand and we observe a larger coefficient on expected liquidity for these assets. Alternatively, it is possible that several investors share a high hedging demand for a hedge asset. Especially if these investors have high risk aversion, their speculative demand will be small and the net effect of high hedging demand can be that most investors optimally short the hedge asset thus decreasing the coefficient on expected liquidity. In the empirical analysis, we construct proxies for hedging demand to capture this cross-asset heterogeneity and assess which of the two effects prevails.

2.3 Applying the theory to the CDS market

2.3.1 Motivation and theoretical predictions

We apply the theory developed above to the market for credit risk. In this market, the key background risk is the systematic credit risk of illiquid corporate bonds and bank loans. We focus on credit default swap (CDS) contracts as assets to hedge this risk. In principle, one could also short liquid corporate bonds to hedge credit risk exposure. Our theory does not restrict that some of the hedge assets are corporate bonds. However, in practice shorting corporate bonds may be difficult and costly (see Nashikkar and Pedersen (2007)). In addition, Gârleanu and Pedersen (2009) document that margins on (unfunded) corporate bond positions are considerably higher than those for CDS trades. Hence, we abstain from including corporate bonds as hedge assets and focus on the pricing of CDS contracts.

Table 2.1 is a summary of figures reported by Mengle (2007), providing an overview of buyers and sellers in the CDS market. It shows that insurance companies and funds (pension funds, hedge funds and mutual funds) are net protection sellers in the CDS market, while banks are net protection buyers for their loan portfolio. This suggests that banks typically use the CDS market to hedge credit exposure, while long-term investors buy credit risk to earn a credit risk premium. This supports our assumption that investors are either hedgers (always buying insurance) or speculators who have little or no exposure to non-traded risk and take on credit risk to earn a risk premium.

Linking this market to our theoretical model, the background credit risk is proxied by a general credit index. Credit default swap (CDS) contracts are the hedge assets in zero net supply. We include as non-hedge asset (with positive net supply) the U.S. equity market index. We also construct a proxy to capture hedging demand. The precise definitions of these variables are discussed below.

For this application to the CDS market we can deduce the expected sign for most parameters of the structural model. We define a long position in a CDS to be the case where the investor takes on credit risk, in other words when he sells protection and receives the CDS premium. The non-traded risk factor is given by the return on a portfolio exposed to credit risk, thus giving a negative return in case of defaults or other credit events. Given these definitions, we expect that investors have either a zero exposure q_i to non-traded credit risk (for example institutional investors) or a positive exposure (commercial banks). We thus expect $\lambda \geq 0$ and $\kappa_1 \leq 0$. In addition, investors with zero q_i are likely the 'long' investors (taking on credit risk and earning a risk premium), while those with positive q_i will be the 'short' investors (hedging credit risk). This implies $\kappa_0 > 0$. Finally, as shown in (2.4), the theory always implies $0 \leq \zeta_1 \leq 1$, and $|\zeta_0| \leq 1$, and, in case of zero-net-supply markets, $\phi = 0$. In sum, we expect the following signs and restrictions for the model parameters

$$|\zeta_0| \leq 1,\ 0 \leq \zeta_1 \leq 1,\ \lambda \geq 0,\ \kappa_0 \geq 0,\ \kappa_1 \leq 0,\ \phi = 0 \tag{2.15}$$

2.3.2 Estimation method

For estimation purposes it is useful to write the asset pricing model in Theorem III as a beta-pricing model and invert the model to back out the expected hedge asset return. This gives the estimation equation

$$\begin{aligned} E(r_h) + \tfrac{1}{2}\sigma^2_{\widehat{r}_h} \;=\; & \beta_{r_h,r_b}\psi + X\alpha + W(\zeta)\left\{(A+\zeta_0 I)E(\widehat{c}_h) + B_1 E(\widehat{c}_h)\zeta_1 + \right. \\ & \left. \left[\beta_{\widehat{r}_h,r_n} - A\beta_{\widehat{c}_h,r_n}\right]\tilde{\lambda} + \left[\beta_{\widehat{c}_h,r_n} - A\beta_{\widehat{r}_h,r_n}\right]\tilde{\kappa}_0 + \left[B_1\beta_{\widehat{c}_h,r_n} - B_2\beta_{\widehat{r}_h,r_n}\right]\tilde{\kappa}_1 \right\} \end{aligned} \tag{2.16}$$

with

$$\begin{aligned} W(\zeta) &= (I + \zeta_0 A + \zeta_1 B_2)^{-1} \\ \beta_{\widehat{r}_h,r_n} &= Cov(\widehat{r}_h, r_n)/Var(r_n) \\ \beta_{\widehat{c}_h,r_n} &= Cov(\widehat{c}_h, r_n)/Var(r_n) \end{aligned} \tag{2.17}$$

and $\psi = E(r_b - c_b)$, $\tilde{\lambda} = Var(r_n)\lambda$, $\tilde{\kappa}_0 = Var(r_n)\kappa_0$ and $\tilde{\kappa}_1 = Var(r_n)\kappa_1$. The equation imposes $F_h = 0$ since this term is numerically small (see Appendix 2.9.1). All expectations and covariances are conditional upon the information set at time $t-1$, implying that we have to focus on the innovations in transaction costs when calculating betas. The matrix X denotes any additional explanatory variables (for example, hedging demand or bond market characteristics), including an intercept.

This theoretical model can then be estimated using the Generalized Method of Moments (GMM), since (2.16) defines a system of K_h moment conditions (with K_h denoting the number of hedge assets) and parameter vector $(\psi, \alpha, \zeta_0, \zeta_1, \tilde{\lambda}, \tilde{\kappa}_0, \tilde{\kappa}_1)$. In the estimation, we replace all expectations and betas with their sample counterparts in (2.16) and then perform GMM estimation by minimizing the (weighted) sum of squared errors over the parameters. The system in (2.16) is nonlinear because $W(\zeta)$ depends on the model parameters. But given an initial estimate of ζ, the equations are linear in the parameter vector and can be estimated by weighted least squares. Iterating this procedure yields the GMM estimates. We weight the errors according to the diagonal of the error covariance matrix of (2.16).[7] Following Shanken (1992) we correct the standard errors for the fact that betas, expected costs and expected returns are estimated (see Appendix 2.9.3 for an outline of this procedure).

In asset pricing tests, expected returns are typically estimated by the sample average of realized excess returns. However, given the short sample period this will give noisy estimates of expected returns in our case. Instead, following Campello et al. (2008) and De Jong and Driessen (2007), we use an ex-ante measure of expected returns by correcting CDS spread levels for the expected default losses (the exact procedure is discussed in detail below). This procedure gives the expected simple return $E(R_h)$ on a CDS contract. Using the lognormality assumption, we back out the expected log return from this expected simple return via $E(r_h) + \frac{1}{2}\sigma^2_{\hat{r}_h} = \ln(1 + E(R_h))$.

2.4 Data and construction of main variables

In this section we describe in detail which data we use and how we construct (expected) CDS returns, liquidity measures, and the non-traded risk factor, all of which are needed to estimate the asset pricing model.

2.4.1 Data description

We use CDS data from Datastream, which in turn sources its data from CMA.[8] The data start in January 2004 and contain daily consensus bid, mid and offer CDS

[7] We do not perform the full GMM where the weighting matrix is the inverse of the covariance matrix of pricing errors because these exhibit considerable cross-correlations (see Cochrane (2005), page 194, for a discussion).

[8] The leading Bloomberg data platform obtains its CDS data also from CMA. Nashikkar, Subrahmanyam and Mahanti (2009) compare these CMA data with CDS data provided by GFI group and finds that they are "substantially in agreement".

spreads from a panel of thirty leading financial institutions. In addition, they also report a so called veracity score, which indicates whether the quotes provided are based on market quotes/trades or are derived. We collect these data for the U.S. market (corporates and financials) from January 2004 up to December 2008.

Since we only want to base our analysis on actual market data, we discard all derived quotes. Moreover, we remove all quotes for which both bid and ask are stale. We only select CDS contracts of U.S. companies in U.S. dollars on senior unsecured debt with a maturity of 5 years and a Modified Restructuring (MR) clause. After doing this, we end up with 422,779 daily observations on 595 entities.

Our CDS sample captures a significant part of the market for credit risk. This follows from the fact that the 595 firms for which we have CDS contracts cover 46% of the corporate bond market in terms of amount issued.

To create characteristics for our regressions and to base our sorts on, we match our CDS data to several other data sources. First we match the CDS data to issuer rating data in Moody's Default Risk Services Corporate database. To obtain leverage and total debt outstanding, we match our data to Compustat. We also use corporate bond data from TRACE in order to construct several proxies for corporate bond liquidity. For each firm with CDS quote data, we calculate the total amount of corporate bonds issued by this firm, the total corporate bond trading volume for this firm, and total bond turnover (volume divided by amount issued).

Finally, we construct a proxy for hedging pressure effects. For each firm with CDS quote data, we calculate the total dollar amount of syndicated loans outstanding by this firm for each quarter in our sample. Data on syndicated loans are obtained from Dealscan. Since credit lines are likely to be largely drawn in distress scenarios, we assumed a 100% usage at default.

2.4.2 Portfolio construction

As is usual in the asset pricing literature, we fit the model to different test portfolios rather than to individual assets. We perform five sequential sorts on the cross-section of CDS contracts, always sorting first on credit rating, and then on either (i) firm leverage, (ii) total syndicated loan amount, (iii) total debt outstanding, (iv) CDS bid-ask spread, and (v) CDS quote frequency. The credit rating and leverage should generate variation in market risk exposure, the bid-ask spread and quote frequency are included to capture CDS liquidity variation, and total loan

amount captures hedging pressure effects. In order to have enough observations in each portfolio, we construct five rating categories: Aaa to Aa, A, Baa, Ba, and B to Caa. Within each rating category, we create quartile portfolios based on the second sorting variable. In total, we thus have five sequential sorts with five times four portfolios per sort. We re-sort portfolios each quarter, and calculate the sorting variables over the previous quarter. Given that our data start in January 2004, our first portfolio observations are thus for the second quarter of 2004.

To illustrate the patterns in the CDS spread and bid-ask spread, we present the (geometric) average CDS spread across all firms in Figure 2.2. Before mid-2007, the market-wide CDS spread showed only moderate variation, but since July 2007 spreads increased dramatically, with a peak around November 2008. Figure 2.2 also shows the bid-ask spreads for the sort on rating and bid-ask spreads, where we average each bid-ask spread quartile across all ratings. We see a small peak at the Ford/GM downgrade[9] and a strong increase in bid-ask spreads during the crisis, with the most extreme movements around the Lehman default in September 2008.

2.4.3 CDS portfolio return and transaction costs

Calculating CDS portfolio returns is nontrivial. For some CDS contracts we observe quotes every day, while for other contracts some missing observations occur. We therefore adopt a technique called weighted repeat sales that originates from the real estate literature (for example Bailey, Muth and Nourse (1963) and Case and Shiller (1987)). This method calculates a mid-quote CDS spread index for all CDS contracts in a specific portfolio. Let $k(i)$ be the portfolio that contains constituent i. We assume that the spread mid-quote of a five-year CDS contract $p_{i,t}$ is given by

$$p_{i,t} = CDS_{k(i),t} + u_{i,t}, \tag{2.18}$$

where $CDS_{k(i),t}$ is the portfolio CDS spread level (which is to be estimated) and $u_{i,t}$ is a CDS-specific error term. The repeat sales method employs regression analysis to estimate the innovations in the portfolio CDS spread at different points in time as regression coefficients.[10] The portfolio bid-ask spread is obtained by equally weighting all bid-ask spreads of all CDS contracts in a portfolio in each week.

[9] Acharya, Schaefer and Zhang (2008) provide evidence that liquidity risk for Ford and GM bonds increased correlations within the entire CDS market.

[10] To construct portfolio CDS spread levels from the CDS spread innovations obtained by the repeat sales procedure, we match the accumulated spread change to the level of the portfolio spread at the start of each calendar year.

We then transform the portfolio CDS spreads to excess returns. In the CDS market, bid and ask quotes are given in terms of the CDS spread. Denote this bid-ask spread $s_{k,t}$. Then, consider an investor at time $t-\Delta t$ who sells protection using CDS contract k, at a CDS spread $CDS_{k,t-\Delta t} - \frac{1}{2}s_{k,t-\Delta t}$, paid in quarterly periods. One week later at time t, the investor buys an offsetting contract at $CDS_{k,t} + \frac{1}{2}s_{k,t}$ which generates a net cash flow of $-\frac{1}{4}(CDS_{k,t} - CDS_{k,t-\Delta t}) - \frac{1}{4}(\frac{1}{2}s_{k,t-\Delta t} + \frac{1}{2}s_{k,t})$ each quarter until default or maturity. The value of this stream at time t is the value of a portfolio of defaultable zero-coupon bonds, which gives the excess holding return net of costs[11]

$$R_{k,t} - c_{k,t} = -\frac{1}{4}(\Delta CDS_{k,t} + \tfrac{1}{2}s_{k,t-\Delta t} + \tfrac{1}{2}s_{k,t}) \sum_{j=1}^{T-t} B_t(t+j)\mathbb{Q}_{k,t}^{SV}(t+j) + \frac{\Delta t}{4}(CDS_{k,t-\Delta t} - \tfrac{1}{2}s_{k,t-\Delta t}), \quad (2.19)$$

where $\Delta CDS_{k,t} = CDS_{k,t} - CDS_{k,t-\Delta t}$, $\mathbb{Q}_{k,t}^{SV}(t+j)$ is the risk-neutral survival probability up to time $t+j$ and $B_t(t+j)$ is the price of a risk-free zero-coupon bond maturing at $t+j$.[12] We also include the 'accrued' spread in (2.19), although this term is very small for our weekly return frequency. Time is measured in quarters (the payment frequency) and T is the final payment date. Since we initiated the contract at zero cost, (2.19) directly defines an excess return. Equation (2.19) also shows that proportional transaction costs are equal to

$$c_{k,t} = \frac{1}{4}\left(\tfrac{1}{2}s_{k,t-\Delta t} + \tfrac{1}{2}s_{k,t}\right) \sum_{j=1}^{T-t} B_t(t+j)\mathbb{Q}_{k,t}^{SV}(t+j) + \frac{\Delta t}{4}\tfrac{1}{2}s_{k,t-\Delta t} \quad (2.20)$$

We thus obtain transaction costs by multiplying the bid-ask spreads with a 'duration' factor. This shows that the CDS bid-ask spread (scaled by duration) is already a proportional transaction cost and that it is not necessary to divide this bid-ask spread by the CDS spread to obtain proportional costs: for any notional amount N, the dollar payoff equals $N(R_{k,t} - c_{k,t})$.[13] Note that part of these costs

[11] Of course, if default occurs between $t-\Delta t$ and t, the excess return on the CDS is equal to (minus) the loss given default. However, if we assume that these individual jumps-to-default are not priced, we can ignore these cases for estimating portfolio betas.

[12] This method is very close to the one used by Longstaff, Pan, Singleton and Pedersen (2009), who discount each cash flow with the risk-free rate plus CDS spread, whereas we discount with the risk-free rate and multiply with the risk neutral survival probabilities. Appendix 2.9.5 provides details on the risk-free rate data and the construction of the risk-neutral default probabilities.

[13] To see this in a numerical example, consider a CDS with bid CDS spread of 50 basis points and ask CDS spread of 60 basis points. The bid-ask spread is then equal to 10 basis points. A round-trip CDS transaction would then cost 10 basis points (scaled by the duration) times the

(due to $s_{k,t-\Delta t}$) are known at $t - \Delta t$. To assess liquidity risk we therefore only include the part of $c_{k,t}$ that is not known at $t - \Delta t$, while the full costs $c_{k,t}$ are included for the expected liquidity calculation.

2.4.4 Non-traded credit risk factor and non-hedge asset

For our empirical analysis, we also need to measure the return on the non-traded credit risk factor r_n. As mentioned above, we think of r_n as the return on bank loans and illiquid corporate bonds. Since these returns are, by their very nature, not observable, we construct a proxy for this systematic credit risk using returns on all commonly available credit instruments: corporate bond indices and CDS portfolios. Weekly bond index holding returns are obtained for the intermediate-maturity Lehman Brothers U.S. corporate bond indices per credit rating. The average maturity of all indices is approximately five years. Five-year benchmark treasury returns from Datastream are subtracted from the corporate bond returns to construct excess returns.

In order to capture the systematic credit risk factor in these bond indices and CDS portfolios, we perform a principal component analysis (PCA). We take the excess holding returns of all our CDS portfolios and the excess holding returns on Lehman corporate bond indices for the ratings AAA up to CCC and calculate the first principal component in these returns based on their correlation matrix. Since all these instruments have exposure to systematic credit risk, we would expect the first principal component to be a good measure for systematic credit risk. The loadings on this first component are all close to each other. This first component explains 52% of the variation. As a robustness check we use the return on the investment-grade CDX index as a proxy for the non-traded credit risk factor.

For the non-hedge asset we use returns on the S&P 500 equity index. We do not include transaction costs for this index since S&P futures can be traded with costs that are negligible for our purpose.[14]

2.4.5 Time-series model of liquidity

The betas in the asset pricing model are defined as the ratio of conditional covariances and variances, i.e. the (co)variances of the unpredictable shocks (innovations) in returns and costs. As in Acharya and Pedersen (2005), we assume that returns

notional amount. A similar example is given by Pires, Pereira and Martins (2008).

[14]Karagozoglu, Martell and Wang (2003) report bid-ask spreads on S&P 500 futures of 1.5 to 2 basis points.

have no serial correlation and correct for persistence in the liquidity level by taking the residuals of an autoregressive model as the liquidity innovations. We incorporate the lagged portfolio CDS spread as explanatory variable in the time-series model for liquidity, because, as shown in Figure 2.2, it seems that bid-ask spreads are higher when CDS spreads increase. We thus estimate for each portfolio the regression

$$c_{k,t} = a + b_1 c_{k,t-1} + b_2 CDS_{k,t-1} + \varepsilon_{k,t} \tag{2.21}$$

where $c_{k,t}$ denotes the portfolio-level transaction costs (bid-ask spread times 'duration' factor). Empirically, we indeed find a positive coefficient on the lagged CDS spread equal to 0.047 with t-statistic 4.5 (both averaged across all portfolios), showing that it is important to correct for this level-dependency. The coefficient on the lagged transaction cost b_1 equals 0.74 with t-statistic of 15.5 (again averaged across portfolios).

2.4.6 Expected CDS returns

To calculate the expected excess return $R_{k,t,T}$ on a CDS portfolio at time t, we calculate the expectation under the real world measure of all cash flows resulting from the CDS contract when held till maturity T, discounted at the risk-free rate,

$$\begin{aligned} E_t(R_{k,t,T}) &= \frac{1}{4} CDS_{k,t} \sum_{j=1}^{T-t} B_t(t+j) \mathbb{P}_{k,t}^{SV}(t+j) - \\ &\quad L \sum_{j=1}^{T-t} B_t(t+j) \mathbb{P}_{k,t}^{SV}(t+j-1) \mathbb{P}_{k,t}^{def|SV}(t+j), \end{aligned} \tag{2.22}$$

where L is the expected loss rate in case of default, set at the market-standard rate of 60%, $\mathbb{P}_{k,t}^{SV}(t+j)$ is the real-world survival probability up to time $t+j$ and $\mathbb{P}_{k,t}^{def|SV}(t+j)$ is the probability of a default in period $t+j$ conditional on survival up to time $t+j-1$. Constructing expected excess returns in this way rather than averaging realized excess returns allows us to achieve more accurate estimates and lower standard errors for risk premia. Since we use the expected return to maturity for this calculation, the underlying assumption we make here is that the term structure of expected CDS returns is flat.

Real-world default probability estimates, needed to construct these expected excess returns, are obtained from Moody's-KMV EDF database. We have data on 1-year and 5-year EDFs, which we use to construct 1-year and 5-year default probabilities, and we interpolate linearly to obtain the intermediate default probabilities.

We prefer using Moody's-KMV EDFs over rating-implied default probabilities because especially in the last two years of the sample (2007 and 2008) we observe a strong increase in the EDFs. It is not obvious how to adjust for these new market circumstances when using rating-based historical default frequencies.

We construct these default probabilities at the portfolio level, by taking weighted averages of all individual default probabilities, where the weight is the number of quotes per issuer relative to the total number of quotes in the portfolio.

We construct the expected return in (2.22) over a five-year holding period for each week in the sample. An estimate of the unconditional expected excess return is then obtained by averaging these weekly expected returns over all weeks in the sample. These unconditional expected returns are then used in the estimation of the asset pricing model.

2.4.7 Alternative CDS liquidity measures

In the benchmark analysis we use the bid-ask spread as liquidity measure. As a robustness check, we use two alternative liquidity measures. Our data set consists of bid and ask quotes. Due to the absence of volume data, we can not construct Amihud's (2002) ILLIQ measure of price impact directly, but we can create proxies for price impact. Our first alternative measure (ILLIQ-1) divides the absolute value of the weekly portfolio CDS return by the number of quotes observed for this portfolio in the same week. If the number of quotes is correlated with the actual trading volume, this measure captures price impact of trade in a similar way as Amihud's ILLIQ. Second, we construct a similar measure at the individual CDS level. We take the sum of the absolute values of all observed changes in the CDS spread in a given week, and divide this by the number of quotes observed for this CDS contract in that week. This measure is then aggregated to the portfolio level (ILLIQ-2). The advantage of this latter measure is that it takes the average of individual CDS data, which reduces the noise in the portfolio-level liquidity estimate. On the other hand, individual CDS spread changes are more volatile than portfolio-level CDS returns, which increases the noise in the ILLIQ-2 measure. Since these liquidity measures should capture transaction costs on CDS contracts, we normalize these such that they have the same overall mean and variance as the bid-ask spreads. These two alternative liquidity measures are similar to Tang and Yan's (2007) 'volatility-to-volume' ratio. They divide the volatility of CDS spreads by the total number of quotes and trades observed in each month.

2.5 Empirical Results

This section presents the results of estimating the model on CDS returns. We first discuss the estimated betas, expected returns and transaction costs that go into the asset pricing model. Then we present the benchmark estimates of the structural asset pricing model. We provide a range of robustness checks and present two extensions of the empirical model by including bond liquidity and hedging pressure variables.

2.5.1 Betas, costs and expected returns

For the sake of brevity, we show expected CDS returns, costs, and betas only for the portfolios sequentially sorted on credit ratings and bid-ask spreads in Tables 2.2 and 2.3. Expected returns are reported for a quarterly holding period and costs are equal to the bid-ask spread times the duration factor (see (2.20)). Table 2.2 shows that bid-ask spreads are typically higher for lower-rated firms. We also see that expected returns are higher for lower ratings, as expected. In addition, for each rating category, expected returns are always monotonically increasing with bid-ask spread. Averaged across ratings, the high-liquidity portfolios have an expected return of 0.14% per quarter versus 0.29% per quarter for the low-liquidity portfolios. This provides some first informal evidence that illiquidity may affect expected returns in a positive way. This is further illustrated in Figure 2.3, where we plot expected return pricing errors for a two-factor model with equity and credit risk only (and no liquidity variables) against the expected liquidity per portfolio for all 100 portfolios used in our analysis. The scatter plot shows that a model without liquidity variables generates substantial pricing errors between -0.3% and 0.3% per quarter. Most importantly, these pricing errors exhibit a positive relation with expected liquidity, in line with the strongly positive estimate for ζ_0 reported below.

Table 2.2 also gives t-stats for the expected CDS returns using Newey-West with 24 lags. These are generally high despite our relatively short sample period, which is due to our 'forward-looking' way of backing out expected returns from CDS spreads. Finally, Table 2.2 reports estimated values for $Corr(\widehat{r}_h, \widehat{c}_h)$. We see that both the diagonal and off-diagonal elements of this matrix vary across portfolios, but in some cases differ substantially from zero and are typically negative. Hence, for our empirical analysis we do not impose that $\text{Cov}(\widehat{r}_h, \widehat{c}_h) = 0$ and rely on the general case of Theorem I.

Turning to the betas in Table 2.3, CDS returns have a positive exposure to

equity market returns ($\beta_{r_h,r_b} > 0$), which is higher for CDS contracts with lower ratings and higher bid-ask spreads. Since we defined a 'long' return as the return for a credit protection seller a positive sign for β_{r_h,r_b} can be expected: when equity prices increase, CDS spreads go down. As expected, all betas are below one, since especially high-rated bonds have small market risk (see also Elton, Gruber, Agrawal and Mann (2001)). These betas are always significant for the reported sort. Across all sorts, these betas are significant at the 5% level for 97 out of 100 portfolios. We observe a similar pattern for the exposure to the proxy for systematic non-traded credit risk ($\beta_{\widehat{r}_h,r_n} > 0$), significant at the 5% level for all portfolios. As expected, the return on selling credit protection is positively related to our proxy for systematic credit risk.

The exposure of transaction costs to equity market returns and systematic credit risk is typically negative, suggesting that bid-ask spreads increase in bad times. This is mainly the case for portfolios with low ratings and high bid-ask spreads, and significant at the 5% level for 30 out of 100 portfolios for equity index returns (β_{c_h,r_b}) and for 44 out of 100 portfolios for the credit risk factor ($\beta_{\widehat{c}_h,r_n}$).

2.5.2 Benchmark results

We estimate the asset pricing model for a benchmark setting where we use (i) the bid-ask spread to construct expected liquidity and liquidity risk variables, (ii) a sample period from April 2004 until June 2008 and (iii) assume a holding period of one quarter. The choice of holding period, which is required as there are no data on the typical turnover frequency in CDS markets, implies that we insert expected returns over a quarterly horizon in (2.16). In the benchmark setup we exclude the two final quarters of 2008. Because of the events around the default of Lehman Brothers in September 2008, these two quarters exhibit different behavior compared to the rest of the sample (see Figure 2.2). Below, we perform robustness checks on all choices for this benchmark setup. To assess the fit of the model, we define a cross-sectional R^2 as one minus the ratio of the variance of pricing errors divided by the variance of the expected CDS returns, where we weight both pricing errors and returns with the optimal GMM weights. Hence, this R^2 measures the improvement over a model with constant expected CDS returns across portfolios.

Table 2.4 presents the parameter estimates and R^2 obtained by applying GMM to the moment conditions in (2.16), for the case without heterogenous pricing of liquidity ($\zeta_1 = \kappa_1 = 0$) and with an intercept α_0. The key result is that we find a strong positive effect of expected liquidity on expected CDS returns, both

statistically and economically significant. For the benchmark case with quarterly holding periods, the coefficient ζ_0 equals 0.69 with a t-stat of 13.5. The high statistical precision illustrates the usefulness of constructing forward-looking expected returns from CDS spreads. Note that $|\zeta_0| < 1$, in line with the theory (equation (2.15)). The coefficient on liquidity risk κ_0 is also significantly positive, again in line with theoretical predictions. Turning to the premia on equity market risk (ψ) and credit risk (λ), we find positive and significant estimates for both risk factors. The exposures to these two risk factor are however strongly correlated cross-sectionally. This becomes evident when we exclude the credit risk premium (specification (2) in Table 2.4). This leads to a higher estimate for the equity risk premium (increasing from 0.22% to 0.51% per quarter), but the decrease in R^2 is minimal. Overall, the model explains about 90% of the cross-sectional variation in expected returns. Table IV - specification (3) shows that, if we exclude expected liquidity and liquidity risk from the model, this R^2 goes down to 20%, which shows that the liquidity effects are not simply picking up the effects of equity and credit risk premia.

The intercept is significantly negative at about -11 basis points per quarter. It turns out that without an intercept the model has problems fitting the expected returns on high-rated and liquid portfolios. These portfolios had very low CDS spreads during the period before the crisis, which is in line with anecdotal evidence that high-rated assets were overpriced in the pre-crisis period. A negative intercept helps to fit such portfolios better.

To assess the economic significance of these estimates, we decompose the total expected CDS portfolio return into parts explained by market risk premia, expected liquidity, liquidity risk and a residual. We use (2.16) to explicitly solve for the expected CDS return. Figure 2.4 presents this decomposition for the rating / bid-ask spread sort. It shows that both the expected liquidity effect and market risk effect increase steadily for lower ratings and less-liquid portfolios, while the effect of liquidity risk is only relevant for portfolios with lowest liquidity. Given that $\beta_{\widehat{c}_h, r_n}$ is negative for these portfolios and $\kappa_0 > 0$, liquidity risk decreases the expected CDS return. This is line with our argument in Section 2.3.2.3.1. A negative $\beta_{\widehat{c}_h, r_n}$ lowers the hedge demand of short investors (who care most about this covariance) and this decreases expected returns.

Taking the average across the 20 portfolios in Figure 2.4 (weighted by their optimal GMM weights), we find that equity and credit risk premia together account for 0.060% return per quarter, expected liquidity for 0.175%, and liquidity risk for -0.005%. This shows the large economic significance of expected liquidity.

2.5.3 Backing out structural parameters

With these parameter estimates, we can back out the relative weights of the two investor groups. We consider two cases. First, we use the benchmark setting presented in Theorem I. Using the estimates of specification (1) in Table 2.4 and the definition of ζ_0 in (2.11), the estimates imply that the 'long' investors (taking on credit risk) represent 84.7% of the total wealth-weighted risk tolerance η, while the 'short' investors (hedgers) represent 15.3%. This allows us to interpret the strong positive coefficient on expected liquidity ζ_0. Given that the 'long' investors are much more aggressive (either due to more wealth or lower risk aversion), they require a large compensation for expected liquidity, as explained in the simple example in Section 2.2.2.2.4.

Alternatively, we can relate the parameter estimates to the extension of the theory with long-term investors (Theorem II). For example, we can make the identifying assumption that investors that are short in all hedge assets (hedgers) are always long-term investors. This seems conceivable: commercial banks hedge credit risk using CDS contracts and may not need to trade afterwards. Mathematically, this implies that $\sum_{i:\delta_i=-I} w_i\gamma_i^{-1} = 0$, and from $\zeta_0/(1+\mu_0) = 0.694$ it follows that the long-term hedgers represent 69.4% of the total wealth-weighted risk-tolerance (equal to $\eta(1+\mu_0)$) and the short-term risk takers 30.6%.

In sum, the positive expected liquidity coefficient is consistent with two settings, one where protection sellers are more aggressive than hedgers, and an alternative setting where protection sellers have shorter horizons than hedgers.

An important assumption in these two explanations is the holding period of the short-term investor. The benchmark setting uses a quarterly holding period. From Theorem I it follows that if $Cov(\widehat{r}_h, \widehat{c}_h) = 0$ the empirical model can be translated to a different frequency simply by multiplying the coefficients with the holding period (relative to the quarterly period). Theorem I also shows that this is not exactly true in the general setting, but given that the correlations between $\widehat{r}_h$ and $\widehat{c}_h$ are only moderately different from zero, we do not expect large deviations from the simple multiplication effect. Table 2.4 reports results for monthly and annual holding periods, thus measuring expected returns over shorter or longer horizons. It confirms our intuition: the parameters estimates are approximately scaled by the holding period. This implies that the relative importance of the different premia remains the same irrespective of the holding period and that the empirical model has similar explanatory power across holding periods. The holding period does however affect the interpretation of the coefficients in terms of the theoretical

model. The theory constrains the coefficient on expected liquidity ζ_0 to be below one. For the annual holding period, the estimate for ζ_0 is larger than one. This implies that the empirical estimates are in line with the theoretical predictions as long as the holding period is not too long (roughly less than six months). If the actual holding period would be really one year, setting ζ_0 at its maximum level of one (as opposed to the unrestricted estimate of 2.05) implies that the theoretical model explains about $1/2.05 \cdot 100\% \simeq 49\%$ of the empirically observed effect of expected liquidity. It is also useful to note that the bid-ask spread probably does not capture all transaction costs of a CDS trade. For example, search costs are not explicitly incorporated. Also, our bid-ask spreads are for 'on-the-run' five-year CDS contracts, and unwinding a shorter-maturity CDS contract after some time may be more costly. This could partially explain the high coefficient on the bid-ask spread.

2.5.4 Robustness checks

Table 2.5 provides a range of robustness checks on the benchmark results of Table 2.4.

First, we use an alternative proxy for systematic credit risk: the returns on the investment-grade CDX index. This leads to similar effects for liquidity risk and expected liquidity, but a smaller and less significant estimate on the credit risk premium. The overall R^2 is essentially unchanged.

Second, we change the sample period. We add the two final quarters of 2008 and report estimates for the full sample period April 2004 to December 2008. This leads to an even larger coefficient on expected liquidity, but a somewhat smaller effect of liquidity risk (still significant). We also consider a pure crisis sample: July 2007 to December 2008 and again find very similar results for the liquidity variables. The cross-sectional R^2 is a bit lower when we include the crisis period, which is not surprising since there are some extreme movements in CDS spreads and bid-ask spreads in this period.

Third, instead of the bid-ask spread, we use the two alternative measures for liquidity discussed in Section 2.4.2.4.7, the proxies for price impact ILLIQ-1 and ILLIQ-2. The results show that we find similar liquidity effects for both alternative liquidity measures. Compared to the bid-ask spread, both alternative liquidity measures generate slightly lower values for the R^2.

Fourth, we use different time-series models for transaction costs. Our benchmark model has an autoregressive specification with the lagged transaction cost

and the lagged CDS spread as explanatory variables (denoted as ARX model in the table). As an alternative, we use pure autoregressive models with two or four lags but without the lagged CDS spread (denoted as (AR(2) and AR(4) models in the table). We find that all results are very similar to the benchmark case.

Fifth, we take out the intercept from the asset pricing model. It turns out that this is the only robustness check that does substantially affect the estimate for the expected liquidity premium, lowering it from 0.694 to 0.243. It remains strongly statistically significant with a t-stat of 7.2, and the economic effect equals 0.060% per quarter across the 20 rating/bid-ask-spread portfolios, compared to 0.175% in the benchmark case. The estimate for the equity risk premium becomes negative and statistically significant. This is because in the absence of a constant term, the model exploits the strong cross-sectional correlation between the equity and credit risk betas to mimick the constant term. The sum of the market and credit premia is positive for all portfolios however at an average of 0.076% per quarter across portfolios. Figure 2.5 shows the decomposition of expected CDS returns across rating/bid-ask spread portfolios for the specification without an intercept.

Finally, we incorporate $\beta_{\widehat{c}_h\widehat{c}_m} = Cov(\widehat{c}_h, \widehat{c}_m)/Var(\widehat{c}_m)$ as explanatory variable. According to the theoretical model, this 'CDS-market' liquidity risk should not carry a risk premium ($\phi = 0$ in (2.16)).[15] We include this beta in the empirical model as a specification test, in particular because in positive-net-supply markets this exposure is expected to be priced (Acharya and Pedersen, 2005). To make sure that the exposure to $\beta_{c_h c_m}$ captures systematic risk, we check whether there is commonality in liquidity across CDS portfolios by performing a principal component analysis to the portfolio liquidity innovations. We find that the first factor explains 16.6% of the liquidity variation, which gives some evidence for liquidity commonality. This complements existence evidence of liquidity commonality in other markets (see, for example, Chordia, Roll and Subrahmanyam (2000) for equity markets). Table 2.5 shows a positive estimate for the premium on $\beta_{\widehat{c}_h\widehat{c}_m}$, but insignificant with a t-stat of 0.09. Hence, we do not find evidence that this form of liquidity risk is priced. In addition, the effect of expected liquidity hardly changes when including $\beta_{\widehat{c}_h\widehat{c}_m}$.

In sum, throughout all specifications and robustness checks, we find very strong evidence that expected liquidity positively affects expected CDS returns. The effect of liquidity risk (exposure to $\beta_{\widehat{c}_h r_n}$) is small, but mostly statistically significant.

[15] We do not include the 'total' CDS-market beta $Cov(\widehat{r}_h - \widehat{c}_h, \widehat{r}_m - \widehat{c}_m)/Var(\widehat{r}_m - \widehat{c}_m)$ because the market-wide CDS return exhibits substantial correlation with the factor capturing systematic non-traded credit risk.

2.5.5 Bond liquidity and hedging pressure

We extend the empirical specification of expected CDS returns in two further ways. First, we include several proxies for bond market liquidity as a portfolio characteristic in the asset pricing model. Second, we include a variable capturing hedging pressure effects and allow this variable to interact with the liquidity effects.

Bond market liquidity may affect the pricing of CDS contracts due to an effect described in Bühler and Trapp (2009). CDS contracts often allow for physical delivery of the underlying bonds in case of default. If the delivered bonds are more liquid, their value will be higher, which lowers the effective loss in case of default and in turn should lead to a lower CDS spread and lower expected return (given a fixed loss rate). The maintained assumption is that the current bond liquidity level predicts the bond liquidity in case of a default event. We construct three corporate bond liquidity measures at the firm level: the total amount issued, total volume and turnover. Portfolio-level liquidity measures are then created by averaging these bond-liquidity measures across all firms underlying the CDS contracts. Including these portfolio-level bond-liquidity measures as portfolio characteristic, Table 2.6 shows that we find no evidence for a significant negative effect of bond liquidity on the expected CDS return. For bond turnover we actually find a positive and significant coefficient.

Our second extension concerns potential hedging pressure effects, motivated by the presence of idiosyncratic background risk (Theorem III). To proxy for hedging pressures, we use the amount of loans issued in the syndicated loan market. If large investors, for example commercial banks, are stuck with a large fraction of syndicated loans of a given firm, this could lead to increased hedging demands which push up the expected return on the CDS written on this firm, as shown formally in Theorem III.

Similar to the bond liquidity variables, we first construct the loan amount at the firm level, and then create a portfolio-level loan amount by averaging across all firms corresponding to the CDS contracts in the portfolio. This variable is then included as characteristic in the asset pricing model. Specification (7) in Table 2.6 shows that high hedging demand indeed leads to significantly higher expected returns. Hence, if a firm has taken on a large amount of syndicated loans over the sample period, we find higher CDS spreads and thus a higher expected CDS return.

It turns out that hedging demand is positively correlated with the bond liquidity measures. Firms with many syndicated loans outstanding typically also have

large and liquid bond issues trading in financial markets. To disentangle bond liquidity and hedging effects, we therefore simultaneously include the loan amount and bond liquidity measures in the asset pricing model in specifications (4)-(6) of Table 2.6. Using amount issued or volume as bond liquidity measures, we still find a positive and significant coefficient on the hedging pressure variable, in line with our intuition and Theorem III. When controlling for bond turnover, the hedging effect is positive but insignificant. Specifications (4)-(6) also show that the bond liquidity effects become more negative once we control for hedging effects, but we still find mixed evidence for the Bühler-Trapp effect of bond liquidity on CDS returns.

Finally, we incorporate interaction effects between hedging demand and liquidity as derived theoretically in Theorem III, by including nonzero ζ_1 and κ_1. As discussed in subsection 2.2.2.2.6, the net effect of hedging demand on the liquidity premia can be positive or negative. In terms of the theory, the long/short group with position signs given by the matrix D, could be either long or short when hedging demand for those assets is high.

Empirically, we proceed as follows. We again use the amount of syndicated loans outstanding as proxy for hedging demand. Specifically, for each CDS portfolio we set the corresponding diagonal element of D equal to 1 if the loans outstanding variable is above the overall median level, and equal to -1 otherwise. Specifications (8) and (9) in Table 2.6 show that high hedging demand increases the coefficient on expected liquidity and decreases the coefficient on liquidity risk. Theoretically, this is in line with the case that high hedging demand generates more investors with long positions, since this generates a positive coefficient for ζ_1 and negative for κ_1.[16] As discussed in Section 2.3.2.3.1, high hedging demand pushes up the expected return, which may induce more investors to hold long positions in the hedge asset (especially if the hedging demand is concentrated within a few investors). Indeed, we found above that loans outstanding had a direct positive effect on expected returns. The liquidity-hedging interaction effect is only significant for liquidity risk (κ_1) and small and insignificant for expected liquidity (ζ_1), irrespective of whether we control for the direct hedging effect on expected returns. The increase in R^2 is also small, showing that the interaction effect of hedging pressure and liquidity is economically modest.

Finally, it is useful to note that for both extensions the effects of expected

[16]Obviously, specifying D in the opposite way (1 in case of low hedging demand and -1 in case of high demand) would generate exactly the opposite results: a negative ζ_1 and positive κ_1, which would thus not be in line with the theoretical predictions.

liquidity and liquidity risk are essentially unchanged. Both effects remain strongly significant.

2.6 Conclusion

We develop a theoretical asset pricing model with liquidity risk, incorporating (i) positive-net-supply assets and derivatives, (ii) heterogeneous investors, (iii) optimal short-selling, and (iv) background risk. Our model builds on Acharya and Pedersen (2005) whose model has investors with long positions in positive net-supply assets. Our first main theoretical result is that the sign of liquidity effects depends on investor heterogeneity in wealth, risk aversion, non-traded risk and horizon. Second, we derive that some liquidity risk premia should be equal to zero if the assets are derivatives in zero net supply.

We test this model for one of the key derivative markets: the market for credit default swaps. The nonlinear asset pricing model is estimated by applying GMM to a sample of CDS bid and ask quotes over a sample period from 2004 to 2008. We find significant and robust evidence that liquidity affects CDS prices, in a way that is generally consistent with the predictions of the theoretical model. Our results thus suggest that CDS spreads cannot be used as frictionless measures of default risk, as is often done in the recent literature.

On the theoretical side, several extensions of this chapter are possible. In our model, investors trade in derivatives due to heterogenous exposure to non-traded risk. Obviously, there may be other reasons for why people trade derivatives, such as heterogeneity in beliefs or intertemporal hedging demands that would arise in a multi-period setting. Further, explicitly modeling the preferences and constraints of a market maker (who earns the bid-ask spread) may also generate interesting effects. On the empirical side, our model can be applied to other markets, either derivative markets or positive-net-supply markets with considerable short-selling activity.

2.7 Tables

Table 2.1: Buyers and sellers in the CDS market
This table shows the fraction of CDS contracts held by various parties. Source: 2006 Survey of the British Bankers Association, reported in Mengle (2007).

	Buy protection	Sell protection	Net position
Banks - Loan portfolio	20%	9%	11%
Banks - Trading activity	39%	35%	4%
Insurers	6%	17%	-11%
Funds	32%	39%	-7%
Hedge funds	28%	32%	-4%
Pension funds	2%	4%	-2%
Mutual Funds	2%	3%	-1%
Corporates & other	3%	2%	1%

Table 2.2: Descriptive statistics CDS returns and transaction costs
The table presents summary statistics for the CDS returns and transaction costs for the sequential sort on credit rating (five categories) and bid-ask spread (four quartiles). Panel A presents expected CDS returns for a quarterly horizon in percentages, constructed by averaging equation (2.22) over all weeks in our sample. Panel A also contains average proportional transaction costs per portfolio, defined as the bid-ask spread times a duration factor (equation (2.20)). In square brackets t-stats of the weekly averages are given, calculated using Newey-West with 24 lags. Panel B contains the correlation matrix of the time series of CDS returns and transaction cost innovations, $Corr(\widehat{r}_h, \widehat{c}_h)$, presenting both the 'diagonal' elements and average of each row of this 20 by 20 matrix. Sample period is April 2004 until June 2008.

Panel A: Descriptive statistics expected transaction costs and expected CDS returns

	Expected CDS return (%/quarter)				Expected transaction cost (%)			
Rating/Bid-ask spread	Low	Q2	Q3	High	Low	Q2	Q3	High
Aaa to Aa	-0.038	0.036	0.047	0.104	0.121	0.143	0.175	0.299
	[-0.88]	[2.17]	[2.06]	[1.73]	[24.62]	[25.28]	[29.22]	[5.08]
A	0.047	0.055	0.060	0.104	0.158	0.185	0.205	0.289
	[4.35]	[4.28]	[3.56]	[1.97]	[44.6]	[46.78]	[40.76]	[14.63]
Baa	0.077	0.100	0.131	0.202	0.178	0.207	0.243	0.356
	[6.52]	[4.91]	[5.02]	[3.45]	[56.36]	[39.48]	[35.43]	[19.81]
Ba	0.174	0.241	0.308	0.403	0.260	0.348	0.443	0.618
	[5.49]	[5.21]	[6.12]	[5.78]	[36.80]	[36.96]	[31.52]	[14.11]
B to Caa	0.434	0.527	0.570	0.627	0.392	0.532	0.619	1.120
	[5.24]	[7.45]	[5.10]	[3.61]	[21.85]	[26.31]	[27.28]	[3.18]

Panel B: Time-series correlations transaction cost innovations and CDS returns

	Diagonal				Average			
Rating/Bid-ask spread	Low	Q2	Q3	High	Low	Q2	Q3	High
Aaa to Aa	0.121	-0.129	-0.061	-0.376	-0.004	-0.010	-0.101	-0.108
A	-0.187	-0.083	-0.020	-0.240	-0.038	0.018	-0.040	-0.085
Baa	-0.102	-0.012	-0.117	0.142	-0.005	0.002	-0.026	0.067
Ba	-0.014	-0.075	-0.024	0.026	0.005	-0.017	0.027	-0.099
B to Caa	-0.012	-0.023	-0.039	-0.135	-0.082	-0.087	-0.055	-0.127

Table 2.3: Beta estimates

The table presents beta estimates for the sequential sort on credit rating (five categories) and bid-ask spread (four quartiles). The upper left panel contains the beta of CDS portfolio returns with respect to S&P 500 index returns (β_{r_h,r_b}). The upper right panel contains the beta of transaction cost innovations (residuals of the AR-X model in equation (2.21)) with respect to the S&P 500 index returns (β_{c_h,r_b}). The lower left panel contains the beta of CDS returns (orthogonalized for S&P 500 index returns) with respect to the PCA factor capturing systematic credit risk ($\beta_{\widehat{r}_h,r_n}$). The lower right panel contains the beta of transaction cost innovations (orthogonalized for S&P 500 index returns) with respect to the PCA systematic credit risk factor ($\beta_{\widehat{c}_h,r_n}$). Sample period is April 2004 until June 2008. t-statistics are given in square brackets.

	β_{r_h,r_b}				β_{c_h,r_b}			
Rating/Bid-ask spread	Low	Q2	Q3	High	Low	Q2	Q3	High
Aaa to Aa	0.041	0.048	0.054	0.190	-0.001	-0.002	-0.001	-0.015
	[8.52]	[7.34]	[6.85]	[5.27]	[-1.38]	[-2.2]	[-0.91]	[-2.17]
A	0.046	0.045	0.061	0.134	-0.001	-0.001	-0.001	-0.005
	[8.59]	[9.72]	[6.86]	[6.56]	[-1.18]	[-1.58]	[-1.6]	[-2.97]
Baa	0.062	0.069	0.077	0.12	-0.001	-0.001	-0.001	-0.001
	[8.64]	[9.57]	[8.48]	[8.82]	[-1.69]	[-1.12]	[-0.97]	[-1.11]
Ba	0.113	0.159	0.198	0.245	0.000	-0.002	-0.005	-0.001
	[7.17]	[8.76]	[7.32]	[7.79]	[-0.08]	[-1.08]	[-1.4]	[-0.23]
B to Caa	0.285	0.271	0.218	0.396	-0.003	-0.005	-0.007	-0.024
	[7.72]	[5.63]	[4.62]	[5.97]	[-1.00]	[-1.61]	[-2.24]	[-1.43]

	$\beta_{\widehat{r}_h,r_n}$				$\beta_{\widehat{c}_h,r_n}$			
Rating/Bid-ask spread	Low	Q2	Q3	High	Low	Q2	Q3	High
Aaa to Aa	0.186	0.315	0.310	1.401	-0.004	-0.003	-0.006	-0.106
	[8.94]	[12.8]	[9.21]	[9.04]	[-1.23]	[-0.79]	[-1.86]	[-3.06]
A	0.267	0.244	0.349	0.821	-0.005	0.000	-0.004	-0.024
	[13.62]	[14.89]	[9.15]	[9.48]	[-2.17]	[-0.11]	[-1.32]	[-2.67]
Baa	0.331	0.397	0.473	0.648	-0.002	-0.002	-0.004	0.008
	[11.75]	[16.54]	[14.63]	[12.36]	[-0.83]	[-0.89]	[-1.31]	[1.32]
Ba	0.762	0.969	1.095	1.000	-0.004	-0.008	0.002	-0.065
	[12.62]	[15.21]	[9.64]	[7.01]	[-0.43]	[-1.10]	[0.12]	[-2.51]
B to Caa	1.713	2.121	1.838	2.482	-0.022	-0.019	-0.019	-0.207
	[11.83]	[10.86]	[9.13]	[8.61]	[-1.62]	[-1.35]	[-1.22]	[-2.49]

Table 2.4: Benchmark GMM estimation results
The theoretical asset pricing model in Theorem I is estimated by applying GMM to the moment condition (2.16) for 100 CDS portfolios (sorted first on credit rating, and then either on leverage, total debt, total syndicated loan amount, bid-ask spread, or quote frequency). Moment conditions are weighted by the diagonal of the optimal GMM weighting matrix. The model also includes an intercept. t-stats (in square brackets) are calculated in GMM fashion using Newey-West with 24 lags, and incorporating that expected returns, costs and betas are estimated, following Shanken (1992), see Appendix 2.9.3. The table also reports a cross-sectional R^2, where pricing errors are weighted using the GMM weights. Finally, the table reports results for a benchmark holding period of one quarter, and results for holding periods of one month and one year. Sample period is April 2004 until June 2008.

	(1)	(2)	(3)	(4)	(5)
Holding period	Quarterly	Quarterly	Quarterly	Annual	Monthly
Intercept	-0.106	-0.113	-0.012	-0.333	-0.040
(α_0)	[-11.59]	[-13.18]	[-0.39]	[-10.98]	[-12.32]
Equity risk	0.224	0.512	-0.032	0.660	0.073
(ψ)	[4.46]	[4.38]	[-0.82]	[3.53]	[3.16]
Credit risk	0.066		0.226	0.462	0.015
($\tilde{\lambda}$)	[2.48]		[8.58]	[4.69]	[1.66]
Expected liquidity	0.694	0.763		2.050	0.270
(ζ_0)	[13.51]	[14.04]		[12.61]	[14.42]
Liquidity risk	1.819	1.72		5.978	0.753
($\tilde{\kappa}_0$)	[3.25]	[2.80]		[3.40]	[4.13]
R^2	0.899	0.892	0.203	0.880	0.652

Table 2.5: Robustness and specification tests

The table reports estimates of the asset pricing model in Theorem I, obtained by applying GMM to the moment condition (2.16) for 100 CDS portfolios (sorted first on credit rating, and then either on leverage, total debt, total syndicated loan amount, bid-ask spread, or quote frequency). The setting described in Table 2.4 (included as specification (1) for convenience) is changed in the following ways. First, the PCA factor is replaced by returns on the IG CDX index. Second, results are presented for two alternative sample periods: April 2004 to December 2008 ('full') and July 2007 to December 2008 ('crisis'). Third, two alternative measures for liquidity are used instead of the bid-ask spread (see Section 2.4.2.4.7). Fourth, the AR-X time series model for transaction costs is replaced by either an AR(2) model or an AR(4) model. Fifth, the intercept is excluded from the model. Finally, a premium on the cost-cost beta ($\beta_{\hat{c}_h,\hat{c}_m}$) for the CDS market is included.

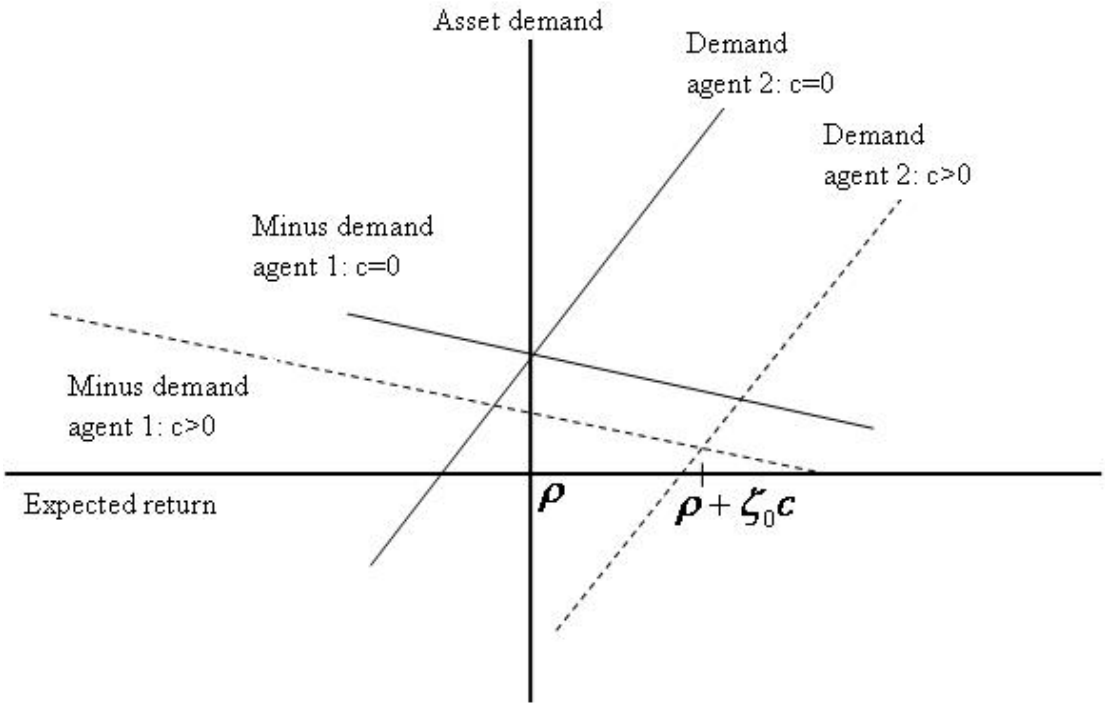
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Non-traded risk	PCA	CDX	PCA	PCA	PCA	PCA	PCA	PCA	PCA	PCA
Sample period	base	base	full	crisis	base	base	base	base	base	base
Liquidity measure	BAS	BAS	BAS	BAS	ILLIQ-1	ILLIQ-2	BAS	BAS	BAS	BAS
Cost innovations	ARX	ARX	ARX	ARX	ARX	ARX	AR(2)	AR(4)	ARX	ARX
Intercept	-0.106	-0.115	-0.114	-0.135	-0.290	-0.154	-0.108	-0.108		-0.106
(α_0)	[-11.59]	[-13.06]	[-17.06]	[-7.01]	[-24.52]	[-10.49]	[-10.95]	[-11.08]		[-8.34]
Equity risk	0.224	0.428	0.104	0.202	0.527	0.183	0.279	0.302	-0.179	0.221
(ψ)	[4.46]	[7.12]	[1.77]	[3.76]	[5.15]	[1.46]	[4.51]	[4.75]	[-4.18]	[3.64]
Credit risk	0.066	0.023	-0.001	0.020	0.093	0.020	0.057	0.054	0.162	0.066
($\tilde{\lambda}$)	[2.48]	[1.23]	[-0.16]	[1.02]	[3.28]	[0.81]	[2.05]	[1.90]	[6.88]	[2.15]
Expected liquidity	0.694	0.717	0.900	0.923	0.990	0.925	0.707	0.710	0.243	0.692
(ζ_0)	[13.51]	[14.12]	[9.65]	[9.33]	[18.12]	[17.33]	[13.08]	[13.24]	[7.23]	[11.42]
Liquidity risk	1.819	1.087	0.279	0.936	0.880	0.433	1.394	1.400	1.427	1.844
($\tilde{\kappa}_0$)	[3.25]	[2.79]	[1.38]	[4.19]	[3.41]	[3.64]	[2.61]	[2.63]	[5.75]	[4.67]
Liquidity risk										0.155
($\phi_{\hat{c}_h,\hat{c}_m}$)										[0.09]
R^2	0.899	0.890	0.770	0.775	0.721	0.868	0.878	0.879	0.577	0.899

Table 2.6: Bond market liquidity and hedging demand effects
The left panel reports estimates of the theoretical asset pricing model of Theorem I, obtained by applying GMM to the moment condition (2.16) for 100 CDS portfolios (sorted first on credit rating, and then either on leverage, total debt, total syndicated loan amount, bid-ask spread, or quote frequency) and adding corporate bond liquidity as a portfolio characteristic. Corporate bond liquidity is measured using either the log of total dollar amount issued for corporate bonds, the log of dollar corporate bond trading volume, or log of corporate bond turnover (volume divided by amount issued). These measures are constructed using TRACE data at the firm-level (for those firms underlying CDS contracts), and then aggregated to the portfolio level. In the middle panel another portfolio characteristic is added to this model, the log of the dollar amount of syndicated loans outstanding ('loan amount'). This variable is constructed again at the firm level using Dealscan data, and then aggregated to the portfolio level. Finally, the right panel presents estimates for the model extension in Theorem III with interaction between hedging demand and liquidity premia (ζ_1 and κ_1). Specifically, the diagonal elements in matrix D in (2.16) are set to 1 for portfolios with above-median loan amount, and -1 for portfolio with below-median loan amount.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bond liquidity	outstanding	volume	turnover	outstanding	volume	turnover	outstanding	volume	turnover
Intercept	-0.107	-0.112	-0.109	-0.104	-0.109	-0.111	-0.112	-0.107	-0.110
(α_0)	[-12.38]	[-12.6]	[-11.76]	[-11.97]	[-12.04]	[-12.84]	[-12.62]	[-12.36]	[-12.76]
Equity risk	0.225	0.231	0.135	0.198	0.211	0.143	0.217	0.223	0.219
(ψ)	[4.27]	[4.39]	[2.53]	[3.81]	[4.10]	[2.60]	[4.23]	[4.27]	[4.23]
Credit risk	0.065	0.059	0.070	0.063	0.0580	0.065	0.055	0.056	0.053
($\tilde{\lambda}$)	[2.73]	[2.48]	[2.65]	[2.68]	[2.46]	[2.6]	[2.18]	[2.26]	[2.17]
Expected liquidity	0.697	0.732	0.726	0.705	0.730	0.743	0.745	0.725	0.744
(ζ_0)	[12.80]	[12.46]	[13.17]	[12.90]	[12.54]	[13.76]	[13.59]	[13.9]	[13.5]
Interaction								0.016	0.005
(ζ_1)								[1.63]	[0.44]
Liquidity risk	1.822	1.846	1.598	1.754	1.797	1.622	1.814	2.011	1.893
($\tilde{\kappa}_0$)	[3.37]	[3.23]	[2.77]	[3.25]	[3.17]	[2.77]	[3.05]	[3.70]	[3.50]
Interaction								-0.223	-0.216
($\tilde{\kappa}_1$)								[-3.18]	[-3.07]
Loan amount				0.016	0.014	0.005	0.012		0.010
(α_1)				[4.41]	[3.97]	[1.45]	[3.24]		[2.22]
Bond liquidity	0.004	0.039	0.566	-0.068	-0.023	0.050			
($\alpha_2 \times 10$)	[0.09]	[1.07]	[4.74]	[-1.54]	[-0.61]	[4.26]			
R^2	0.899	0.903	0.916	0.909	0.909	0.918	0.909	0.910	0.912

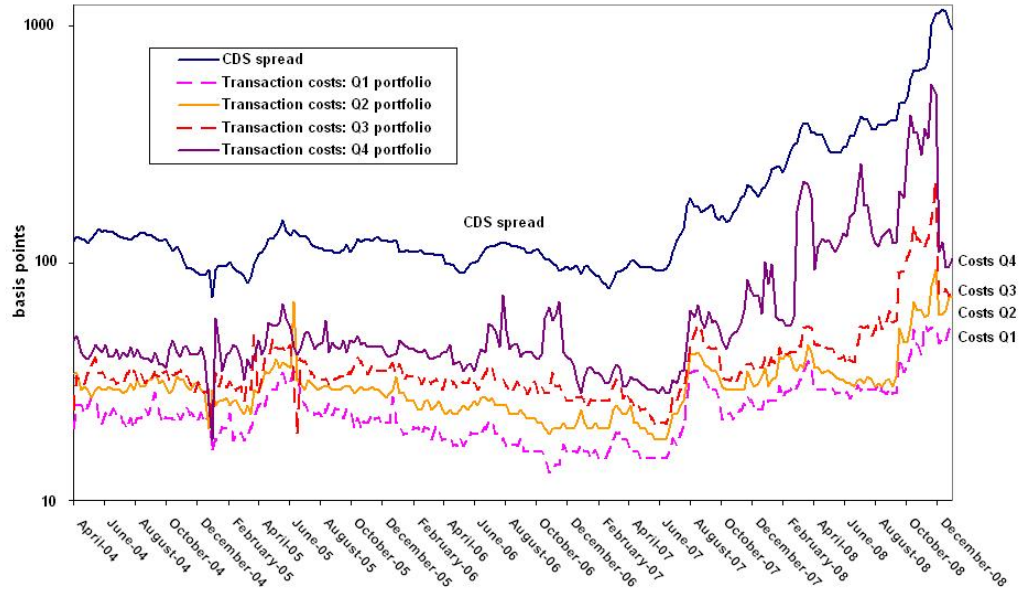
2.8 Figures

Figure 2.1: Asset pricing equilibrium with transaction costs



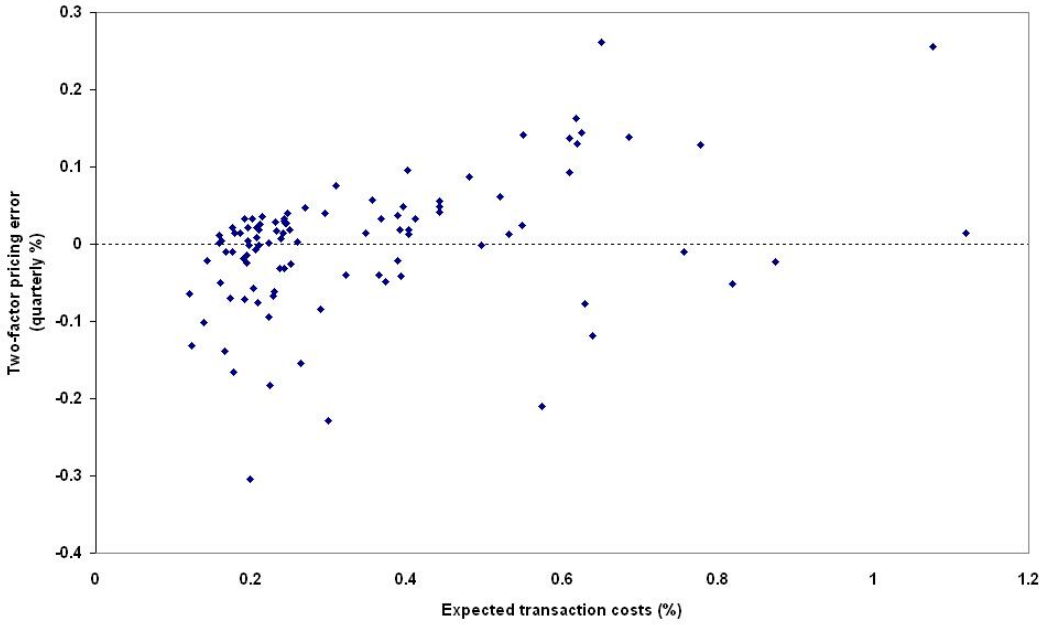
The figure illustrates the asset pricing equilibrium with constant liquidity costs, as in the example of Section 2.2.2.2.4. The figure graphs (minus) the asset demand of an investor with hedging needs $(-w_1 y_1)$ who is short in the asset and a less risk averse investor with no hedging demand $(w_2 y_2)$ who is long. The solid lines reflect the situation without transaction costs, the dashed lines reflect the situation with transaction costs c. ρ is the equilibrium expected return without transaction costs, $\rho+\zeta_0 c$ is the equilibrium expected return with transaction costs.

Figure 2.2: Time-series of CDS spreads and bid-ask spreads



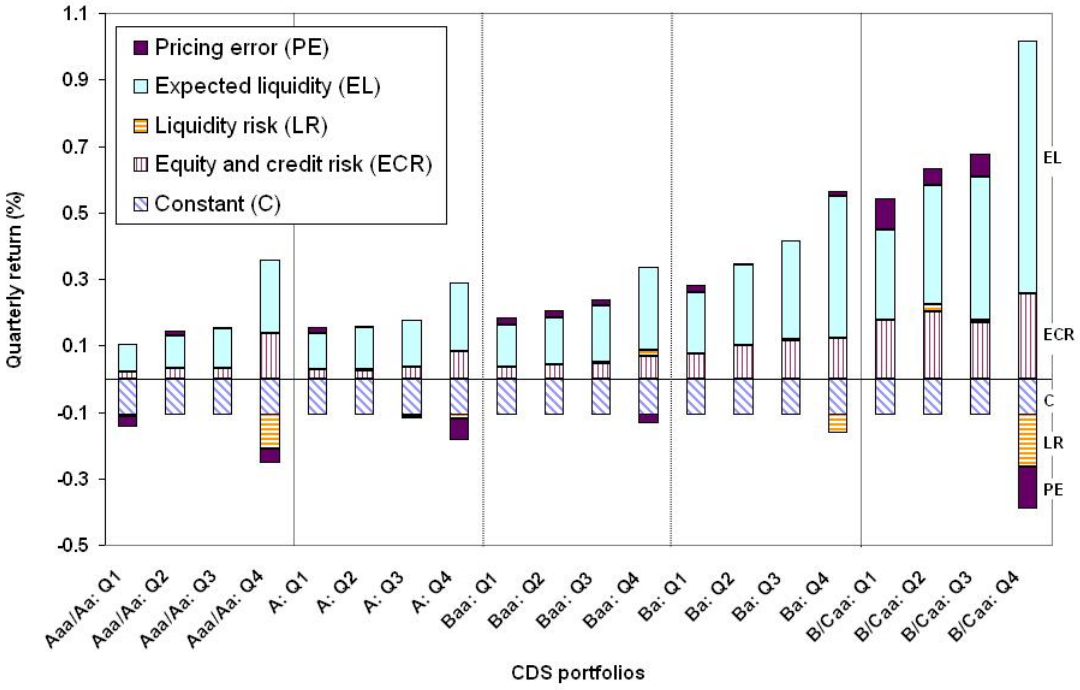
The graph presents the time-series of weekly CDS spreads (geometric average across all CDS portfolios) from April 2004 to December 2008 on a log scale in annual basis points. Also included are time series of bid-ask spreads for four bid-ask spread quartiles. These are calculated from the sequential sort on credit rating and bid-ask spread, with bid-ask spreads averaged across portfolios with different credit ratings.

Figure 2.3: Two-factor pricing errors versus expected liquidity



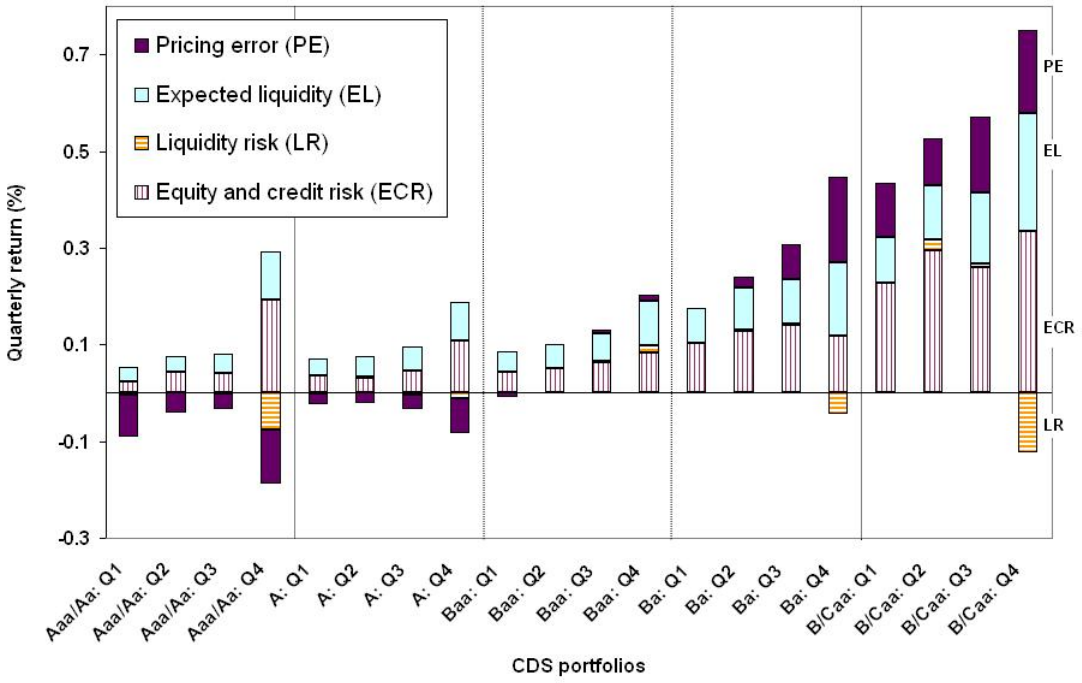
On the y-axis, the graph has pricing errors from a two-factor asset pricing model with equity market risk and systematic credit risk (PCA factor) as factors (specification (3) in Table IV), for 100 CDS portfolios (sorted first on credit rating, and then on leverage, total debt, total syndicated loan amount, bid-ask spread, or quote frequency). The x-axis has the expected liquidity of each portfolio (in percentage), calculated as the average of the weekly transaction costs of each portfolio. All returns are in percentages for a quarterly period.

Figure 2.4: Decomposition of expected CDS returns: Benchmark model



Using the benchmark GMM estimates in Table 2.4, specification (1), for the model for expected CDS returns in equation (2.16), the graph decomposes expected portfolio CDS returns into an intercept, market risk premia (sum of equity risk premium and credit risk premium), expected liquidity, liquidity risk and a pricing error. Results are presented for the sequential sort on credit rating (five categories) and bid-ask spread (four quartiles). All returns are in percentages for a quarterly period.

Figure 2.5: Decomposition of expected CDS returns: Model without intercept



Using the GMM estimates of a model without intercept in Table 2.5, specification (9) and the model for expected CDS returns in (2.16), the graph decomposes expected portfolio CDS returns into market risk premia (sum of equity risk premium and credit risk premium), expected liquidity, liquidity risk and a pricing error. Results are presented for the sequential sort on credit rating (five categories) and bid-ask spread (four quartiles). All returns are in percentages for a quarterly period.

2.9 Appendix

2.9.1 Proof of Theorems I to III

We work out the market clearing conditions for the most general case (including long-horizon investors and idiosyncratic background risk). Theorems I to III are all special cases of these market clearing conditions.

One-period agent i maximizes at time $t-1$ utility over terminal wealth (at time t)

$$\max_{x_i,y_i} E_{t-1}\left(\frac{W_{i,t}^{1-\gamma}}{1-\gamma}\right) \tag{2.23}$$

where $W_{i,t} = W_{i,t-1}(1+R_{i,p,t})$ with $R_{i,p}$ the total portfolio return. If the portfolio return is lognormal, the optimization can be written as

$$\max_{x_i,y_i} \left\{E_{t-1}(r_{i,p,t}) + \tfrac{1}{2}(1-\gamma)V_{t-1}(r_{i,p,t})\right\} \tag{2.24}$$

where log portfolio returns (in excess of the risk free rate) are denoted by $r_{i,p,t}$.

The simple gross return on the background risk for investor i is assumed to be $q_i e^{r_{n,t}+\varepsilon_{i,t}}$. We then use Campbell and Viceira's (2002) approximation of the log portfolio return: assuming that individual asset returns are jointly lognormal, the portfolio return is approximately lognormal. Dropping all time subscripts again, we have

$$\begin{aligned} r_{i,p} \approx x_i'(r_b - c_b) + y_i'(r_h - \delta_i c_h) + q_i(r_n + \varepsilon_i) + \\ \tfrac{1}{2}(x_i'\ y_i'\ q_i)\sigma_i^2 - \frac{1}{2}\mathrm{Var}(x_i'(r_b - c_b) + y_i'(r_h - \delta_i c_h) + q_i(r_n + \varepsilon_i)) \end{aligned} \tag{2.25}$$

where r_b, r_h and r_n are defined in excess of the risk-free rate, and σ_i^2 is a vector with the diagonal of $\mathrm{Var}((r_b - c_b)\ \ (r_h - \delta_i c_h)\ \ q_i(r_n + \varepsilon_i))$.

We then orthogonalize the hedge asset returns for the net return on the non-hedge assets, and optimize with respect to $\widehat{x}_i$ and y_i with $\widehat{x}_i = x_i - (\beta'_{r_h,r_b} - \delta_i \beta'_{c_h,r_b})y_i$. Dropping terms that do not depend on x_i or y_i and using (2.25), the objective function in (2.24) can be rewritten as

$$\max_{\widehat{x}_i,y_i} \left[\begin{array}{c} \widehat{x}_i'\mathrm{E}(r_b + \frac{1}{2}\sigma_b^2 - c_b) + y_i'\mathrm{E}(\widehat{r}_h + \frac{1}{2}\sigma_{i,h}^2 - \delta_i \widehat{c}_h) - \\ \frac{1}{2}\gamma_i \mathrm{Var}(\widehat{x}_i'(r_b - c_b) + y_i'(\widehat{r}_h - \delta_i \widehat{c}_h) + q_i(r_n + \varepsilon_i)) \end{array}\right] \tag{2.26}$$

with $\sigma_{i,h}^2 = diag(\mathrm{Var}(\widehat{r}_h - \delta_i \widehat{c}_h))$. Taking derivatives with respect to y_i gives the

first order condition for investor i

$$\mathrm{E}(\widehat{r}_h) + \tfrac{1}{2}\sigma^2_{i,h} - \delta_i \mathrm{E}(\widehat{c}_h) - \gamma_i \mathrm{Var}(\widehat{r}_h - \delta_i \widehat{c}_h) y_i - \gamma_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, r_n + \varepsilon_i) q_i = 0 \quad (2.27)$$

with solution for the optimal portfolio weights

$$y_i = \gamma_i^{-1} \mathrm{Var}(\widehat{r}_h - \delta_i \widehat{c}_h)^{-1} [\mathrm{E}(\widehat{r}_h) + \tfrac{1}{2}\sigma^2_{i,h} - \delta_i \mathrm{E}(\widehat{c}_h) - \gamma_i \mathrm{Cov}(\widehat{r}_h - \delta_i \widehat{c}_h, r_n + \varepsilon_i) q_i] \quad (2.28)$$

This result can be used to show the restrictions implied by the assumptions in the theoretical model on the three groups of investors (long, short, long/short). These restrictions are given by

$$y_i \geq 0 \;\text{ if }\; \delta_i = I,\; y_i \leq 0 \;\text{ if }\; \delta_i = -I,\; Dy_i \geq 0 \;\text{ if }\; \delta_i = D \quad (2.29)$$

where $\mathrm{E}(\widehat{r}_h)$ are the equilibrium expected returns derived below. Although these are complicated expressions, it is clear that to satisfy these restrictions one needs heterogeneity in risk aversion and/or hedging demand, and hedge assets that correlate sufficiently with the non-traded risk. This is also illustrated by the simple example in Section 2.2.2.2.4, where the constraint simplifies to $q_1 \gamma_1 Cov(r, r_n) > 2c$.

The portfolio problem for the long-horizon investors is particularly simple. These investors have an arbitrarily long horizon and maximize utility of terminal wealth, similar to (2.23). Given the assumptions that rebalancing is costless for these investors and that returns are IID, Campbell and Viceira (2002) show that the optimal portfolio weights are constant and equal to the myopic portfolio rule

$$y_i = \gamma_i^{-1} \mathrm{Var}(\widehat{r}_h)^{-1} [\mathrm{E}(\widehat{r}_h) + \tfrac{1}{2}\sigma^2_{\widehat{r}_h} - \gamma_i \mathrm{Cov}(\widehat{r}_h, r_n + \varepsilon_i) q_i] \quad (2.30)$$

with $\sigma^2_{\widehat{r}_h} = diag(\mathrm{Var}(\widehat{r}_h))$. Given the assumption of IID returns and that the one-period investors have the same characteristics each period, pre-multiplying by

wealth gives the equilibrium pricing condition for each period

$$\begin{aligned}
&\left[\sum_{i:T_i=1} w_i\gamma_i^{-1}V(\delta_i)^{-1} + \sum_{i:T_i=L} w_i\gamma_i^{-1}V_r^{-1}\right]\left(E(\widehat{r}_h) + \tfrac{1}{2}\sigma^2_{\widehat{r}_h}\right) + \\
&\tfrac{1}{2}\left[\sum_{i:T_i=1} w_i\gamma_i^{-1}V(\delta_i)^{-1}(\sigma^2_{i,h} - \sigma^2_{\widehat{r}_h})\right] - \\
&\left[\sum_{i:T_i=1} w_i\gamma_i^{-1}V(\delta_i)^{-1}\delta_i\right]E(\widehat{c}_h) - \\
&\left[\sum_{i:T_i=1} w_iq_iV(\delta_i)^{-1} + \sum_{i:T_i=L} w_iq_iV_r^{-1}\right]Cov(\widehat{r}_h, r_n) + \\
&\left[\sum_{i:T_i=1} w_iq_iV(\delta_i)^{-1}\delta_i\right]Cov(\widehat{c}_h, r_n) - \\
&\left[\sum_{i:T_i=1} w_iq_iV(\delta_i)^{-1}\mathrm{Cov}(\widehat{r}_h - \delta_i\widehat{c}_h, \varepsilon_i) + \sum_{i:T_i=L} w_iq_iV_r^{-1}\mathrm{Cov}(\widehat{r}_h, \varepsilon_i)\right] = S_h
\end{aligned} \tag{2.31}$$

where $V(\delta_i) = V(\widehat{r}_h - \delta_i\widehat{c}_h)$ and $V_r = V(\widehat{r}_h)$, and where $T_i = 1$ denotes one-period investors and $T_i = L$ long-horizon investors. We multiply this equation on both sides by $V(I) = V(\widehat{r}_h - \widehat{c}_h)$ and divide by $\eta = \sum_{i=1}^{N} w_i\gamma_i^{-1}$, and then apply a Taylor approximation to $V(I)V(\delta_i)^{-1}$ around $\widehat{c}_h = 0$ (see Appendix 2.9.2). Using that

$$V(I)S_h = Cov(\widehat{r}_h - \widehat{c}_h, (\widehat{r}_h - \widehat{c}_h)'S_h) \tag{2.32}$$

the resulting equation directly leads to Theorems I to III, which are all special cases of the general setup of this appendix. In all theorems, an extra term due to the convexity correction for log returns is defined as follows:

$$F_h = \frac{1}{2\eta}(I - H_1)^{-1}V(I)\left[\sum_{i:T_i=1} w_i\gamma_i^{-1}V(\delta_i)^{-1}(\sigma^2_{i,h} - \sigma^2_{\widehat{r}_h})\right]. \tag{2.33}$$

This term would be equal to zero if transaction costs are constant. Empirically, this term is small, so that we can safely neglect the term F_h in the empirical analysis. Specifically, in case $Cov(\widehat{r}_h, \widehat{c}_h) = 0$, (2.33) simplifies to $F_h = \frac{1}{2}Var(\widehat{c}_h)$ which is smaller than 0.2 basis points per quarter (except for one low-rating/low-liquidity portfolio for which it equals 1.3 basis points). For the crisis period, F_h is larger but still below 1 basis point for almost all portfolios.

2.9.2 Taylor approximations

This appendix provides a Taylor approximation to the matrix $V(I)V(\delta_i)^{-1}$ around $\widehat{c}_h = 0$. Empirically, transaction costs are small, in the sense that the standard deviation of c is smaller than the standard deviation of r. Write $\widehat{c}_h = \xi\tilde{c}$ so that

$$V(\delta_i) = V_r - \xi(\delta_i\widetilde{C} + \delta_i\widetilde{C}') + \xi^2 V_{\tilde{c}} \tag{2.34}$$

where $V_{\tilde{c}} = Var(\widetilde{c})$ and $\widetilde{C} = Cov(\widetilde{c}, \widehat{r}_h)$ and use a Taylor approximation around $\xi = 0$

$$V(I)V(\delta_i)^{-1} \approx V(I)V(\delta_i)^{-1}_{|\xi=0} + \xi\frac{\partial(V(I)V(\delta_i)^{-1})}{\partial\xi} \tag{2.35}$$

We have

$$\frac{\partial V(\delta_i)^{-1}}{\partial\xi} = -V(\delta_i)^{-1}\frac{\partial V(\delta_i)}{\partial\xi}V(\delta_i)^{-1} = V(\delta_i)^{-1}(\delta_i\widetilde{C} + \delta_i\widetilde{C}' - 2\xi V_{\tilde{c}})V(\delta_i)^{-1} \tag{2.36}$$

Evaluating this in $\xi = 0$ we obtain

$$\begin{aligned} V(I)V(\delta_i)^{-1} &\approx I + \xi(V_r V_r^{-1}(\delta_i\widetilde{C} + \delta_i\widetilde{C}')V_r^{-1}) + \xi(-(\widetilde{C} + \widetilde{C}')V_r^{-1}) \\ &= I + (\delta_i C + \delta_i C')V_r^{-1} - (C + C')V_r^{-1} \end{aligned} \tag{2.37}$$

If $\delta_i = -I$, this simplifies to $I - 2H_1$, and if $\delta_i = D$ this equals $I + H_2 - H_1$. Finally, using a similar derivation we obtain that $V(I)V_r^{-1} \approx I - H_1$.

2.9.3 GMM standard errors

In this appendix we outline the calculation of standard errors along the lines of Shanken (1992) for the GMM estimation of (2.16). To avoid complicated notation, we discuss a simplified example; the full derivation is available on request. The simplified example is given by

$$E(r) = X\alpha + E(c)\zeta + \beta\theta \tag{2.38}$$

with $\beta = (\beta_{r_h,r_b}\ \beta_{\widehat{r}_h,r_n}\ \beta_{\widehat{c}_h,r_n})$ and $\theta = (\psi, \lambda, \kappa)'$. In practice, the regressors are replaced by estimates and the second step regression is

$$\overline{er} = X\alpha + \overline{c}\zeta + \widehat{\beta}\theta + \eta \tag{2.39}$$

with

$$\eta = (\overline{er} - E(r)) - (\overline{c} - E(c))\zeta - (\widehat{\beta} - \beta)\theta \tag{2.40}$$

and $\overline{er} = T^{-1}\sum_{t=1}^{T} er_t$, with er_t our weekly estimate for the expected CDS returns in (2.22), and likewise for $\overline{c}$.

The second step estimates for (α, ζ, θ) are given by $(Z'\Sigma^{-1}Z)^{-1}Z'\Sigma^{-1}\overline{er}$ with $Z = (X\ \overline{c}\ \widehat{\beta})$ and Σ^{-1} the weighting matrix. The standard errors of these estimates are given by $(Z'\Sigma^{-1}Z)^{-1}Z'\Sigma^{-1}Var(\eta)\Sigma^{-1}Z(Z'\Sigma^{-1}Z)^{-1}$ with

$$Var(\eta) = Var(\overline{er}) + \zeta^2 Var(\overline{c}) + Var(\widehat{\beta}\theta) \tag{2.41}$$

The elements $Var(\overline{er})$ and $Var(\overline{c})$ can be estimated using a Newey-West procedure,

$$Var(\overline{er}) \widehat{=} T^{-2}\sum_{t}\sum_{k} w_k(er_t - \overline{er})(er_{t-k} - \overline{er}) \tag{2.42}$$

and likewise for $\overline{c}$, and

$$Var(\widehat{\beta}\theta) \widehat{=} T^{-2}\sum_{t=1}^{T}(u_t\theta)(u_t\theta)' \tag{2.43}$$

where $u_t = (Y'Y)^{-1}Y'\nu_t$, with ν_t the regression errors of the first step estimation of $\widehat{\beta}$, and Y the regressor variable (either r_b or r_n).

2.9.4 Repeat sales method

This appendix contains details on the repeat sales method used to form returns on CDS portfolios. Let $k(i)$ be the portfolio that contains constituent i and let T the number of periods in our sample. For constituent i, we assume that the spread quote of a CDS contract $p_{i,t}$ is given by

$$p_{i,t} = CDS_{k(i),t} + u_{i,t}, \tag{2.44}$$

where $CDS_{k(i),t}$ is the portfolio spread level (which is to be estimated) and $u_{i,t}$ is a quote specific error term. $u_{i,t}$ has mean zero and constant variance σ_u and is uncorrelated with the other variables and its own lags. To illustrate the approach, suppose we have three transactions in constituent i, say at times s, s' and s'' with

$s < s' < s''$. We can then specify spread innovations

$$\Delta p_{i,ss'} = p_{i,s'} - p_{i,s} = \sum_{j=2}^{T} x_{i,j,ss'} \Delta CDS_{k(i),j} + (u_{i,s'} - u_{i,s}) \tag{2.45}$$

$$\Delta p_{i,s's''} = p_{i,s''} - p_{i,s'} = \sum_{j=2}^{T} x_{i,j,s's''} \Delta CDS_{k(i),j} + (u_{i,s''} - u_{i,s'})$$

where $x_{i,j,ss'}$ is a dummy that defines whether $j \in [s, s']$. The error covariance matrix is given by

$$\text{Var}(\Delta p_{i,ss'}) = 2\sigma_u^2, \ \text{Var}(\Delta p_{i,s's''}) = 2\sigma_u^2, \ \text{Cov}(\Delta p_{i,ss'}, \Delta p_{i,s's''}) = -\sigma_u^2. \tag{2.46}$$

We can write our spread innovations for all constituents of $k(i)$ up to time T in matrix form as

$$\Delta p = x \Delta CDS_{k(i)} + v \tag{2.47}$$

where $v = \Delta u$. The best linear unbiased estimator of $\Delta CDS_{k(i)}$ is given by

$$\widehat{\Delta CDS}_{k(i)} = (x' M^{-1} x)^{-1} x' M^{-1} \Delta p, \tag{2.48}$$

where M is the (sparse, block diagonal) covariance matrix of v. Empirically, σ_u is unknown. However, because M is known up to a scalar which drops out, it turns out to be possible to consistently estimate $\Delta CDS_{k(i)}$ without knowledge of σ_u using regression.

2.9.5 Risk-free rates and default probabilities

To construct excess returns from CDS spread changes, we need risk-free discount rates. Lando and Feldhütter (2008) argue that despite the AA default risk premium present in LIBOR rates, the best estimates of risk-free rates are obtained from swap rates. Therefore, we use daily data on the 3-month LIBOR based swap curve with a maturity of 1 up to 6 years. Swap rates are obtained from Datastream. To construct zero-coupon rates, we assume that these are piece-wise constant and subsequently bootstrap these rates from the observed term structure of swap rates.

To obtain the risk-neutral default probabilities, also needed to construct excess returns, we assume for simplicity that CDS spreads only reflect default risk, that the risk-neutral default intensity is constant over the maturity period and that there is a deterministic loss rate $L = 60\%$. We then solve the CDS pricing equation under these assumptions to obtain the default intensity and compute the risk-

neutral probabilities (Duffie and Singleton (2003)):

$$CDS_{k,t} = 4\frac{L\sum_{j=1}^{(T-t)}\mathbb{Q}_{k,t}^{SV}(t+j-1)\mathbb{Q}_{k,t}^{def|SV}(t+j)B_t(t+j)}{\sum_{j=1}^{(T-t)}\mathbb{Q}_{k,t}^{SV}(t+j)B(t,t+j)}, \tag{2.49}$$
$$\mathbb{Q}_{k,t}^{SV}(t+j) = \exp(-\lambda_{k,t}j),\ \mathbb{Q}_{k,t}^{def|SV} = 1-\exp(-\lambda_{k,t}),$$

where $\mathbb{Q}_{k,t}^{def|SV}(t+j)$ is the risk neutral probability of a default in period $t+j$ conditional on survival up to time $t+j-1$. We calculate these probabilities for each CDS portfolio and for each week in the empirical analysis.

Naturally, there is an inconsistency in assuming that CDS prices are only driven by default risk where the goal is to identify a non-default component. However, if we iterate our estimation procedure, by correcting the CDS spread and λ for the estimated liquidity effect and re-estimating the model, we find results that are extremely close to the results reported here. Note that we only need $\mathbb{Q}^{SV}$ to calculate excess returns.

Chapter 3

Tiebreaker: Certification and Multiple Credit Ratings

This chapter is based on Bongaerts, Cremers and Goetzmann (2009).

3.1 Introduction

Credit Rating Agencies (CRAs) produce information about the risk of fixed income securities. However, the various ways the information is used by financial, legal and regulatory entities may potentially influence the nature of the information production process. Bond ratings are not only used to assess risk, they are also used for certification, e.g. to classify securities into investment grade (IG) and high yield (HY, or junk) status. These classifications in turn influence institutional demand and serve as bright-line triggers in corporate credit arrangements and regulatory oversight. For example, regulations may mandate banks and insurance companies to keep much higher reserve capital for high yield issues than for investment grade. The institutional and regulatory importance of credit ratings to issuers and investors has raised questions about whether the current system provides the proper incentives to optimally produce reliable, value-relevant information about risk.

Almost all large, liquid US corporate bond issues are rated by both S&P and Moody's. Fitch typically plays the role of a "third opinion" for large bond issues.[1]

[1]For smaller issues, Fitch is occasionally one of two raters. However, almost all bonds in our final sample are rated by both Moody's and S&P (see also Figure 1). Specifically, about 95% of all bonds in our database with at least 2 ratings are rated by both S&P and Moody's. This lack of cross-sectional variation in having an S&P or Moody's rating means that we can only study the implications for having Fitch as a third rating. Accordingly, we remove from our sample all bond issues that do not have ratings from both S&P and Moody's. For this sample of bond issues

The most prevalent institutional rule used for classifying rated bonds is that, if an issue has two ratings, only the worse rating can be used to classify the issue (e.g. into investment-grade or non-investment grade). However, if an issue has three ratings, the middle rating should be used (see for example the Basel II accord or the NAIC guidelines).[2] Therefore, if S&P and Moody's ratings are on opposite sides of the investment grade boundary, the Fitch rating (assuming it is the marginal, third rating) will decide into which class the issue falls.

Fitch thus plays the role of tie-breaker in the corporate bond ratings system. In this chapter, we explore the nature of this tie-breaking role in the context of the broader question of why the market for multiple credit ratings exists. We consider three hypotheses that could lead to demand for multiple credit ratings: An 'information production' hypothesis, a 'rating shopping' hypothesis and a 'certification' hypothesis. Under the information hypothesis, investors are averse to uncertainty, which is reduced by adding extra ratings. Under the rating shopping hypothesis, issuers 'shop' until their average rating at least conforms to their own credit assessment. Under the certification hypothesis, market and regulatory forces create a need for credibly separating bond issues into two types: informationally sensitive and non-informationally sensitive. These correspond to non-investment grade (also called high yield) and investment grade ratings, respectively. If the certification role of CRA dominates, only the weaker issuers would need a third rating. This leads us to investigate whether the option of a third rating leads to adverse selection effects. For all three hypotheses, we derive implications which are tested in the empirical section of the chapter. For example, for information production, one would not expect systematic differences in ratings across CRAs, whereas for rating shopping (by selection) and certification ('niche' rating) one would expect an extra rating to be more optimistic.[3]

---

rated by both Moody's and S&P and using quarterly observations for 2000-2007, about 60% of observations have a Fitch rating. As a result, the main focus of this chapter will be to consider the 'marginal' role of Fitch ratings, while controlling for S&P and Moody's ratings. Throughout the chapter, we only consider the three major credit rating agencies (CRAs), ignoring all others, as they are very much smaller than the top 3 CRAs.

[2]The National Association of Insurance Commissioners (NAIC) is the organization of state insurance regulators.

[3]Previous literature supports the plausibility of each of the three hypotheses. Guntay and Hackbarth (2006) show that analyst dispersion leads to higher credit spreads, suggesting uncertainty aversion among corporate bond investors. Poon and Firth (2005) show evidence of rating shopping in unsolicited ratings, Skreta and Veldkamp (2009) suggest this is increasing in issue complexity. Sangiorgi, Sokobin and Spatt (2009) consider theoretically rating shopping and any biases in ratings if there is heterogeneity across issuers in the extent to which different raters agree. Brister, Kennedy and Liu (1994) provide evidence of super-premiums for high-yield bonds due to certification.

For our empirical analysis, we use bond price data, issue and firm characteristics and credit ratings for U.S. corporate bond issues over the period 2000 through 2007. Consistent with previous research (see for example Cantor and Packer (1997)) we find that Fitch, on average, assigns the highest (i.e., most credit-worthy) ratings to corporate bonds in our sample, while Moody's on average assigns a lower rating than both S&P and Fitch. Given these systematic differences, we conduct further tests on the three hypotheses. Logit models predicting whether an issue is rated by Fitch show little evidence that proxies for asymmetric information or dispersion of opinion predict a Fitch rating, which is evidence against both rating shopping and information production.

Instead, for industrials, having a Fitch rating is quite strongly associated with S&P and Moody's ratings being on opposite sides of the investment grade boundary. This is consistent with the Fitch rating having a significant certification value as a "tie-breaking" rating agency for purposes of certification of investment grade status. Financial firms, which are extremely dependent on a credit rating, are consistently more likely to have a Fitch rating when Moody's and S&P disagree. However, we do not observe this pattern for other measures of uncertainty or opaqueness. We also do not find that Fitch "tie-breaker" ratings at the investment grade boundary are different from the average Fitch ratings. This result also seems inconsistent with the rating shopping hypothesis.

Next, we consider the impact of multiple ratings on credit spreads in order to estimate the economic importance of the certification and information effects. While credit ratings, in general, contain information about risk, the information about risk provided by the third rating agency (assumed to be Fitch) seems marginal. The major and critical exception is around the investment grade boundary, where Fitch ratings lead to lower credit spreads if they are relatively positive. In particular, bond issues for which the Fitch rating pushes a bond over the investment grade threshold (i.e., where S&P and Moody's are on opposite sides of this boundary) have a credit spread that is 45 basis points lower than when it confirms the high-yield [HY] status, controlling for risk characteristics. This economically very large difference suggests that the certification effect can significantly lower the issuer's cost of capital (apart from endogeneity considerations, which do not seem obvious for the very specific case of S&P and Moody's being on opposite sides of the IG boundary, whereas we control for various measures of uncertainty, including credit rating dispersion).

For bond issues that are not at the margin of the investment-grade classification, the certification effect of adding a Fitch rating is negative on average,

increasing the credit spread of about 8 basis points when Fitch confirms the average rating given by Moody's and S&P. Thus, absent the benefit of certification, the third rating seems associated with a higher risk-adjusted cost of capital. This is further evidence against information production and rating shopping as an explanation for multiple ratings.

Finally, we further investigate consider certification as a co-ordination mechanism to help differentiate securities with respect to their information sensitivity. Following Gorton and Pennacchi (1990) and Boot and Thakor (1993), we consider a setting with two types of investors in which issues with a lower credit quality carry more uncertainty. With one type of investors having regular trading needs and only the other type able to efficiently conduct costly research to reduce uncertainty, there could be a market breakdown for intermediate quality bonds. In this setting, credit ratings can restore trading by reducing the uncertainty about the value of information. Theoretically, this should lead to lower liquidity of high yield bonds, a concentration of Fitch (certification-induced) ratings around the IG-HY boundary or for issues with greater potential for future rating changes, and finally to higher credit spreads for Fitch rated bonds especially in periods of high uncertainty when the value of acquiring information increases. These predictions are confirmed empirically, such that the certification effects documented in this chapter seem consistent with an equilibrium outcome in credit markets with information-sensitive (i.e., high yield) and insensitive (i.e., very high credit quality) bonds. In particular, the on average higher credit spreads for Fitch-rated bonds seem to stem from periods in which aggregate uncertainty is high, and the need for certification may be greatest.

Taken together, our work suggests that a major function of CRAs is to certify to relatively uninformed traders that they do not face a significant informational disadvantage. Absent the IG-HY boundary certification, there might be a no-trade equilibrium due to adverse selection. In the long run, a necessary condition for any credit rating agency to have credibility about the IG-HY classification is that it produces and uses value-relevant information about the firm. A rubber-stamp without research will not serve the certification purpose in the long run, especially if the regulatory emphasis on credit ratings would change in the aftermath of the current credit crisis. Thus, the research by CRAs - to the extent that it is independently verifiable - is a means to earn the trust of the marketplace. Competition among CRAs in information-production seems a necessary condition for effective certification, even if in equilibrium the third rater does not seem to provide significant new information.

The remainder of the chapter is organized as follows. Section 2 contains our motivation for the empirical tests and the various hypotheses, and also considers related literature. In section 3, we discuss the sample construction and methodology. Section 4 presents the empirical results on the three hypotheses. Section 5 explores the certification effect in more depth and section 6 concludes.

3.2 Motivation

3.2.1 Credit Rating Agencies and Regulation

There are three major credit rating agencies (CRAs) in the U.S. market: S&P, Moody's and Fitch. In addition to these big three, there are seven minor CRAs that issue credit ratings that qualify for meeting regulatory standards. While the purpose of a credit rating is to reflect the creditworthiness of an issue or issuer, the rating agencies have some discretion in the philosophy underlying their rating system and are not required to make their rating methodology public.[4]

CRAs are licensed as Nationally Recognized Statistical Rating Organizations (NRSRO) by the Securities and Exchange Commission. This official designation has a number of effects. First, CRAs are exempt from Regulation FD, allowing corporations to share value-relevant information with the rating agency without disclosing it publicly. Second, the SEC designation allows credit ratings to be used for meeting regulatory requirements that call for a minimum or an average rating value. For example, until June, 2008 the SEC required that money market mutual funds hold instruments with a credit rating in one of the two short-term higher credit rating categories. This effectively provided a "safe harbor" for mutual funds with respect to litigation over fund failures.

Banking regulations enacted under the so-called 'Basel II accords' explicitly rely on NRSRO ratings for determining risk-based capital. In particular, bonds held by banks are assigned risk "weights" based upon their credit ratings, which in turn are used to calculate how much reserve capital should be held. US insurance companies are subject to very similar risk-based capital requirements and European financial companies will follow soon with the implementation of 'Solvency II.' Although there is much discussion about treating bank and insurance assets in the context of their total portfolio that would take into account co-variance rather than security-

[4]Indeed, some ratings have a point-in-time perspective, whereas others (including the three major CRAs) employ a 'through-the-cycle' vision. Similarly, while some rating agencies aim to reflect cross-sectional variation in default probabilities (like S&P and Fitch), others aim to also incorporate loss given default and reflect dispersion in expected loss (like Moody's).

specific risk, as of mid-2008, a large portion of U.S. institutional portfolios are still subject to regulation tied to ratings by a relatively small number of NRSROs.

In June, 2008, the SEC proposed to eliminate language in many regulations pertaining to NRSROs, and instead allow an alternative decision-making function, perhaps recognizing that reliance on credit ratings agencies had the potential to distort the information gathering and investment decision-making process. In addition, several other regulations were implemented to try to make rating agencies more accountable and increase the transparency of the rating process. The motivation for these (proposed) changes stemmed from the subprime mortgage crisis that began in 2007, and from concerns that the top three CRAs may represent an artificial, effective oligopoly enabled by government regulation. Among other things, the concern is that this oligopoly might not be the optimal mechanism for revealing information related to the risk of fixed income securities, and instead might be used as an artificial safe-harbor to excuse investment managers from exercising business judgment. As such, it could allow the CRAs to extract rents from corporations by virtue of serving as "gate-keepers" to the investment-grade (IG) rating, especially as the CRAs are paid by the corporations whose bonds are rated. Moreover, competition among CRAs could lead to a so called "race to the bottom", i.e. competition over deteriorating standards to attract more customers. This is an often heard concern about the structured finance market in the (subprime) mortgage crisis.

While all of the aforementioned issues are of a regulatory nature, the wider financial industry has also grown increasingly dependent on CRAs. Financial institutions typically center self-regulation around credit ratings, e.g. mutual funds stating in their charter to only invest in investment-grade (IG) quality fixed income securities. Trading and internal risk management models often take credit ratings either as primary or as calibration inputs. Many corporate credit arrangements, like collateral requirements and haircuts are further driven by credit ratings. Moreover, ratings are an important factor in determining whether a bond qualifies for inclusion in prominent corporate bond indices like the Lehman Brothers US Corporate IG Index. Inclusion in such an index may greatly improve the liquidity of an issue, since for example index tracking institutions will trade more in them. Several papers show that a higher liquidity leads to lower credit spreads (see for example Chen et al. (2007)). Typically, these procedures tend to incorporate all (multiple) rating information available, extending possible certification effects well beyond those resulting from financial regulation.[5]

[5]See, for example, the Lehman Brothers IG Index (now called Barclays US corporate IG

3.2.2 Why Multiple Ratings Matter

In this section, we consider different mechanisms that could lead firms to solicit and pay for multiple ratings. We base these hypotheses also on empirical evidence provided by the previous literature. The three hypotheses we consider are (i) the "information production" hypothesis, (ii) the "rating shopping" hypothesis and (iii) the "certification" (or clientele or regulation) hypothesis. Below, we will give a short description of each and discuss its testable empirical predictions. Table 1 summarizes their empirical predictions.

To start with, the reason for multiple ratings could be the need for increased information production, with more ratings reducing uncertainty about the credit quality of the rated bonds. Each CRA produces potentially different and new information relative to the other CRAs. If investors appreciate this additional information, it may lead to a reduction in uncertainty and result in lower credit spreads for bonds with more ratings. The natural implication of this hypothesis is that the marginal value of an extra rating will be largest for the bonds that are subject to most uncertainty. However, in a rational asset pricing framework, an information effect will only take place when the rating errors made by, or disagreements amongst, CRAs are systematic. If not, rating errors or disagreements would average out in a well-diversified portfolio of bonds. For example, this can happen when each rating agency fails to incorporate important information from different systematic factors. In this case, ratings can unconditionally be accurate, but not conditional on these factors. Another setting in which an information effect can arise is more behavioral in nature. If investors are averse to even idiosyncratic rating errors, for example if they have utility functions that are averse to Knightian uncertainty (Knight, 1921), they would be willing to pay for bonds with reduced uncertainty caused by more ratings. One would expect that issuers with greater ex-ante uncertainty are more likely to apply for extra ratings since the potential reduction of uncertainty is largest for them.

Second, the "rating shopping" effect arises in a setting in which credit rating agencies (CRAs) make rating errors and issuers have better information about their own credit quality and try to optimize their average rating. Assuming an unbiased expected rating for each CRA, the optimal strategy for the issuer may be to apply for a rating at the first CRA, and if it is better than the true credit quality, stop, and otherwise apply with the next CRA. Applying for private ratings and making these public if favorable, or deciding which CRA to use based on advice from an

Index) Factsheet.

investment bank that has knowledge about each CRA's precise rating algorithms leads to similar patterns. For a rating shopping effect, not only the existence of the effect would be of interest. The way this behavior is priced by investors would also be interesting. If aware of this behavior, investors would prefer an average rating given by three CRAs to the same average rating given two, and also to a rating by a single agency. They would thus accept a lower credit spread for multiple ratings, as is the case for an information story. However, in contrast to an information effect, we would expect to see better extra ratings compared to their base rating for issuers with more uncertainty. Uncertainty in ratings over time (time variation in ratings) would reduce the rating shopping effect, because the optimal outcome is more likely to change quickly.

The third explanation for multiple ratings is "certification," e.g., whether a bond issue is investment grade (IG) or high yield (HY), arising when financial regulation and institutional rules impose frictions on the formation of optimal portfolios. Financial regulation has traditionally relied heavily on credit ratings to determine the suitability and riskiness of fixed income investments. One important purpose of ratings is to determine the reserve capital that banks and insurance companies need to hold for corporate bonds in their portfolio. However, the universe of rules in which credit ratings play a role extends well beyond the corporate bond market. Ratings are also of importance in the structured finance market, the commercial paper market, when determining haircuts on collateral on the discount window of the central bank and when determining whether projects can qualify for government assistance (see for example Basel Committee on Banking Supervision (2000)). The recent government "rescue" of AIG in 2008 followed a change in the rating of AIG's corporate debt which, in turn, triggered a need for increased collateral in its counterparty arrangements. This event underscores the enormous potential impact of certification, especially for financial firms.

The most prominent distinction based on credit ratings is whether an issue, issuer or structured product is investment grade (IG) or high yield (HY). Much financial regulation is based on this classification, which creates strong incentives for issuers. In particular, the most prevalent institutional rule used for classifying rated bonds is that, if an issue has two ratings, only the worse rating can be used to classify the issue (e.g. into investment-grade or non-investment grade). However, if an issue has three ratings, the middle rating should be used (see the Basel II accord or the NAIC guidelines). Therefore, if S&P and Moody's ratings are on opposite sides of the investment grade boundary, the Fitch rating (assuming it is the marginal rating) will decide into which class the issue falls.

Under the certification hypothesis, a CRA systematically giving better ratings than the other CRAs could be used to (at least partially) satisfy financial regulation. A rating from this CRA could be requested by issuers for which the extra rating might make them qualify for IG. Alternatively, issuers that consider themselves likely to experience a downgrade from IG to HY could opt for an extra rating from a precautionary motive. This could lead to adverse selection effects, as relatively weaker firms with higher credit spreads would then be more likely to apply for a Fitch rating. For financial firms, their credit rating is one of their most vital business assets, since it is used in so many market practices and regulations. Therefore, under the certification hypothesis, split ratings by Moody's and S&P should give incentives to get a Fitch rating. Moreover, in terms of rating changes, an extra rating may provide a hedge against the regulatory and rule-based effects of rating downgrades, while also increasing the probability to reap regulatory benefits from upgrades. This effect should be more pronounced for more volatile ratings over time.

Each of the three explanations of multiple ratings (information production, rating shopping and certification), thus have distinct empirical predictions, though different explanations can co-exist. There are potential differences in whether or not we would expect (i) systematic differences across CRAs, (ii) informational content of each rating and (iii) the number of ratings, (iv) an impact of the additional rating on credit spreads independent of the information contained therein, (v) the importance of regulatory boundaries and (vi) the association with the time series of rating changes.

Under information production, there would be no systematic differences across CRAs , each rating will contain information, more uncertainty would lead to more ratings but not affect their average level; and if the additional rating confirms the other ratings and/or gives better information, credit spreads will be lower. Under rating shopping, systematic differences across CRAs are likely to exist, with additional / later ratings being better; more uncertainty would again lead to more ratings but now also to better ratings. Better ratings would lower the credit spread. Finally, under certification, systematic differences across CRAs again could exist (in fact help the marginal CRA to establish a position in the market); uncertainty would play no role; unconditionally an additional rating could be a manifestation of adverse selection (only weaker issuers take an extra rating) and consequently be associated with higher credit spreads; and strongest effects are expected when the marginal rating matters most for whether the bond issue satisfies the investment grade classification. The various empirical predictions are summarize in the table

below, where '-' indicates that reverse implication is supported, '+' means it is supported, and '0' means not predicted.

[INSERT TABLE 1]

3.2.3 Related Research

As asset pricing relies fundamentally on the production and dissemination of information, and this process is endogenously determined, the extent of the related literature is vast. CRAs are only one type of research and information provider to the securities markets. Much of the academic literature about the role of research and information providers has focused on equity analysts rather than debt rating agencies. Studies on the equity markets have addressed a broad range of questions about research providers, ranging from whether analysts' opinions convey value-relevant information, to whether conflicts of interest and personal strategic considerations influence the nature of the information provided. CRAs present a different institutional structure for analysis. While the same basic principals regarding information production apply, CRAs have become integral to regulation pertaining to the credit market (see also the discussion above).

Research about the role of CRAs is more limited, but has provided a useful framework for empirical study. Theory has asked what role CRAs play in the equilibrium pricing process. Boot, Milbourn and Schmeits (2006) highlight CRAs as a valuable coordination device. In a setting in which it is optimal for firms to separately offer informationally-insensitive securities, the investment-grade boundary provides a common signal delineating which securities of the firm can be regarded as such. In this framework, the CRAs provide little value-relevant information at the investment grade boundary other than certification, but some useful valuation information about riskier issues. The further implication of this theory is that firms might specialize at these contrasting tasks.
citeasnounCarlsonHale05 point out that when each investor's optimal strategy is dependent on the strategy followed by other investors, the public rating provided by the rating agency can serve to coordinate investor actions. This dynamic can make multiple equilibria problems more likely and, in contrast to Boot et al. (2006), potentially be destabilizing. In a similar model, Bannier and Tyrell (2006) introduce reputation and competition among rating agencies. Under certain conditions, this will stimulate investors to search for private information and will thus not only restore a unique equilibrium, but could even lead to a more efficient one.

Each of the three potential explanations for multiple ratings finds support in

the existing academic literature. On the issue of information production, a number of papers have looked at the effects of rating changes on asset prices. For example, Kliger and Sarig (2000) use a refinement in the Moody's ratings system to show that rating changes channel information to the market that changes the value of the debt. However, their results also suggest that this information leaves the aggregate company value intact and thus only influences the value of the debt relative to the value of the equity.
citeasnounGuntayHackbarth06 investigate the effect of analyst dispersion on credit spreads. They find that higher analyst dispersion is associated with higher credit spreads and conclude that this is probably due to cash flow uncertainty. Becker and Milbourn (2008) consider what happened when Fitch became the third rating agency after Moody's and S&P. They find that that "ratings became friendlier to issuers and less informative as competition increased." Morgan (2002) finds that banks, being inherently more opaque than industrials, are more likely to have rating disagreement between Moody's and S&P. On the theoretical side, Doherty, Kartasheva and Phillips (2009) derive equilibria with multiple rating agencies where different rating agencies are complements rather than substitutes with respect to information production in oligopoly and a monopoly setting with entry respectively.

Jewell and Livingston (1999) investigate whether ratings differ systematically across rating agencies. They find that the average Fitch rating is much better than Moody's and S&P ratings, but that this effect disappears once they restrict their sample to bonds only rated by all three CRAs. They also investigate whether rating shopping takes place, but find no evidence. Covitz and Harrison (2003) look at the trade-off that rating agencies face between income resulting from giving out favorable ratings and expected future fees from customers resulting from reputation. They argue that reputation concerns dominate and prevent CRAs from being "bribed" by wealthy customers. Bannier et al. (2009), like Poon (2003) and Poon and Firth (2005), investigate possible adverse selection and hold-up in the context of CRA and issuer incentives when CRAs issue ratings on an unsolicited basis.[6]

[6]Adverse selection may explain why unsolicited ratings are on average worse than solicited ones. That is, firms that receive a favorable unsolicited rating do not apply for a solicited rating anymore, whereas firms with an unfavorable unsolicited rating pay for another (solicited) opinion. On the other, CRAs could create a holdup problem by underestimating the creditworthiness of companies in their unsolicited ratings to prompt those companies to seek (improved) paid-for solicited rating subsequently. The general conclusion of this literature is that for industrials unsolicited ratings are lower than solicited ratings, and that this difference is largely due to adverse selection of debt issuers. There seems to be some evidence for holdup by CRAs, but this

Inspired by the financial crisis and the allegations addressed at CRAs, several recent theoretical papers put forward models to motivate rating shopping. Skreta and Veldkamp (2009) develop a model where incentives for rating shopping increase as the complexity of the products increases. Bolton, Freixas and Shapiro (2009) show that naïve investors in the market may give incentives to CRAs to inflate their ratings and that in a duopoly, this gives extra incentives for rating shopping, which in turn aggravates the problem. Sangiorgi et al. (2009) consider theoretically rating shopping and any biases in ratings if there is heterogeneity across issuers in the extent to which different raters agree.

In research most closely related to our own, Cantor and Packer (1997) also look for evidence of the information effect, the shopping effect and the certification effect. They use issuer-level ratings data for the year 1994 to understand the motivation for using a third rating agency, but do not use bond price and yield data to evaluate the market effects and price implications of the third rating. Like this chapter, they find that the third CRA rating is systematically higher, however, they fail to find evidence that the use of a third CRA is motivated by information, rating shopping or certification effects. Since the time of their study, bond price data has become more widely available for research. This allows us to conduct more powerful tests of the market response to the additional rating, and to understand in greater detail how market participants interpret ratings.

Brister et al. (1994) find evidence of a "super-premium" in yields of junk bonds due to regulation around the IG boundary. Based on only S&P rating data, they find that yields increase disproportionally from a BBB to BB rating relative to the increase in default risk. Finally, in a recent paper Kisgen and Strahan (2009) find that credit spreads change in the direction of a Dominion bond rating after the accreditation of Dominion as an NRSRO. Moreover, they find that this effect is much stronger around the IG boundary, indicating the importance of certification.

With respect to the nature of the certification effect that we find, our research relates to earlier work on security design. Gorton and Pennacchi (1990) set up a model that incentivizes uninformed investors to transform risky assets into information-sensitive and information-insensitive parts, where for the latter category they can avoid losses due to trading with informed investors. Boot and Thakor (1993), on the other hand, develop a model in which security issuers lower funding costs by making informed trading more profitable. Our setup motivating the exploration of the certification hypothesis uses key insights of both papers. In

is concentrated mainly on financials. Our dataset does not include information on unsolicited ratings for US corporate bonds, so this chapter does not address these findings.

particular, the non-trading region in our setup is the result of the absence of the uninformed investor, whereas the uninformed investor is needed to make trading profitable for the informed investor.

3.3 Sample Construction and Methodology

3.3.1 Measures and controls

Section 2.2 derives empirical implications regarding systematic rating differences, the number of ratings and pricing for each of our three hypotheses. These implications originate from relevance of regulation, uncertainty/opaqueness about quality and time series variation in ratings. In our regressions, we measure uncertainty or opaqueness by analyst dispersion of the firm's earnings per share or by rating dispersion of the bond. We measure the importance of regulation by a dummy variable indicating whether a Fitch rating is or can be decisive for satisfying certain regulatory constraints like crossing the IG-HY barrier. To avoid capturing timing mismatches between (multiple) rating transitions, we require that any particular ratings situation has existed for at least a quarter. For the financials, we measure the importance of regulation by the effect of rating dispersion contrasted to that of analyst dispersion. Rating dispersion can also be a measure of uncertainty or opaqueness (like the IG-HY barrier dummies, we also require stability of the difference over at least 1 quarter).[7] While rating dispersion is also a measure of regulatory relevance, analyst dispersion is not, which will get us the required identification. For financials, we also use dummies similar to those for industrials but focused around the AAA, AA and A boundaries rather than the IG boundary, since financials are typically highly rated. Time variation in ratings is hard to measure, since ratings are rather persistent. Therefore, we do not explicitly include time variation in ratings as a variable in our regressions but analyze the correlation between having a Fitch rating and the likelihood of experiencing rating changes.

To avoid spurious results due to omitted variables in our regressions, we correct for several issue and issuer characteristics as well as for business cycle effects. On the issue level, we correct for callability (using a dummy), size (offering size), and term structure effects (duration and convexity). On issuer level, we correct for credit risk (using the inputs of the Merton (1974) model, leverage and volatil-

[7] This will also mitigate concerns about not correcting for credit watches and credit outlooks (for these variables our data are too sparse to be useful).

ity), profitability (ROA), systematic risk (equity beta) and tangibility of assets (PPE/total book assets). Tangibility of assets is important since Moody's as the only CRA also incorporates expected recovery in their ratings. We also include R&D intensity (R&D expenditure over book assets) as an additional control. R&D intensity can be associated with several pricing mechanisms in the corporate bond markets. For example, higher R&D industries may have higher growth opportunities and therefore lower credit spreads. On the other hand, R&D projects tend to be riskier than normal projects, which may increase credit risk. We will control for the aggregate effect. In the pricing regressions, we also include macro-economic variables as controls for business cycle effects, since default probabilities, liquidity and risk premia are likely to vary with the business cycle.[8]

3.3.2 Data and filters

For our main analysis, we use corporate bond pricing data from the TRACE database and merge it with bond characteristic and rating data from FISD, equity data from CRSP, financial data from Compustat Industrial Quarterly and analyst data from I/B/E/S. Our time series ranges from July 1st 2002 up to December 31st 2007.[9] The TRACE data contain all trades in TRACE-eligible bonds by NASD members that were disseminated to the public. The dissemination to the public happened in phases, resulting in an expanding universe of bonds. A more comprehensive description of the TRACE database as well as the dissemination process is given in Downing et al. (2005).

We apply several filters to our dataset to remove bonds with special features that we do not want to consider, and to remove seemingly erroneous entries.[10] Next, we use the FISD characteristics to match the trades to bond characteristics using CUSIPs. [11] We only use senior unsecured notes and bonds. We discard all bonds that are exchangeable, putable, convertible or pay-in-kind, that have a

[8] As an alternative, we included month fixed effects, but results were virtually identical.

[9] The TRACE database starts in July 2002.

[10] We remove all trades that include commission, have a settlement period of more than 5 days, and all trades that are canceled. Trades that are corrected, we correct. Moreover, we remove all trades for which we have a negative reported yield, since these will be mainly driven by implicit option premia in the yield. We also found trades with a settlement date later than or equal to the maturity date and removed those bonds. Furthermore, we found several records that we suspect to be duplicates, resulting from both parties involved in a trade reporting to the system. Thus, we filter out duplicate trades that have identical prices, trading time and volume. Moreover, some of the yields changes are extremely high or low. We remove trades with yields of more than 1500 bps. Finally, we deleted all issues with a duration of less than 1 year.

[11] of non-exchange traded bonds do not change in case of mergers, acquisitions, etc (see www.cusip.com).

non-fixed coupon, that are subordinated, secured or guaranteed or are zero coupon bonds. Removing callable bonds would reduce our sample substantially, so we leave those in, but correct for this feature in our regressions using a dummy variable.

To diminish the impact of remaining data errors, we average all trades in each bond by trading day. To reduce the effect of over-representation of very liquid bonds, we then make monthly observations by only recording for each bond the last available daily average credit spread of every month. To avoid issues with severe illiquidity and distressed debt as well as issues relating to non-linearity of credit spreads with respect to rating scales, we remove all issues with an average (based on Moody's, S&P and Fitch ratings, if available) worse than BB- (Ba3). For all bond trades in our sample, we calculate yields and credit spreads. The benchmark rate that is used to construct credit spreads is based on an interpolation of the yields of the two on-the-run government bonds bracketing the corporate bond with respect to duration.

Ratings data is obtained from FISD as provided by Mergent. The credit ratings data provider confirmed that due to changes in their data collecting procedures, the rating data before 2000 is incomplete. This is illustrated by Figure 1, which shows the number of rated bond issues each quarter by Moody's, S&P and Fitch as well as the proportion of all bond issues in the sample rated by each of these CRAs in a given quarter from 1994 - 2007. While the number of rated bond issues is steadily increasing over time for all three CRAs, the sudden jump in the number of issues rated by S&P strongly suggests that too many bond issues before 2000 have missing S&P ratings (i.e., issues had S&P ratings, but these are missing from the database). Specifically, the percentage of all issues rated by S&P equals 58% at the end of 1999 and jumps to 94% in 2000, and remains above 90% until the end of the sample. There is likewise a significant, though smaller, jump in the percentage of bond issues rated by Fitch, from 29% at the end of 1999 to 39% in 2000. As a result, for the analyses that can done without pricing data, we use rating data from the second quarter of 2000 onwards. For our credit spread regressions the impact of this will be minor, as TRACE only starts in the middle of 2002 and is dominated by data from 2004 onwards (when the number of bond issues contained in TRACE is greatly expanded).[12]

We follow convention and use a numerical rating scale to convert ratings. Therefore, for Fitch and S&P (with Moody's rating between parentheses), the

[12]FISD confirmed that from mid-2003 on, they have been using automated rating feeds from the CRAs, whereas before that time these ratings were collected by hand, increasing the potential for data errors in the earlier period.

numerical scores corresponding to the rating notches are, respectively, 1 for AAA (Aaa), 2 for AA+ (Aa1), 3 for AA (Aa2), 4 for AA- (Aa3), 5 for A+ (A1), 6 for A (A2), 7 for A- (A3), 8 for BBB+ (Baa1), 9 for BBB (Baa2), 10 for BBB- (Baa3), 11 for BB+ (Ba1), 12 for BB (Ba2), 13 for BB- (Ba3), 14 for B+ (B1), 15 for B (B2), 16 for B- (B3), 17 for CCC+ (Caa1) and 18 for CCC (Caa). However, we will still refer to more optimistic ratings, i.e. implying lower bankruptcy likelihood, as 'higher' or 'better' ratings.

Equity market data is obtained from CRSP. We calculate (rolling window) historical daily volatility and betas to the CRSP value-weighted index based on half a year of historical trading data. An AR(1) filter is used to filter out bid-ask bounces in daily closing prices. For an observation to be included, we need at least 111 return observations in the last half year.

Company data is obtained from Compustat Quarterly. We download data on firm size (total book assets), debt (long and short term debt), profitability (earnings), tangibility of assets (PPE), R&D spending (obtained from Compustat Annual, since usually reported in the annual only) and industry (SIC code). From these data, we construct a leverage variable (total debt over total book assets), a tangibility of assets variable (PPE/total book assets), an R&D spending variable (R&D expenses/total book assets and a dummy for missing values) and a profitability variable (total earnings over total assets). We also construct a 'SIC division' variable that is defined as the division that the 2-digit SIC belongs to.

Monthly analyst forecast data on the one yearly EPS are obtained from I/B/E/S. We download summary data including number of analysts, standard deviation of forecasts, minimum and maximum forecast from the unadjusted file. Following Guntay and Hackbarth (2006), we divide forecast dispersion measured by analyst standard deviation by the share price to end up with dispersion per dollar value invested.

We also include several macro-economic variables. From the website of the Federal Reserve of Saint Louis, we obtain GDP growth and inflation. From the CBOE website, we get the VIX as a measure of market wide volatility. Following Campbell and Taksler (2003), we include the risk-free rate that was also used to construct the credit spread and the 10 year minus the 3 month yield on government bonds as a measures for the level and the slope of the term structure, respectively. Finally, again following Campbell and Taksler (2003), we include the TED spread, defined as the difference between the yield of 3-month LIBOR versus 3-month treasury debt, as a measure for liquidity and aggregate credit market sentiment capturing flights to quality and liquidity.

Almost all bonds in our final sample are rated by both Moody's and S&P (see also Figure 1). Specifically, about 95% of all bonds in our database with at least 2 ratings are rated by both S&P and Moody's. This lack of cross-sectional variation in having an S&P or Moody's rating means that we can only study the implications for having Fitch as a third rating.

Accordingly, we remove from our sample all bond issues that do not have ratings from both S&P and Moody's. For this sample of bond issues rated by both Moody's and S&P and using quarterly observations for 2000-2007, about 60% of observations have a Fitch rating. As a result, the main focus of this chapter will be to consider the 'marginal' role of Fitch ratings, while controlling for S&P and Moody's ratings. Table 2 presents summary statistics for the quarterly ratings sample, and Table 3 for the monthly credit spread sample.

3.4 Empirical results

3.4.1 Rating Differences and Rating Information

Following Cantor and Packer (1997), we first test whether Fitch ratings are on average better than Moody's and S&P ratings for the same issue in the same quarter, and present the results in Table 4 and Figure 2. The table presents evidence against an information effect, since the extra Fitch rating is in general significantly better than the Moody's and S&P rating. S&P is also in general more optimistic than Moody's but the difference is much smaller (both for the full sample and for the Fitch-rated sample alone). These differences are potentially explained by differences in philosophies between the two major firms. Moody's rates issues on the expected loss due to default, while S&P focuses on the probability of default. The effect of these philosophical differences is most apparent in the low rating categories. Issues with a low rating usually have a high loss given default. Consequently, Moody's systematically gives a worse rating in this category, whereas Fitch and S&P seem to agree, on average. It is mainly in the two middle categories, where regulation is likely to have the most impact, that the optimism of Fitch is largest.

Having established that Fitch is on average more optimistic for IG bonds than Moody's and S&P, we investigate the bond market reaction to the ratings issued by Fitch. Specifically, we are interested in the informational content of a Fitch rating compared to the informational content of a Moody's or S&P rating. To minimize issues relating to selection, we limit ourselves for this test to the sample

that is rated by all three CRAs. For this sample, we regress end-of-month credit spreads on dummy variables for the median rating, controls and dummy variables for each of the three CRAs indicating whether the CRA gave a rating above or below the median rating for that bond (we also interact these directional dummies with the distance to the median rating in number of notches). Results can be found in Table 5, using directional differences to the median rating in Panel A and using the size and direction of differences to the median rating in Panel B. All credit spread regressions in the chapter use standard errors clustered by issuer, include a large number of controls with year dummies, and are run with and without issuer fixed effects. Because the subprime crisis had such a dramatic effect on financial markets, we also added a dummy indicating the crisis period (from July 2007 onwards).

The credit spread regressions in Panels A and B of Table 5 indicate that S&P ratings appear to be highly informative. Both directional dummies have highly significant coefficients in the expected directions, with or without issuer fixed effects and in both panels. In the full specifications including directional dummies for all three CRAs (columns 7 and 8 of Panel A, with and without issuer fixed effects, respectively), the results are symmetric, indicating that the credit spread is about 8 to 15 basis points higher (lower) if the S&P rating is worse (better) than the median rating.

Moody's directional dummies also show clear evidence of containing information that is relevant to the bond price. In all specifications, credit spreads are 9 to 14 basis points higher if the Moody's rating is worse than the median rating. For Moody's, the directional variables are only significant for those indicating a worse rating, which may be due to a lack of data on the positive direction (see Panel C of Table 5).

For Fitch ratings, there is no evidence of informational content in the directional dummies. There is no significance with the 'right' sign in any of the four specifications with Fitch directional dummies in Panel A without issuer fixed effects, nor in any of the four specifications also incorporating the size of the difference of the Fitch rating to the median rating in Panel B (with or without issuer fixed effects). The only marginal significance is in columns 4 and 8 of Panel A (with issuer fixed effects). When investigating this further, we find that this effect disappears completely when we restrict our sample to issues with a median rating of BBB or better (column 9). Thus, the only impact Fitch seems to have is around the regulatory IG boundary and this impact does not change with the size of the Fitch rating difference.

As a side note, the distribution of differences with the median rating (see Panel C of Table 5) confirm the results in Table 4. For both Moody's and Fitch, these are clearly asymmetric and significantly different, with Moody's having a greater frequency of ratings worse (i.e., more pessimistic, 20.9%) than ratings better than the median (i.e., more optimistic, 4.17%), with the opposite for Fitch (3.6% and 34%, respectively). For S&P, whose ratings are most often the median rating, deviations are more symmetric, with 11.4% worse and 7.3% better than the median.

Table 6 presents another test to investigate the informational content of Fitch ratings on credit spreads. Here, the sample consists of all issue rated by both Moody's and S&P, and thus no longer conditions on also having a Fitch rating as for the sample used for Table 5. While correcting for the average Moody's and S&P rating (using 4 rating group dummies), we look at the informational content of having a Fitch rating and of the Fitch rating dummy (also using 4 rating groups). We also test whether the coefficients on the four Fitch rating dummies are jointly equal to zero. We include all the controls of Table 5, though their coefficients are not reported to save space. Each specification also includes year dummies and is run with and without issuer fixed effects.

The results of Table 6 are broadly consistent with Table 5. Without issuer fixed effects, none of the Fitch rating dummies are significant, while the rating dummies for the average Moody's and S&P ratings are highly significant. With issuer fixed effects, some of the Fitch dummies are significant, but this is mainly due to the fact that the two most extreme rating categories (AAA and BB) are associated with a higher credit spread after taking into account standard controls. There seems to be little distinctive information in Fitch ratings of AA, A and BBB. This point is also clear from column 5 which is identical to column 4, except for the fact that a Fitch A rating is taken as the 'base case' for creating Fitch rating dummies. Jointly, these 'middle ratings' by Fitch seem to differ only marginally, with no evidence of any difference at all if issuer fixed effects are included (p-value of 74%, column 4).

Moreover, the regression with issuer fixed effects provides some evidence that when a Fitch rating is added, this is associated with an increase of credit spreads by at least 6.75 basis points. As we separately control for the Fitch rating group, this increase does not depend on the actual rating Fitch has given. This suggests that the market may consider having a Fitch rating to be a negative signal due to adverse selection.

These findings clearly conflict with an information and a rating shopping effect

since under both effects one would expect the credit spread to be influenced by the direction of the extra Fitch rating. Neither hypothesis would one expect that having a Fitch rating itself may be a negative signal. This leaves us with a puzzle that we will try to address in the remainder of this chapter. Why would an issuer apply for a Fitch rating if there is no informational benefit from doing so, even if such a rating is on average better than the Moody's and S&P ratings? A possible explanation could be certification. Therefore, in later regressions we will specifically consider any certification benefit, which seems most likely to occur for issues whose ratings are close to the investment grade boundary.

3.4.2 Likelihood for Having a Fitch Rating

In this section, we use logit regressions to consider which factors explain having a Fitch rating. We include in our model variables that may be related to each of the three hypotheses. We employ several proxies for information uncertainty: (i) the dispersion or the absolute difference in number of notches of the Moody's and S&P ratings, (ii) volatility of daily stock returns, (iii) equity analyst dispersion. Further, we include variables that may be related to the relative importance of ratings, such as leverage, firm size and issue offering size. A positive coefficient on the variables relating to information uncertainty could be interpreted as evidence for an information or rating shopping effect.

We investigate the certification effect by including variables pertaining to the possible impact (assuming Fitch as the marginal rater) of an additional Fitch rating on regulatory effects around the IG-HY boundary. As these are greater if the average Moody's and S&P rating is closer to the IG-HY boundary, we include the number of notches the average Moody's and S&P rating is below and above this boundary (columns 2 - 4 of Table 7). As the number of notches their average rating is away from the IG-HY boundary is by construction positive in both directions, Fitch ratings having a certification effect would imply that these variables have a negative coefficient.

Next, we exploit the regulation feature that if an issue has three ratings, the median rating should be used to determine the issue's rating. We construct a dummy 'Fitch could push IG' which is equal to one if Moody's and S&P ratings are on opposite sides of the IG-HY boundary. In this case, an additional Fitch rating would be decisive about whether or not the issue becomes investment grade. Without a third rating, an issue with Moody's and S&P ratings on opposite sides of the boundary would be below investment grade for regulatory purposes, as in

case of two ratings the worse rating should be used. Therefore, if the Fitch rating is above investment grade, the median rating will be above investment grade as well. A positive coefficient on the dummy indicating the condition that Fitch could push the bond over the IG-HY boundary would be evidence for a certification effect. As a robustness check, we also include a dummy variable indicating whether Moody's and S&P ratings are on opposite sides of the A- boundary. The A- boundary obviously does not have the same regulatory importance as the investment grade boundary, such that its coefficient would be expected to be insignificant.

Finally, we add several other controls that influence bond prices, such as rating group dummies based on the average Moody's and S&P ratings, whether the issue is redeemable, the maturity, liquidation values (using proxies for fixed assets and R&D expenses), and always include industry dummies. Standard errors are again clustered by issuer. The marginal effects of the logit regressions are presented in Table 7, where the dependent variable equals 1 if the issue has a Fitch rating, and zero otherwise. The sample consists of all issues that are rated by both Moody's and S&P.

Empirically, we find that all the coefficients on variables related to uncertainty (i.e., analyst dispersion, idiosyncratic equity volatility and the dispersion between Moody's and S&P ratings) are either insignificant, or have the wrong (i.e., negative) sign for an information or rating shopping effect. Thus, we find no support in the data for either the information or the rating shopping effects.

On the other hand, column 2 indicates that the closer the average of the Moody's and S&P ratings is to the IG-HY boundary, the more likely it is that the issue has a Fitch rating. Once controls are included in columns 3 and 5, or rating group dummies are added in columns 4 and 5, this effect becomes asymmetric. Therefore, it is especially for issues whose Moody's and S&P rating is above the IG-HY boundary, that being further away from the boundary is associated with a lower likelihood of having a Fitch rating. The marginal effects show an economically large impact, with a Fitch rating likelihood being reduced by about 10% for each notch the average Moody's and S&P rating is above (i.e., better than) the IG-HY boundary. In general, this result suggest that having a Fitch rating is strongly related to certification or the regulation pertaining to ratings.

We consider the importance of the regulation effect more directly in columns 6 and 7 of Table 7 (excluding and including rating group dummies, respectively). The coefficient on the 'Fitch could push IG' dummy is large, positive and strongly statistically significant in both specifications. The coefficient of 0.112 in column 4 means that issues where Moody's and S&P ratings are on opposite sides of the IG-

HY boundary are 11.2% more likely to have a Fitch rating.[13]We interpret this as strong evidence in favor of a certification effect: it is precisely in those cases where the marginal rating (i.e., Fitch) is decisive for the critical regulation classification of the bond issue into investment and non-investment grade, that Fitch is most likely to (be asked to) give a rating. Finally, the positive coefficients on leverage and log total assets indicates that issuers for whom the monetary impact of ratings is largest are more likely to have an extra Fitch rating.

However, there is no evidence that Fitch ratings are relatively better (relative to the average S&P and Moody's rating, and as compared to other Fitch ratings) if the Fitch rating is decisive for the investment grade classification, as compared to all other Fitch ratings. This is notwithstanding the significant economic consequences of Fitch's decision there. This latter result also seems inconsistent with the rating shopping hypothesis or that issuers paying for ratings can significantly influence such ratings when they would, at the margin, benefit most (these results are not reported in a table to save space).

The results presented above possibly suffer from endogeneity concerns, as having or getting a Fitch rating is clearly a choice of the firm. For that reason, we next model the time that elapses before an issue gets a Fitch rating, thus only using a sample of issues that start without a Fitch rating. In particular, we estimate a Cox proportional hazard model where a 'failure' is defined as the event of getting a Fitch rating. The Cox model has the convenient property that one can focus on the relative rank of each subject in the cross-section by ignoring the baseline hazard rate and optimizing the partial likelihood function only. The baseline hazard rate can be separated out (as in any proportional hazard model), but also needs no specific parametric form that can influence our results. Estimates of this regression can be found in Table 8, which confirms that 'Fitch could push IG' is strongly associated with getting a Fitch rating, while none of the three main measures of uncertainty provide any evidence for the information production hypothesis.[14]

[13]Whether S&P or Moody's is more negative does not make a difference here (result not reported).

[14]Finally, the subsample of issues where Moody's and S&P ratings are on opposite sides of the IG-HY boundary is possibly so different from the whole sample, that once other characteristics are controlled for within that subsample, Fitch ratings may no longer be more prevalent for them within the subsample. To check this, we run logit regression for the likelihood that Moody's and S&P ratings are on opposite sides of the IG-HY boundary, in the sample of bonds with an average Moody's and S&P rating from BBB to BB (41,140 observations). The most important explanatory variable is whether or not the issue has a Fitch rating, both economically and statistically, even when controlling for the various controls of Table 7. Another important variable is idiosyncratic volatility, with a large positive coefficient. Results are not reported to save space.

3.4.3 Price Effects of Certification

In this section, we consider possible price effects of certification. We previously documented that there is little evidence a Fitch rating provides new information to investors, i.e., we found no association between bond prices and Fitch rating differences with respect to the median rating or the average rating of Moody's and S&P. However, we also found that having a Fitch rating is strongly related to Moody's and S&P ratings being on opposite sides of the investment grade boundary. Therefore, a natural question is how important for credit spreads could a marginal Fitch rating be in this latter case where (assuming it is the marginal or third rating) a Fitch rating would decide whether the issue is investment grade?

Our sample consists of all bonds with both Moody's and S&P ratings. The endogeneity of having a Fitch rating is a major concern, i.e. companies self-selecting on quality or other characteristics in their decision to have a Fitch rating. Table 7 finds that lower Moody's or S&P ratings, lower idiosyncratic volatility, higher leverage and large size are all characteristics associated with a greater likelihood of having a Fitch rating. In the subsequent credit spread regressions, we control for all of these characteristics, and also include rating group, industry and year dummies, as well as dummies for whether the issue has a Fitch rating, and whether any Fitch rating is below or above the average Moody's and S&P rating. The rating group dummies are based on the average Moody's and S&P ratings[15], such that they do not incorporate any effect of the Fitch rating on the mean rating. Directly controlling for whether the issue has a Fitch rating should significantly mitigate selection worries, unless issues where Moody's and Fitch are on opposite sides of the boundary are significantly different in some characteristics that we do not control for. However, as we control for several other measures of uncertainty, including the dispersion of the Moody's and S&P ratings and a dummy for their average rating, we do not think that we have missed any such obvious characteristic. However, our strongest control for self-selection may be the inclusion of issuer fixed effects, for which the estimated certification effects are also strongly reduced.

A robustness check for certification is the coefficient on a dummy variable indicating that the Moody's and S&P ratings are on opposite sides of the relatively innocuous A- boundary. This coefficient would not be expected to be significant

[15]We code notched rating categories with consecutive integers that increase as quality declines. However, when one rating notch is odd and the other is even, then the mean rating is not an integer. To avoid too many rating classes, we round up to the nearest integer. This potentially produces a bias towards lower average ratings. To correct for this, we include in the regressions a dummy indicating whether the average rating was rounded or not.

under any of the hypotheses considered.

Table 9 presents the pooled panel regressions of credit using monthly credit spreads for the sample of bond issues with both Moody's and S&P ratings, for the time period of 2002-2007. The first three rows show the impact of a Fitch rating when it is better than, equal to or worse than, the average Moody's and S&P rating. Confirming the results of Tables 5 and 6, when the Fitch rating is better, this does not lead to a lower credit spread. Instead, the sign is even opposite, and significantly so with issuer fixed effects. This does not support a rating shopping effect, but would be consistent with an information effect or a certification effect where only weaker issuers apply for the third rating. However, when a Fitch rating confirms the average Moody's/S&P rating, credit spreads are even higher and significantly different from zero. This lends support to a certification effect with adverse selection and goes strongly against the information and rating shopping hypotheses.

Around the IG-HY boundary, however, we see that Fitch ratings are strongly associated with credit spreads if Moody's and S&P are on opposite sides of the investment grade boundary. If the Fitch rating tips such an issue into investment grade, that issue has a substantially lower credit spread, and the opposite if the Fitch rating is below investment grade. The difference in credit spread is not only statistically but also economically quite large, e.g. equal to 45 basis points in column 2 of Table 9. This would suggest that there are significant certification effects for bond prices associated with a Fitch rating. If issuer fixed effects are used (see column 6), the size of the effects around the IG boundary become much weaker (22.5 basis points) and insignificant. We believe that this is mainly due to a lack of time variation of our specific experiment pertaining to the more general certification effect: cases where Moody's and S&P are on opposite sides of the IG-HY boundary are not very frequent to begin with and changes to these dummy variables occur even more rarely for a given issuer.[16]Alternatively, the lack of robustness with issuer fixed effects could also be due to the endogeneity of the certification estimates, which cannot be ruled out, our many controls for uncertainty notwithstanding. However, the coefficients of the role of the Fitch rating around the A- boundary do not show evidence of any large or significant effects (e.g., they are not statistically different from zero or have the 'wrong' sign).[17]

Interacting the proxies for uncertainty with the dummy for a more positive

[16]For the variables 'Fitch makes IG' and 'Fitch denies IG' the frequency of changes in these variables is only 0.165% and 0.07% of bond/month observations, respectively.

[17]Other unreported robustness checks showed that these findings also hold for credit spreads around the issue date of a bond and when the Fitch rating scale is adjusted by one notch.

Fitch rating gives interesting results. Uncertainty measured by analyst dispersion goes in the direction predicted for an information production effect, but with no statistical significance. Uncertainty measured by credit rating dispersion seems to have a statistically and economically significant impact on pricing in the direction predicted by information production. This result could be driven by non-linearity in the rounding of the rating scale as described above, especially since A and BBB rated bonds are much more likely to have Fitch rating. Therefore, we do the test excluding all observations where the rating disagreement is only 1 notch, since these observations always lead to rounding and are dominating the sample of split rated bonds, which after their removal will be dominated by disagreement of 2 notches which will not give a rounding effect. In this test, the direction is still the same, but there is no statistical significance anymore. Finally, adding issuer fixed effects removes the effect completely (see column 11).

3.4.4 Financials

For firms in the financial industry, a strong credit rating is one of their core assets, due to the business they are in as well as due to the high level of regulation that they are subject to. Thus, for financials the question of what drives multiple ratings is most relevant, but also harder to answer than for industrials. One of the reasons is that financials actively manage their credit rating and that several controls like leverage for industrials have a different meaning than for financials. Even within the group of financials, one would expect different controls for different segments. For that reason, we do not conduct credit spread regressions for financials, since they tend to be very sensitive to time-varying firm and sector-specific controls. This issue seems less prevalent in the credit rating regressions for financials, so we focus on those.

Under the certification hypothesis, financials would value an additional opinion very highly if it qualified them for a better rating, that is, in the case of a split rating by Moody's and S&P. However, split ratings can also be an indication of opaqueness. To distinguish between the cases of information production and rating shopping, we also use equity analyst dispersion and stock return standard deviation as proxies for informational uncertainty. The results in Table 10 present the equivalent of the results in Table 7 for financials.

Credit rating dispersion between Moody's and S&P is strongly associated with a higher probability of having a Fitch rating, whereas the other measures of uncertainty are not. This can be seen by looking at the boundaries of the regular rating

buckets. Similarly, we present the equivalent of Table 8 for financials in Table 11 (Cox regressions for the time to getting a Fitch rating). In the Cox regressions, the effect of rating dispersion is confirmed (as well as the contrasting, insignificant, result for analyst dispersion). The results on the boundaries are not significant, but this can be due to the smaller sample and most prominently due to the very high proportion of bonds that already have a Fitch rating when they enter the sample.

3.5 The nature of certification

In this section, we further explore the main empirical finding of this chapter, namely strong evidence that multiple ratings are used for certification purposes. The certification effect can be motivated by rules and regulation, but could also have a deeper origin going back to the fundamentals of security design. In this section, we first develop the theoretical intuition for how (multiple) ratings could help resolve market breakdowns in a setting with information-sensitive and insensitive assets and heterogeneous investors. Next, we show that the empirical patterns in the data are in line with the empirical predictions of such a setting.

3.5.1 Information-sensitive versus Information-insensitive securities

Imagine a bond market with two types of risk averse investors: type I investors with a time-varying natural demand for bonds and high research costs, and type II investors without the natural demand but with low research costs. For simplicity, one could think about type I investors as commercial banks, insurance companies and pension funds, where the natural demand for bonds stems from the random flow of deposits and claims, and type II investors as hedge funds and proprietary trading desks. Both types of investors are aware of each other's properties and existence. Rating agencies can give noisy signals about the credit quality of the firm at some cost per rating.

Next, suppose that there is a continuum of firms wanting to issue credit risky bonds with unobserved credit quality. The true credit quality of each firm is known by the firm itself, but it can signal this to the market only in a noisy way by releasing public information. Each investor forms an estimate of the true credit quality based on this public information. However, uncertainty about fundamentals among investors increases with decreasing credit quality. Type II investors

can purchase extra information about bond i at a cost Mi. With probability pi this information gives a reduction in uncertainty by a fixed fraction of total uncertainty for each type II investor that bought the information, where pi is increasing with declining credit quality and Mi is increasing and convex in decreasing credit quality (thus, in terms of expected uncertainty reduction, it has increasing costs to scale).

Since type I investors are at an information disadvantage relative to type II investors, they will invest in securities for which the informational gain of type II investors is small, i.e. in informationally insensitive assets, to avoid losses due to trading with informed investors (see Gorton and Pennacchi (1990)). Type II investors can trade these assets with type I investors without problems. Typically, type II investors will provide liquidity to this market to accommodate aggregate demand shocks.

On the other end of the credit quality spectrum, it is worthwhile for type II investors to generate the information needed, because they do not suffer from the negative effect to utility due to uncertainty; if they need to trade due to liquidity shocks, they trade amongst themselves on an equally informed basis. The region in the middle suffers from a market breakdown. Type II investors could make money if they could profit from informed trading with type I investors (as in Boot and Thakor (1993)). However, for type I investors, the losses due to informed trading prevent them from investing in this region. Because pi and true credit quality are correlated, an extra rating will not only yield information about credit quality, but also about profitability of research. If the conclusion is "no substantial information benefit", then type I investors would invest and type II would not bother to research. If the conclusion is "significant information benefit", then type I investors would not invest and type II investors would invest to hold the security. The IG-HY boundary is the prime candidate for the location on the credit quality spectrum where the unconditionally expected gains from informational trading offset the costs for acquiring information. As it is not possible to acquire a rating instantly, firms may purchase an extra rating from a precautionary motive if the likelihood of an adverse change in credit quality is high enough.

3.5.2 Empirical implications

Several implications follow from the setup described above. First, controlling for systematic risk, HY assets will have a substantially higher yield than IG assets, since the research costs would have to be covered and the type II investors would

require some form of rent (assuming capital for these investors is limited and low credit quality firms compete for funding). Moreover, firms whose credit risk is far away from the IG-HY boundary have little incentive to add an extra rating, since the probability that it will change anything is small (pi is either very small or very large in these regions). Therefore, we expect the most extra ratings in the middle region. Both of these predictions are confirmed by several of the findings in the previously discussed results. Specifically, Tables 6, 7 and 9 document the discontinuity of credit spreads and the importance of the (marginal) Fitch rating around the IG-HY boundary, consistent with the discontinuity between informational-sensitive and insensitive securities. For example, Table 7 indicates that most Fitch ratings are found for firms in the middle of the credit risk spectrum, i.e. for issues with ratings closer to the boundary, and, foremost evidence for the certification effect, that Fitch is significantly more likely to give a rating if Moody's and S&P ratings are on opposite sides of the boundary. These effects are confirmed by Table 8, which models to time to getting a Fitch rating. Both are indications of the importance of the IG-HY boundary.

Second, since type I investors expect to be hit by (idiosyncratic) liquidity shocks, they are not only interested in current information sensitiveness, but also in future information sensitiveness. A future switch from securities being information-insensitive to information-sensitive can be due to changes in firm information-sensitiveness, or higher expected gains resulting from research. By adding a Fitch rating, issuers can try to prevent such transition and to strengthen beliefs about their securities' information-insensitiveness in periods when benefits of research are high. Thus, if firms use (marginal) Fitch ratings to try to qualify their issues as informationally-insensitive securities, then the need to do so will be greater if they expect their other ratings (i.e., Moody's and S&P) to change in the future.

Unfortunately, ratings are too persistent to empirically estimate the frequency of rating changes reliably from the rating history. However, due to data constraints we can do the analysis of this precautionary effect the other way around, i.e. we estimate the association of the probability of undergoing a future rating change with a dummy for having a Fitch rating and several controls for opacity and volatility. The results can be found in Table 12, using only issues rather by both Moody's and S&P, and using the sample of all corporate bonds except financials in Panel A and the sample of financials only in Panel B. Indeed, we find that having future rating changes is positively related to having a Fitch rating for both samples, over and beyond the usual measures of volatility and opacity. For industrials,

having a Fitch rating is associated with a quarterly transition probability that is 0.6% to 0.8% higher, which is economically sizable (Moody's and S&P average transition probabilities are 5% and 4.6% respectively).

Third, as the market-wide degree of uncertainty varies over time, so will the relative benefit of information trading. Specifically, when market wide uncertainty goes up, the marginal benefit of informational trading goes up as well, such that some credit issues will then move from information-insensitive to information-sensitive. Typically, these will be credit issues close to the IG-HY boundary that ex-ante may have needed more ratings to protect against downgrades. As a result, in times of greater aggregate uncertainty type I investors will, on average, move away from the issues with credit quality close to the IG-HY boundary, to be substituted by type II investors, leading to higher credit spreads in lower quality categories. This leads to two empirical predictions. First, the certification effect of Fitch ratings is more important for firms that are more likely to transition from information-sensitive to insensitive if aggregate uncertainty increases, and such firms should have larger credit spreads. As a result, we would predict a positive coefficient on the interaction between the dummy for having a Fitch rating and our proxy for aggregate uncertainty. Second, changes in aggregate uncertainty should matter most for credit issues around the IG-HY boundary.

Table 13 uses the CBOE VIX-level (i.e., the implied volatility of options on the S&P 500 index) as a time-varying measure of uncertainty, and uses it as an additional control in pooled credit spread regressions for the sample of all issues rated by both Moody's and S&P. In column 1, we find that credit spreads are generally higher when the level of the VIX is higher, even if all the other controls as well as rating and year dummies are included. Therefore, VIX seems an important additional control. Column 2 shows that the major certification result, of significantly lower credit spreads if Fitch pushes the issue into the IG classification, is robust to the addition of the VIX control. In column 3, we find the predicted result that the interaction of VIX and having a Fitch rating has a significant and positive coefficient, such that having a Fitch rating is associated with a larger credit spread during times of greater uncertainty. Importantly, adding this interaction also reverses the (significance of the) unconditional effect of having a Fitch rating in columns 1 and 2 (and see also Table 9).

The larger credit spread for Fitch-rated issues in Table 9 had raised the question of whether a Fitch rating contains a negative signal, and if so, why. These new results suggest that there may be no negative signal in having a Fitch rating per se (given the insignificance of the unconditional effect of having a Fitch rating).

Rather, Fitch ratings seem to be used for certification purposes, where the need for certification is greater when aggregate uncertainty is larger. Those issues shifting from information-insensitive to sensitive when aggregate uncertainty increases tend to be rated by Fitch. Firms add Fitch for certification purposes, but the effect is not strong enough to put them at par with issues that do not need Fitch when aggregate uncertainty is high. However, when aggregate uncertainty is low, the total effect of having a Fitch rating and the interaction with VIX cancel each other.

Confirming the second prediction, the results in column 4 of Table 13 indicate that changes in VIX matter most for credit issues with BBB and BB ratings. It is exactly for issues that are most informationally-sensitive, that changes in aggregate uncertainty increase the benefit of acquiring additional information the most.

Finally, as trading in informationally-insensitive securities is less costly, the liquidity of IG credit issues would naturally be much larger. This would even hold when the trading demands of all type I investors are perfectly correlated. In a competitive market, type II investors would provide liquidity and take the other side of the trades in exchange for only a fraction of the utility improvement of the type I investors. In order to show this, we measure monthly bond trading as each issue's aggregated trading volume over the total value of its outstanding bonds, and provide bond turnover regressions results in Table 14. As we include issue fixed effects in this regressions, these results measure the relationship between time series changes in the issue's ratings classification and bond turnover. We find that the investment grade classification has a substantial impact on liquidity, exactly as predicted. Using a sample of all bonds (excluding financials) rated by both Moody's and S&P, we find that having a Fitch rating is not related to bond turnover, but Fitch (as the marginal third rater) giving the issue an investment grade classification significantly increases turnover. The economic magnitude of these effects seems large. The mean monthly turnover is 0.64% (this variable is multiplied by a factor of 1,000 in the regression). Becoming HY is associated with a decrease in turnover by 0.19% points, which is 30% of the mean turnover.

3.6 Conclusion

Credit ratings play an important role in the capital markets. They are used by regulators and market participants to establish capital requirements and, in a legal setting, to provide safe harbor for fiduciaries. This widespread dependency upon credit ratings has the potential to influence how credit rating agencies (CRAs) are used by issuers and how their ratings are evaluated by the market. A number of

theories have been proposed regarding how such dependency will affect the use of multiple CRAs, the type of rating issued by CRAs depending upon their strategic position, and finally about how the market interprets the informational output of rating agencies though the price formation process. Some theory suggests that they may further serve a useful coordination function that allows efficient allocation of information production in the capital markets.

In this chapter, we utilize bond issue credit ratings, characteristics and market prices to evaluate some of these proposed theories. We test three hypotheses: (i) "Information Production," whether the third rater adds value-relevant information, (ii) "Rating Shopping" and (iii) "Certification," in particular whether a third agency plays the role of tie-breaker at the boundary of being classified as investment-grade versus high-yield.

Our empirical work contains several results. First, we find that significant differences exist across multiple credit ratings of the same bond issue at the same point of time, with Fitch ratings on average clearly more positive than Moody's and S&P ratings. This is consistent with Fitch playing a strategic role that reduces the threat that the other two CRAs could withhold investment-grade ratings and extract compensation for certification, i.e., Fitch being available to push bonds into the investment grade classification when the other two firms may disagree.

Bond price data reveal how the market regards a rating by the third agency. In general, credit rating agencies provide useful information to the market about credit risk. However, we find no robust evidence that Fitch ratings provide additional information incorporated in bond prices, relative to the information already contained in the Moody's and S&P ratings. Thus even though Fitch ratings are on average clearly better than Moody's and S&P ratings, there seems little information contained in these ratings that the bond market incorporates. This is inconsistent with both the information and rating shopping hypotheses.

We find strong evidence that Fitch ratings have a certification effect. The likelihood of having a Fitch rating is strongly associated with Moody's and S&P ratings being on opposite sides of the investment grade boundary. This suggests that in equilibrium, Fitch ratings are sought as a kind of 'tie-breaker' in these cases. However, there is no evidence that Fitch ratings are relatively better if the Fitch rating is decisive for the investment grade classification, as compared to all other Fitch ratings. This is further evidence against ratings shopping or that issuers paying for ratings can significantly influence such ratings when they would, at the margin, benefit most.

In the cross-section of bond prices, we find that the certification effect is

strongly associated with credit spreads. Controlling for the average Moody's and S&P rating, for issues where Moody's and S&P ratings are on opposite sides of the investment grade boundary, a Fitch rating pushing the issue into the investment grade category has credit spreads that are about 45 basis points lower than if the Fitch rating would push the issue into the high yield category.

To explain the certification effect, we introduce a setting with bonds having information sensitivity that increases with declining credit quality. With profit-seeking agents on one side using costly information to trade (i.e., 'informed' investors) and agents with fluctuating demand for credit issues but a disadvantage for getting costly information (i.e., 'uninformed' investors) on the other, markets can break down for medium quality bonds, where informed investors can only profit if it is at the expense of the uninformed investors, who thus stay out of that market. Ratings as noisy signals for the potential of trading against informed investors can restore markets again, effectively limiting or erasing this medium quality category (Gorton and Pennacchi (1990), and Boot and Thakor (1993)).

Empirical results such as higher liquidity for IG bonds, an increase in credit spreads for Fitch rated bonds in times of high uncertainty about fundamentals, as well as a concentration of Fitch ratings in the middle category of the rating spectrum, are all consistent with this setup. Therefore, the reported certification effects seem consistent with an equilibrium outcome in a market with information-sensitive and insensitive bonds, where Fitch, often tie-breaker, ratings help to prevent market breakdowns.

3.7 Figures

Figure 3.1: FISD database coverage by CRA

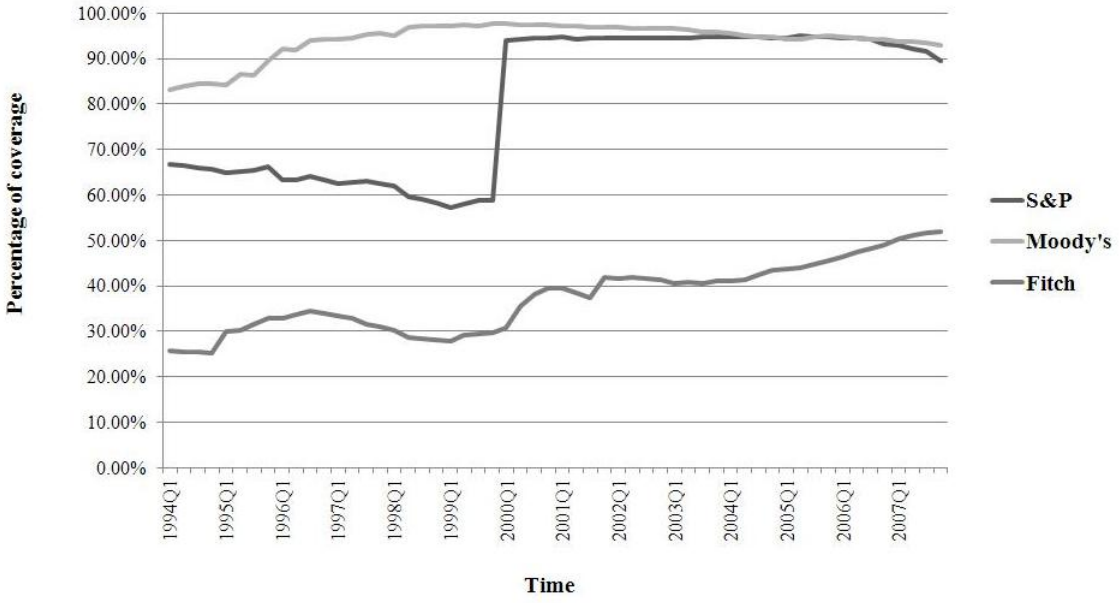
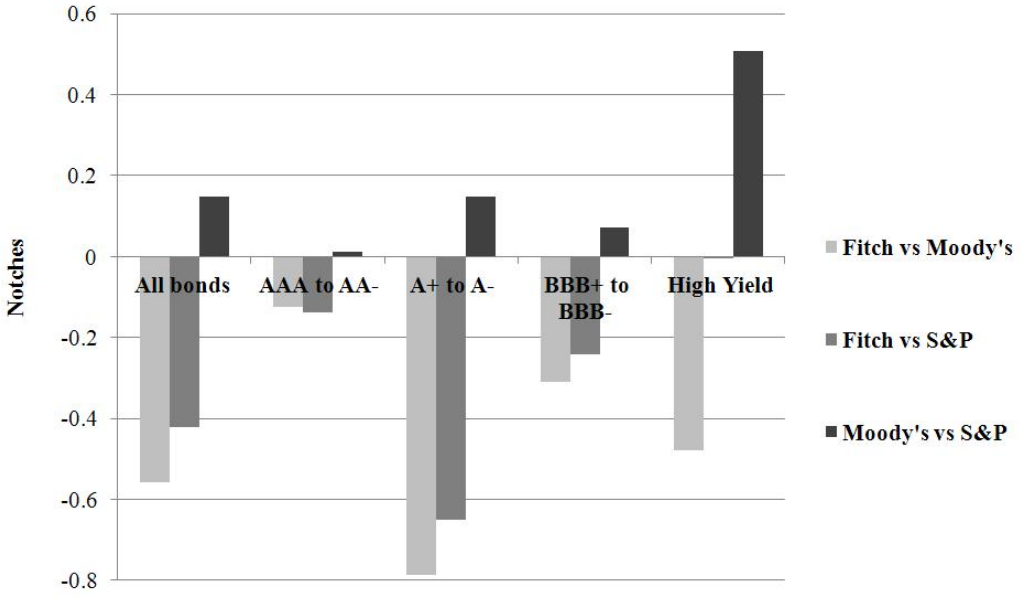


Figure 3.2: Rating Differences Across CRAs

The figure plots rating differences for different pairs of credit rating agencies (CRAs). We use a numerical scale for ratings, where a lower rating score means a better (more optimistic or lower bankruptcy likelihood) rating (see Table 4 for the full rating scale). In the figure, a negative number thus means that the first mentioned rating agency gives on average a better rating than the other CRA in that comparison.



3.8 Tables

Table 3.1: Empirical predictions

Reason for multiple ratings	**Information Production**	**Rating Shopping**	**Certification Effect**
(i) Systematic differences across different CRAs	−	+	+
(ii) All ratings contain information	+	0	0
(iii) Uncertainty increases # of ratings	+	+	0
(iv) Extra rating equal or better than existing ratings lowers credit spread	+	+	0
(v) Regulatory / investment grade boundary crucial	0	0	+
(vi) Extra rating associated with higher time variation in ratings	0	−	+

Table 3.2: Summary Statistics of Quarterly Ratings Sample

The table presents summary statistics and a brief description for the sample of bond issues that have both a Moody's and a S&P rating in the quarterly rating sample for 2000 - 2007.

Variable	Obs	Mean	Std.dev	Min	Max	Description
Stdev	102141	0.017	0.008	0.001	0.12	Daily idiosyncratic equity volatility (past 180 days)
beta	102141	0.91	0.41	-1.01	3.08	Equity beta (past 180 days)
Log Total Assets	102141	10.29	1.62	18.42	26.45	Log of total book value of assets
Log Offering Size	102141	11.06	2.29	7.09	18.42	Log of offering_mat
PPE/assets	101874	0.34	0.23	0.003	0.94	PPE over total book assets
R&D/Assets	102141	0.013	0.021	0	0.2	R&D expenditure over total book assets
R&D missing	102141	0.39	0.49	0	1	R&D expenditure missing
Leverage	102141	0.36	0.15	0	1.74	Book leverage (debt/total assets)
Roa	102141	0.012	0.019	-0.63	0.41	Return on book assets (earnings/total assets)
N_analysts	102141	15.29	6.8	1	42	Number of analyst earning forecasts
Analyst Dispersion	101040	0.003	0.005	0	0.21	Standard deviation of analyst earnings
Analyst Spread	102141	0.009	0.017	0	0.62	Maximum minus minimum analyst earnings
Redeemable	102141	0.52	0.5	0	1	Dummy if the bond is redeemable
Maturity	102141	9.75	10.5	0	98.52	Maturity left (years)
F_rated	102141	0.6	0.49	0	1	Dummy for Fitch rating
N_ratings	102141	2.6	0.49	2	3	Number of ratings
IG_distance_SPM	102141	3.05	2.48	0	8	Distance of avg_SPM_rating to IG boundary
Avg_SPM_rating	102141	6.74	3.17	1	13	Average of S&P and Moodys rating
Fitch push IG	102141	0.03	0.18	0	1	Fitch could push IG
Fitch push A-	102141	0.05	0.22	0	1	Fitch could push A-

Table 3.3: Summary Statistics for Credit Spreads Sample
The table presents summary statistics and a brief description for the sample of bonds issues that have both a Moody's and a S&P rating in the monthly credit spreads sample for 2002 - 2007.

Variable	Obs	Mean	Std.Dev.	Min	Max	Description
Duration	119,514	6.4	3.78	1	18.91	Average duration
Convexity	119,514	55.29	57.8	1	357.47	Convexity
Benchmark Yield	119,514	0.043	0.007	0.011	0.055	Risk free benchmark yield
CS	119,514	120.72	78.63	-326.75	1496.8	Credit spread
F_rating	78,651	7.08	2.47	1	17	Rating Fitch (numeric, see Table 4 desciption)
M_rating	119,514	6.65	3.27	1	17	Rating Moodys (numeric, see Table 4)
SP_rating	119,514	6.5	3.2	1	18	Rating S&P (numeric, see Table 4)
Redeemable	119,514	0.64	0.48	0	1	Dummy, 1 if the bond is redeemable
Maturity	119,514	10.1	9.77	1.02	98.48	Maturity left (years)
Stdev	119,514	0.014	0.005	0.001	0.09	Daily equity volatility (past 180 days)
Beta	119,514	0.95	0.37	-0.49	3.12	Equity beta based on 180 day historical data
Mcap	119,514	78900	119000	5835.76	505000	Market cap of the equity (in millions of $)
Log Total Assets	119,514	10.52	1.57	5.79	13.54	Log of total book value of assets
Log Offering Size	119,514	11.82	1.86	4.09	15.42	Log of offering amount
Leverage	119,514	0.34	0.15	0	1.13	Book leverage (debt/total assets)
Roa	119,514	0.014	0.018	-0.45	0.26	Return on book assets (earnings/total assets)
PPE/assets	119,142	0.34	0.23	0.004	0.94	PPE over total book assets
R&D/Assets	119,514	0.012	0.022	0	0.2	R&D expenditure over total book assets
R&D missing	119,514	0.39	0.49	0	1	R&D expenditure missing
N_analysts	119,514	16.21	7.06	1	42	Number of estimates
Avg_analyst	119,514	0.061	0.031	-1.78	0.31	Average analyst earning forecast (per $ share value)
Analyst_disp	118,566	0.002	0.006	0	0.47	Standard deviation of analyst earning forecasts
Analyst_spread	119,514	0.009	0.019	0	1.28	Max minus min analyst earning forecast
VIX	119,514	14.95	4.27	9.89	40.52	VIX implied volatility index (1 day lagged)
Inflation	119,514	0.26	0.33	-0.49	1.33	Inflation from CPI index (1 month lagged)
GDP Growth	119,514	1.4	0.42	0.58	2.35	GDP growth (1 qtr lagged)
TED Spread	119,514	0.55	0.4	0.07	2.13	Yield spread between 3M eurodollar and treasury
Yield Slope	119,514	0.98	1.13	-0.53	3.85	Yield spread between 3M and 10-year treasury
SP_rated	119,514	1	0	1	1	Dummy for rating S&P
M_rated	119,514	1	0	1	1	Dummy for rating Moodys
F_rated	119,514	0.66	0.47	0	1	Dummy for rating Fitch
N_ratings	119,514	2.66	0.47	2	3	Number of ratings
Avg_SPM_rating	113,614	6.46	3.21	1	14.33	Average of S&P and Moodys rating
MSP Rating Dispersion	119,514	0.44	0.71	0	12	Absolute dispersion of Moodys and S&P rating
Fitch Below Avg MSP Rating	119,514	0.37	0.48	0	1	Dummy if Fitch rating worse than avg_SPM_rating
Fitch Above Avg MSP Rating	119,514	0.03	0.18	0	1	Dummy if Fitch rating better than avg_SPM_rating
Fitch confirms Avg MSP Rating	119,514	0.26	0.44	0	1	Dummy if Fitch rating equal to avg_SPM_rating
F Pushes Above IG	119,514	0.015	0.12	0	1	Dummy if Fitch pushes over IG boundary
F pushes below IG	119,514	0.009	0.09	0	1	Dummy if Fitch pulls under IG boundary
F Pushes Above A-	119,514	0.028	0.16	0	1	Dummy if Fitch pushes over A- boundary
F Pushes Below A-	119,514	0.013	0.11	0	1	Dummy if Fitch pulls under A- boundary
Crisis	119,514	0.13	0.34	0	1	Dummy for crisis period (from Jul 1st 2007)

Table 3.4: Average Rating Differences

Average rating differences for issues simultaneously rated by multiple CRAs, measured in rating notches, and split up by rating categories. Rating categories are defined by average Moody's and S&P ratings. We follow convention and use the numerical rating scale to convert ratings. For Fitch and S&P (with Moody's rating in parentheses), the numerical scores corresponding to the rating notches are, respectively, 1 for AAA (Aaa), 2 for AA+ (Aa1), 3 for AA (Aa2), 4 for AA- (Aa3), 5 for A+ (A1), 6 for A (A2), 7 for A- (A3), 8 for BBB+ (Baa1), 9 for BBB (Baa2), 10 for BBB- (Baa3), 11 for BB+ (Ba1), 12 for BB (Ba2), 13 for BB- (Ba3), 14 for B+ (B1), 15 for B (B2), 16 for B- (B3), 17 for CCC+ (Caa1) and 18 for CCC (Caa). Therefore, a negative number means that the first mentioned rating agency gives on average a better rating than the other CRA in that comparison. Quarterly data for 2000-2007 are used. T-statistics based on robust standard errors clustered by issuer are in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Fitch vs Moody's	Fitch vs S&P	Moody's vs S&P (Fitch rated sample)	Moody's vs S&P (full sample)
All Bonds				
Difference	-0.558***	-0.421***	0.149**	0.157***
	[-5.16]	[-3.83]	[2.45]	[3.55]
N	60989	61121	61136	101947
Number of issuers	397	396	397	667
AAA to AA-				
Difference	-0.124	-0.139	0.011	0.0308
	[-1.57]	[-1.15]	[0.07]	[0.72]
N	3216	3210	3281	19361
Number of issuers	36	36	36	60
A+ to A-				
Difference	-0.787***	-0.651***	0.148	0.172*
	[-5.51]	[-4.90]	[1.41]	[1.94]
N	30893	30968	30954	40175
Number of issuers	137	137	137	219
BBB+ to BBB-				
Difference	-0.310***	-0.241***	0.0725	0.120***
	[-5.03]	[-3.53]	[1.17]	[2.61]
N	21045	21069	21063	33111
Number of issuers	262	263	262	438
BB+ and lower				
Difference	-0.478***	-0.00579	0.507***	0.489***
	[-4.19]	[-0.03]	[3.51]	[4.93]
N	5835	5874	5838	9300
Number of issuers	154	152	154	277

Table 3.5: Credit Spread Regressions of Rating Differences Relative to the Median Rating

Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds that are rated by all three CRAs on rating directions and sizes for all three CRAs, bond and firm characteristics, and macro-economic variables, with fixed median rating and year effects. Panel A includes dummies indicating whether each of the three CRAs rating was worse or better than the median rating, i.e. the direction in which the rating may be different. Panel B includes the size of the different to the median rating as well, interacting the dummy with the number of notches of the different with the median rating. Panel C gives the frequency of the difference to the median rating. The firm and bond controls include Leverage, liquidation/intrinsic value (PPE/total assets), R&D expenses (divided by total assets and a dummy if not available), ROA (return of assets), Stdev (daily equity volatility), Historical Equity Beta (half year daily corrected for BA-bounces), Log Total Assets (firm size, book value) and Log Offering Size (issue size), Redeemable (dummy for callability), Duration and Convexity. Macro-economic controls include market wide implied volatility (VIX), Inflation, GDP Growth, TED spread, and the level and slope of the term structure. Crisis is a dummy indicating the crisis period (from July 2007 onwards). T-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Directional difference of median rating

	1	2	3	4	5	6	7	8	9
Moody's worse than median	11.95***	9.656***					13.65***	10.39***	4.854**
	[3.49]	[2.77]					[3.68]	[2.99]	[2.19]
Moody's better than median	-2.683	4.919					-4.102	3.979	4.899
	[-0.45]	[0.76]					[-0.74]	[0.67]	[1.14]
Fitch worse than median			2.957	14.52**			8.172	15.93***	3.813
			[0.50]	[2.25]			[1.35]	[2.63]	[0.49]
Fitch better than median			-0.637	-1.793			-0.961	-0.845	-0.18
			[-0.15]	[-0.49]			[-0.22]	[-0.22]	[-0.06]
S&P worse than median					5.204	10.94***	8.761***	13.07***	6.750**
					[1.61]	[2.72]	[2.88]	[3.32]	[2.47]
S&P better than median					-10.17***	-14.96***	-10.94***	-13.21***	-9.352***
					[-2.87]	[-4.50]	[-3.03]	[-3.80]	[-3.09]
Crisis	17.12***	19.03***	17.35***	19.30***	17.33***	19.23***	17.07***	19.15***	17.40***
	[7.31]	[8.19]	[7.47]	[8.28]	[7.37]	[8.24]	[7.31]	[8.20]	[10.89]
ROA	-335.2***	-187.9***	-346.1***	-188.1***	-335.5***	-184.4***	-320.2***	-190.5***	-215.4***
	[-3.91]	[-2.79]	[-3.94]	[-2.81]	[-3.86]	[-2.75]	[-3.83]	[-2.89]	[-4.27]
Leverage	-15.5	-15.36	-19.2	-20.38	-21.38*	-14.29	-15.2	-17.15	18.36
	[-1.43]	[-0.39]	[-1.46]	[-0.51]	[-1.76]	[-0.37]	[-1.30]	[-0.44]	[0.84]
PPE/total assets	-16.55*	51.92	-18.53**	52.54	-19.94**	45.56	-18.67**	47.59	-40.43
	[-1.78]	[1.33]	[-1.98]	[1.43]	[-2.17]	[1.27]	[-1.99]	[1.23]	[-1.16]

R&D expense/total assets	-153.9**	304.2**	-117.5*	291.0**	-114.5*	289.8**	-145.6**	288.2**	160.3
	[-2.24]	[2.16]	[-1.69]	[2.06]	[-1.67]	[2.34]	[-2.04]	[2.17]	[0.97]
R&D missing	5.4	3.607	7.084	4.582	6.574	2.34	4.671	2.538	9.093*
	[1.11]	[0.70]	[1.39]	[0.92]	[1.28]	[0.50]	[1.01]	[0.51]	[1.67]
Log Total Assets	2.941	-4.587	3.243	-3.939	3.28	-4.429	3.214	-4.906	-6.486
	[1.22]	[-0.61]	[1.33]	[-0.52]	[1.24]	[-0.60]	[1.43]	[-0.68]	[-0.84]
Log Offering Size	-5.688***	-5.526***	-5.519***	-5.336***	-5.436***	-5.584***	-5.590***	-5.716***	-5.142***
	[-7.79]	[-6.29]	[-7.37]	[-5.96]	[-7.35]	[-6.30]	[-7.90]	[-6.50]	[-7.50]
Beta	-23.23***	-26.33***	-24.90***	-26.42***	-25.20***	-26.66***	-23.54***	-25.96***	-16.66***
	[-3.39]	[-4.39]	[-3.55]	[-4.37]	[-3.64]	[-4.43]	[-3.41]	[-4.34]	[-3.73]
Stdev	3698.7***	3595.2***	3778.5***	3578.9***	3773.4***	3559.7***	3691.8***	3542.1***	2415.5***
	[5.04]	[4.64]	[5.08]	[4.61]	[5.08]	[4.62]	[5.03]	[4.62]	[4.74]
VIX	1.519***	1.401***	1.485***	1.385***	1.493***	1.427***	1.524***	1.423***	1.206***
	[7.08]	[7.44]	[6.96]	[7.43]	[7.01]	[7.50]	[7.15]	[7.56]	[9.97]
Inflation	4.036***	4.386***	4.088***	4.292***	4.143***	4.366***	4.039***	4.324***	3.847***
	[4.21]	[4.95]	[4.18]	[4.77]	[4.32]	[4.93]	[4.21]	[4.91]	[5.52]
GDP Growth	-4.222***	-4.634***	-4.150***	-4.743***	-4.130***	-4.559***	-4.219***	-4.655***	-4.794***
	[-3.12]	[-3.70]	[-3.05]	[-3.81]	[-2.99]	[-3.60]	[-3.13]	[-3.77]	[-4.90]
TED Spread	23.55***	24.47***	23.58***	24.43***	23.81***	24.80***	23.70***	24.70***	24.80***
	[13.03]	[13.51]	[12.77]	[13.26]	[13.09]	[13.73]	[13.26]	[13.75]	[15.99]
Term Structure Slope	-4.427***	-5.690***	-4.554***	-5.695***	-4.562***	-5.780***	-4.401***	-5.651***	-4.340***
	[-3.63]	[-4.44]	[-3.73]	[-4.53]	[-3.64]	[-4.48]	[-3.59]	[-4.37]	[-4.29]
Benchmark Yield	-643.9***	-659.1***	-647.9***	-672.5***	-657.6***	-680.1***	-662.8***	-679.7***	-405.4***
	[-3.55]	[-4.06]	[-3.54]	[-4.11]	[-3.63]	[-4.20]	[-3.69]	[-4.17]	[-3.03]
Duration	15.60***	14.39***	15.77***	14.51***	15.75***	14.44***	15.66***	14.44***	12.36***
	[11.58]	[11.63]	[11.33]	[11.74]	[11.51]	[11.69]	[11.61]	[11.61]	[10.80]
Convexity	-0.574***	-0.492***	-0.586***	-0.497***	-0.584***	-0.494***	-0.576***	-0.493***	-0.394***
	[-7.88]	[-7.86]	[-7.70]	[-7.95]	[-7.80]	[-7.88]	[-7.88]	[-7.84]	[-6.78]
Redeemable	0.319	1.513	0.178	1.352	-0.115	1.469	0.0668	1.502	1.456
	[0.12]	[0.57]	[0.07]	[0.50]	[-0.04]	[0.55]	[0.03]	[0.56]	[0.58]
Issuer FE	no	yes	no	yes	no	yes	no	yes	no
Median Rating Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
Only BBB or better MSP	no	no	no	no	no	no	no	no	yes
N	78488	78488	78488	78488	78488	78488	78488	78488	65338

adj. R-sq	0.593	0.686	0.589	0.686	0.591	0.687	0.595	0.689	0.605
Number of issuers	368	368	368	368	368	368	368	368	262
Panel B: Size and Direction of Difference to Median Rating									
	1	2	3	4	5	6	7	8	9
# of Notches Moody's is worse	12.26***	9.001***					13.08***	9.410***	5.582***
than median	[5.30]	[3.32]					[5.88]	[3.77]	[4.37]
# of Notches Moody's is better	2.822	9.001					2.062	8.164	3.613
than median	[0.40]	[1.29]					[0.32]	[1.38]	[1.11]
# of Notches Fitch is worse			0.568	4.345			2.899	4.992	0.517
			[0.19]	[1.37]			[0.88]	[1.60]	[0.18]
# of Notches Fitch is better			2.388	1.979			1.552	2.372	1.242
than median			[0.63]	[0.60]			[0.45]	[0.75]	[0.42]
# of Notches S&P is worse					4.411*	9.979***	7.743***	11.57***	6.621***
than median					[1.68]	[3.39]	[3.26]	[4.32]	[3.15]
# of Notches S&P is better					-8.295***	-12.97***	-7.735***	-11.31***	-9.147***
than median					[-3.09]	[-5.36]	[-3.04]	[-4.28]	[-2.96]

Panel C: Relative Frequencies of Difference to Median Rating within sample rated by all CRAs		
	Frequency	Freq. 1 Notch Dif.
Moodys worse than median	20.94%	17.67%
Moodys better than median	4.17%	3.51%
Fitch worse than median	3.55%	2.60%
Fitch better than median	34.00%	30.96%
S&P worse than median	11.36%	10.02%
S&P better than median	7.30%	6.31%

Table 3.6: Credit Spread Regressions with S&P-Moody's versus Fitch Rating Dummies
Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds on rating dummies for the average of Moody's and S&P as well as for Fitch, bond and firm characteristics, and macro-economic variables, with fixed median rating and year effects. See Table 5 for descriptions of control variables. T-statistics are in brackets (using robust standard errors clustered by issuer). We also test the joint relevance of the Fitch rating dummies. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1	2	3	4	5
SPM - AA	-1.258	-2.677	-12.72*	1.04	1.04
	[-0.19]	[-0.35]	[-1.79]	[0.16]	[0.16]
SPM - A	12.07	19.87**	8.79	23.83***	23.83***
	[1.45]	[2.29]	[1.04]	[3.04]	[3.04]
SPM - BBB	46.11***	46.50***	42.16***	50.37***	50.37***
	[6.60]	[4.95]	[5.21]	[6.16]	[6.16]
SPM - BB	144.9***	108.7***	129.4***	102.7***	102.7***
	[15.41]	[8.91]	[11.48]	[8.92]	[8.92]
Fitch Rating			11.31	23.35***	6.741**
			[1.10]	[2.81]	[2.18]
F - AAA					16.61**
					[2.07]
F - AA			6.989	-14.33*	2.277
			[0.66]	[-1.82]	[0.50]
F - A			-10.06	-16.61**	
			[-0.95]	[-2.07]	
F - BBB			-8.5	-14.23	2.381
			[-0.72]	[-1.64]	[0.60]
F - BB			13	10.9	27.50***
			[0.99]	[0.87]	[2.81]
Issuer Fixed effect	no	yes	no	yes	yes
Year FE	yes	yes	yes	yes	yes
N	119571	119571	119571	119571	119571
adj. R-sq	0.581	0.695	0.585	0.697	0.697
Number of issuers	616	616	616	616	616
Test F(AA)= F(A)= F(BBB) (p-val)	.	.	0.0735	0.74	.

Table 3.7: Logistic Regressions for Having a Fitch Rating

Logit regressions of having a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P), distance to IG boundary ('MSP Notches Below/Above IG,' both solely based on Moody's and S&P average rating) and whether the Fitch rating 'could push' the issue to IG or A-. 'F could push IG' ('F could push A-') is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the IG (A-) boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. Only marginal effects are reported, and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10

	1	2	3	4	5	6	7
AAA to AA-				0.376***	0.211**		
				[2.81]	[2.39]		
A+to A-	0.426***			0.465***	0.302***		0.425***
	[3.62]			[4.25]	[3.01]		[3.59]
BBB+ to BBB-	0.385***						0.383***
	[3.82]						[3.74]
High Yield (below IG)	0.293***						0.287***
	[5.96]						[5.62]
MSP Notches Below IG		-0.0936***	-0.0185	-0.0382*	0.00427		
		[-2.76]	[-0.90]	[-1.91]	[0.25]		
MSP Notches Above IG		-0.0784***	-0.0741***	-0.147***	-0.128***		
		[-2.67]	[-3.06]	[-3.14]	[-2.97]		
F could push IG						0.116**	0.0989**
						[2.34]	[2.13]
F could push A-						0.031	0.0118
						[0.53]	[0.20]
MSP rating dispersion	0.00333		0.0104		0.00321	0.00805	-0.00454
	[0.11]		[0.34]		[0.11]	[0.21]	[-0.13]
Idiosyncratic volatility	-9.068***		-9.143***		-9.120***	-9.011***	-9.059***
	[-4.68]		[-4.94]		[-4.88]	[-5.11]	[-4.73]
Equity Beta	0.0786***		0.0835***		0.0637**	0.141***	0.0789***
	[2.94]		[2.97]		[2.32]	[4.16]	[2.97]
Analyst Dispersion	0.442		-1.297		0.215	1.219	0.592
	[0.18]		[-0.50]		[0.09]	[0.48]	[0.24]
Leverage	0.355**		0.428***		0.311**	0.599***	0.364**
	[2.31]		[2.86]		[2.15]	[2.97]	[2.36]
PPE/total assets	-0.216		-0.266*		-0.229	-0.304**	-0.214
	[-1.54]		[-1.74]		[-1.55]	[-2.29]	[-1.53]
R&D expense/total assets	0.878		0.719		0.985	-0.251	0.915
	[1.08]		[0.99]		[1.31]	[-0.38]	[1.11]
R&D missing	-0.0465		-0.0287		-0.0213	-0.0464	-0.0452
	[-0.90]		[-0.54]		[-0.42]	[-0.87]	[-0.88]
ROA	0.143		0.342		0.285	-0.707	0.119
	[0.35]		[0.69]		[0.69]	[-1.19]	[0.29]
Log Total Assets	0.166***		0.176***		0.176***	0.135***	0.166***
	[7.90]		[7.98]		[8.98]	[4.38]	[7.86]
Redeemable	-0.0361		-0.0491		-0.0163	-0.0686	-0.0359
	[-0.93]		[-1.13]		[-0.49]	[-1.24]	[-0.92]
Log Offering Size	-0.00352		-0.0113		-0.0157*	0.0142	-0.00313
	[-0.42]		[-1.31]		[-1.94]	[1.09]	[-0.37]
Maturity left (years)	-0.0005		-0.00039		-0.00011	-0.00159	-0.00053
	[-0.31]		[-0.24]		[-0.07]	[-1.01]	[-0.33]
Maturity left squared	1.34E-05		1.95E-05		1.17E-05	0.0000297*	1.34E-05
	[0.71]		[1.06]		[0.67]	[1.70]	[0.72]
Industry FE	yes	yes	yes	yes	yes	yes	yes
N	88484	101947	88484	101947	88484	88484	88484
pseudo R-sq	0.226	0.104	0.221	0.174	0.248	0.177	0.227
Number of issuers	656	667	656	667	656	656	656

Table 3.8: Cox Regressions for time to getting a Fitch Rating
Cox Proportional Hazard model regressions of time to getting a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P), distance to IG boundary ('MSP Notches Below/Above IG,' both solely based on Moody's and S&P average rating) and whether the Fitch rating 'could push' the issue to IG or A-. 'F could push IG' ('F could push A-') is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the IG (A-) boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. The coefficients in the partial likelihood are reported, and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1	2	3
A+to A-	1.489***		1.489***
	[2.84]		[2.87]
BBB+ to BBB-	1.152**		1.172**
	[2.22]		[2.28]
High Yield (below IG)	1.184**		1.336**
	[2.20]		[2.47]
F could push IG	0.851**	0.684**	
	[2.48]	[2.01]	
F could push A-	0.143	0.114	
	[0.57]	[0.46]	
MSP rating dispersion	-0.0814	-0.0372	-0.0209
	[-0.44]	[-0.20]	[-0.14]
Analyst Dispersion	-42.94*	-36.15	-46.49*
	[-1.74]	[-1.45]	[-1.78]
Idiosyncratic volatility	-26.83***	-24.72***	-26.29***
	[-3.59]	[-3.46]	[-3.44]
Beta	0.293**	0.389**	0.283**
	[2.31]	[2.28]	[2.18]
Redeemable	0.341***	0.167	0.354***
	[4.59]	[1.20]	[4.74]
Log Offering Size	0.0062	0.0222	0.00327
	[0.15]	[0.47]	[0.08]
Log Total Assets	0.321***	0.212**	0.319***
	[5.85]	[2.36]	[5.87]
Leverage	1.695***	1.868***	1.619***
	[4.22]	[3.74]	[4.08]
PPE/total assets	-0.452	-0.756*	-0.431
	[-1.31]	[-1.95]	[-1.24]
R&D expense/total assets	4.047*	1.593	3.732
	[1.74]	[0.70]	[1.60]
R&D missing	-0.183	-0.184	-0.192
	[-1.15]	[-1.28]	[-1.20]
ROA	-3.925***	-4.173***	-3.950***
	[-3.12]	[-3.42]	[-3.13]
Maturity left (years)	-0.0001	0.00107	-3.60E-05
	[-0.02]	[0.17]	[-0.01]
Maturity left squared	-5.90E-05	-4.90E-05	-0.00006
	[-1.03]	[-0.82]	[-1.02]
Industry dummies	yes	yes	yes
N	32589	32589	32589
pseudo R-sq	0.032	0.022	0.031
Number of issuers	654	654	654

Table 3.9: Credit Spread Regressions, Full Sample

Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds on bond and firm characteristics and macro-economic variables, with fixed rating and year effects. Main variables of interest are whether a Fitch rating is better (FR<MSP), equal to (FR=MSP) or worse (FR>MSP) than the average Moody's and S&P rating, as well as variables relating to regulator (IG) and random (A-) boundaries and variables measuring uncertainty (for description see Table 7), also interacted with having a Fitch rating. See Table 5 for other control variable descriptions. T-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1	2	3	4	5	6	7	8	9	10	11
FR<MSP	4.78	5.898*	5.166*	5.497	8.909**	10.29***	5.211	5.205	4.135	4.394	10.01***
	[1.48]	[1.81]	[1.66]	[1.35]	[2.05]	[3.09]	[1.63]	[1.63]	[1.31]	[1.40]	[3.04]
FR=MSP	6.747**	6.856**	6.571**	7.545**	12.27***	10.54***	6.811**	7.101**	8.705***	7.663***	10.65***
	[2.43]	[2.50]	[2.41]	[2.11]	[3.34]	[3.27]	[2.52]	[2.56]	[2.95]	[2.79]	[3.06]
FR>MSP	24.46***	20.35***	19.76***	24.02***	22.62**	26.82***	24.53***	24.49***	22.86***	22.30***	28.33***
	[3.18]	[3.03]	[2.93]	[3.53]	[2.46]	[3.90]	[3.11]	[3.09]	[3.12]	[3.06]	[3.77]
F Pushes < IG		-27.95**	-27.46**	-24.82**	-30.03**	-6.419					
		[-2.38]	[-2.36]	[-2.34]	[-2.03]	[-0.74]					
F Pushes > IG		17.14	17.2	12.05	19.14	16.01					
		[1.18]	[1.18]	[0.80]	[0.65]	[0.95]					
F Pushes < A-			11.20*								
			[1.76]								
F Pushes > A-			11.07								
			[1.19]								
Analyst dispersion							1562.0***	1592.2***			
							[5.94]	[5.35]			
Analyst dispersion * FR=MSP								-111.7			
								[-0.32]			
Rating dispersion									4.857**		1.857
									[2.04]		[0.94]
Rating dispersion* FR=MSP									-5.618*		0.333
									[-1.71]		[0.13]
Rating dispersion (>1 notch)										5.414**	
										[2.20]	
Rating dispersion (>1 notch)* FR=MSP										-4.949	
										[-1.30]	
Rounding Dummy	-6.53***	-6.55***	-6.79***	-8.76***	-7.49***	-8.07***	-6.12***	-6.13***	-8.62***	-5.28**	-8.78***
	[-3.07]	[-3.01]	[-3.12]	[-3.38]	[-2.69]	[-4.15]	[-2.89]	[-2.89]	[-3.62]	[-2.46]	[-4.68]
Crisis	16.90***	17.03***	17.05***	15.31***	10.08***	18.30***	18.70***	18.68***	16.79***	16.80***	18.23***
	[10.47]	[10.43]	[10.53]	[5.42]	[5.84]	[11.97]	[10.48]	[10.44]	[10.46]	[10.45]	[12.14]
Issuer FE	no	no	no	no	no	yes	no	no	no	no	yes
MSP rating FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Duration > median	no	no	no	no	yes	no	no	no	no	no	no
Rating > median	no	no	no	yes	no	no	yes	no	no	no	no
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	119763	119763	119763	64841	60414	119763	118816	118816	119763	119763	119763
adj. R-sq	0.61	0.611	0.612	0.617	0.583	0.706	0.617	0.617	0.611	0.611	0.706
Number of issuers	617	617	617	551	502	617	608	608	617	617	617

Table 3.10: Logistic Regressions for Having a Fitch Rating: Financials
Logit regressions of having a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P) and whether the Fitch rating 'could push' the issue to different major rating categories (AAA, AA, A or BBB). 'F could push *' is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the * category boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. Only marginal effects are reported, and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1	2	3
A+ to A-	0.00363	-0.0113	-0.0079
	[0.09]	[-0.34]	[-0.20]
BBB+ to BBB-	0.0177	0.0111	0.00798
	[0.36]	[0.23]	[0.14]
BB+ or worse	-0.0381	-0.102	-0.0429
	[-0.38]	[-0.63]	[-0.42]
MSP rating dispersion		0.0989***	
		[2.70]	
F could push AAA			0.0644***
			[3.29]
F could push AA			0.0894***
			[2.82]
F could push A			0.0445*
			[1.88]
Log of total assets	-0.0179	-0.0142	-0.0246
	[-0.84]	[-0.92]	[-1.13]
ROA	-3.36	-2.552	-3.645
	[-1.56]	[-1.42]	[-1.53]
Idiosyncratic volatility	-1.45	-2.228**	-2.471***
	[-1.42]	[-2.49]	[-2.89]
Equity beta	-0.0154	0.0271	0.00965
	[-0.30]	[0.71]	[0.25]
Analyst dispersion	-0.275	0.658	0.219
	[-0.17]	[0.42]	[0.14]
Time to maturity	-0.00305**	-0.00268**	-0.00227**
	[-2.22]	[-2.55]	[-2.12]
Redeemable (d)	-0.00207	0.0208	0.0124
	[-0.04]	[0.57]	[0.26]
N	50255	50255	50255
2 digit SIC FE	Yes	Yes	Yes
pseudo R-sq	0.108	0.181	0.148
Number of issuers	150	150	150

Table 3.11: Cox Regressions for time to getting a Fitch Rating: Financials
Cox Proportional Hazard model regressions of time to getting a Fitch rating on rating category dummies, measures for uncertainty as Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P), distance to IG boundary ('MSP Notches Below/Above IG,' both solely based on Moody's and S&P average rating) and whether the Fitch rating 'could push' the issue to IG or A-. 'F could push IG' ('F could push A-') is a dummy indicating whether the Moody's and S&P ratings are on opposite sides of the IG (A-) boundary. See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. The coefficients in the partial likelihood are reported, and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1	2
A+ to A-	0.543***	0.551**
	[2.59]	[2.28]
BBB+ to BBB-	-0.367	-0.113
	[-0.91]	[-0.37]
BB+ or worse	-0.417	-0.255
	[-0.85]	[-0.56]
MSP rating dispersion	0.406**	
	[2.19]	
F could push AAA		0.553
		[1.08]
F could push AA		0.489
		[1.51]
F could push A		-0.27
		[-0.52]
Redeemable	0.463**	0.449**
	[2.27]	[2.17]
Log offering amount	0.0119	0.00711
	[0.55]	[0.31]
Log of total assets	-0.0173	-0.0639
	[-0.24]	[-0.77]
Analyst dispersion	-0.653	2.422
	[-0.06]	[0.22]
Idiosyncratic volatility	-47.39***	-44.18***
	[-3.86]	[-3.83]
Equity beta	0.332	0.331
	[1.08]	[1.08]
roa	-31.04*	-32.70**
	[-1.86]	[-2.27]
Time to maturity	-0.0225	-0.0166
	[-1.43]	[-1.16]
Time to maturity squared	0.000114	0.0000795
	[0.64]	[0.49]
2 digit SIC FE	yes	yes
N	9791	9791
pseudo R-sq	0.019	0.018
Number of issuers	151	151

Table 3.12: Logistic Regressions for Having a Rating Transitions
Logit regressions of having a rating transition on rating category dummies, a dummy indicating whether the issue has a Fitch rating or not, measures for uncertainty as idiosyncratic volatility, beta, Analyst Dispersion (standard deviation of analyst earning forecasts normalized per dollar share value) and MSP Rating Dispersion (absolute value of the notches difference between Moody's and S&P). See Table 5 for descriptions of bond and firm level control variables. Quarterly data for 2000-2007 are used, the sample consists of all issues with both Moody's and S&P ratings. Only marginal effects are reported, and t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A. Samples of all firms except financials.

	Moody's	S&P
Fitch Rating	0.00799***	0.00599**
	[2.82]	[2.46]
Idiosyncratic volatility	1.055***	0.732***
	[4.61]	[4.18]
Beta	-0.00436	0.000279
	[-1.03]	[0.07]
Analyst dispersion	0.485	0.373***
	[1.20]	[2.85]
MSP rating dispersion	0.00930***	0.00626***
	[5.52]	[3.43]
Issuer FE	no	no
MSP Rating FE	yes	yes
Year FE	yes	yes
N	94871	94871
pseudo R-sq	0.113	0.096
Number of issuers	650	650

Panel B. Sample of financials only.

	Moody's	S&P	Moodys or S&P
Fitch Rating	0.00321*	0.0156**	0.0210***
	[1.75]	[2.28]	[3.13]
A+ to A-	0.00118	-0.00168	-0.0011
	[0.56]	[-0.16]	[-0.09]
BBB+ to BBB-	0.0281	-0.0141	0.0308
	[1.64]	[-1.42]	[1.23]
BB+ or worse	-0.00420*	-0.0205***	-0.0289***
	[-1.65]	[-3.91]	[-3.71]
MSP rating dispersion	0.00163	0.0179**	0.0251**
	[1.47]	[2.09]	[2.50]
Idiosyncratic volatility	0.425	1.836**	2.182***
	[1.39]	[2.54]	[3.31]
Beta	-0.0165***	-0.0473***	-0.0755***
	[-2.90]	[-3.78]	[-4.38]
Analyst dispersion	0.360*	0.566	1.281**
	[1.78]	[1.34]	[2.00]
2 digit SIC FE	yes	yes	yes
MSP Rating FE	yes	yes	yes
year FE	yes	yes	yes
N	50031	50255	50255
pseudo R-sq	0.341	0.168	0.202
Number of issuers	139	150	150

Table 3.13: Credit Spread Regressions, Full Sample
Using monthly panel data between 2002 and 2007, we regress credit spreads for AAA to BB- rated bonds on bond and firm characteristics and macro-economic variables, with fixed rating and year effects. Main variables of interest are whether a Fitch rating is better (FR¡MSP), equal to (FR=MSP) or worse (FR¿MSP) than the average Moody's and S&P rating, as well as variables relating to regulator (IG) and random (A-) boundaries and the level of the VIX as measure for market wide uncertainty, also interacted with having a Fitch rating and rating categories. See Table 5 for other control variable descriptions. T-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	1	2	3	4
FR<MSP	4.786	6.123*	-17.67**	-6.274
	[1.53]	[1.93]	[-2.07]	[-0.96]
FR=MSP	7.481***	7.564***	-16.48*	-5.044
	[2.71]	[2.77]	[-1.93]	[-0.77]
FR>MSP	25.52***	21.34***	-2.388	10.34
	[3.27]	[3.14]	[-0.23]	[1.09]
F Pushes < IG		-27.51***	-27.39***	-27.62***
		[-2.87]	[-2.87]	[-2.97]
F Pushes > IG		17.5	17.98	17.13
		[1.19]	[1.24]	[1.34]
Fitch Rating * VIX			1.602***	0.823**
			[2.91]	[2.02]
(AAA to AA-) * VIX				-0.706*
				[-1.85]
(A+ to A-) * VIX				-0.286
				[-0.60]
(BBB+ to BBB-) * VIX				2.284***
				[4.04]
(BB+ to BB-) * VIX				5.133***
				[6.57]
VIX	1.311***	1.320***	0.293	
	[7.08]	[7.11]	[0.99]	
Controls	yes	yes	yes	yes
MSP rating FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
N	119560	119560	119560	119560
adj. R-sq	0.609	0.611	0.612	0.622
Number of issuers	617	617	617	617

Table 3.14: Regressions for Liquidity effects of certification
OLS regressions of monthly bond turnover, measured as aggregated trading volume over total value of outstanding bonds on rating category dummies, boundary dummies, a dummy indicating whether the issue has a Fitch rating or not and controls for cross-sectional liquidity (age) as well as time series liquidity (TED spread). All other control variables are dropped due to the use of time and issue fixed effects. Monthly data for July 2002-December 2007 are used; the sample consists of all issues with both Moody's and S&P ratings. t-statistics are in brackets (using robust standard errors clustered by issuer). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1	2	3	4	5
AAA to AA-	-0.505	-0.584	-0.584	-0.577	-0.687
	[-0.84]	[-0.99]	[-0.99]	[-0.97]	[-1.12]
BBB+ to BBB-	0.361	0.37	0.39	0.422	0.372
	[1.27]	[1.30]	[1.36]	[1.42]	[1.30]
BB+ to BB-	-1.922***	-1.934***	-2.042***	-2.021***	-2.066***
	[-3.20]	[-3.22]	[-3.29]	[-3.25]	[-3.31]
TED Spread	-0.589**				
	[-2.44]				
Age	-1.214***	0.157	0.174	0.169	0.184
	[-7.08]	[0.08]	[0.09]	[0.09]	[0.10]
F makes IG			1.783***	1.788***	1.846***
			[2.65]	[2.66]	[2.68]
F denies IG			-1.657*	-1.615*	-1.609*
			[-1.78]	[-1.71]	[-1.77]
F makes A-				0.16	
				[0.48]	
F denies A-				-0.503	
				[-1.40]	
Rated by Fitch					-0.728
					[-1.25]
N	118093	118093	118093	118093	118093
adj. R-sq	0.308	0.31	0.31	0.31	0.31
Year FE	yes	no	no	no	no
Month FE	no	yes	yes	yes	yes
Issue FE	yes	yes	yes	yes	yes
Number of issuers	618	618	618	618	618

Chapter 4

Return decompositions: Evidence from the corporate bond market

4.1 Introduction

In the 2007-2009 financial crisis, the world experienced a substantial decline in prices of stocks and credit risky assets. A substantial part of this decline could be traced back to worsening expectations about future profits and default rates. However, changes in discount rates, due to for example changes in risk aversion could also have contributed to the massive price drops. For financial policy and regulation to be effective in resolving the crisis and preventing the next one, knowledge about the origin of returns are vital. For example, much of the criticism on the FASB 157 fair value accounting regulation[1] resulted from large changes in capital ratios. If these changes are due to changes in discount rates rather than expected cash flows, banks may have suffered unnecessary harm since changes in discount rates will not immediately compromise their solvability. This is not unlikely, since several academic studies found that changes in fundamentals only explain a small fraction of the variance of changes in credit spreads (see for example Collin-Dufresne et al. (2001)).

In the 1990s, several papers were written on the decomposition of unexpected stock (and government bond) returns into an expected cash flow news and a discount rate news component[2], inspired by the seminal work of Campbell and Shiller

[1]For example, in October 2008, the former FDIC chair William Isaac blamed the SEC's mark-to-market accounting for banks for destroying 500 bln in bank capital and a resulting loss of 5 trln in bank lending.

[2]See for example Campbell (1991), Campbell and Ammer (1993) and Campbell and Mei (1993)

(1988). This issue was revisited by Campbell and Vuolteenaho (2004), where they show that the beta of a stock consists of two components that are priced differently, a 'good' discount rate beta with a low risk premium and a 'bad' cash flow beta with a high risk premium. They use this decomposition to explain the size and value anomalies. Several recent papers have followed up on this issue and criticized the methods employed in this decomposition. In particular, Chen and Zhao (2009) criticize among others the interpretation of residual return news as cash flow news in a Campbell-style VAR based return decomposition. An important economic motivation for structure in Campbell and Vuolteenaho (2004) was the finding in Fama and French (1996) that value firms are financially distressed, which causes their discount. Their findings support the view of the Fama French three factor model as an economically founded and rational ICAPM rather than a purely statistical artifact or a pricing model with a behavioral nature.

Despite the enormous amount of attention that this decomposition has gotten for the equity market, to my knowledge, no such analysis has ever been performed on corporate bond data. Starting from Campbell and Shiller (1988) style present value model, I derive almost identical expressions for log coupon yields as they derive for log dividend-price ratios. A crucial insight here is that if one chooses an appropriate structure for default losses, the known face value to be repaid at maturity can serve as a substitute for the limiting convergence of discounted dividend-price ratios to zero as a boundary condition.

In addition, I derive that cash flow news for straight bullet corporate bonds is credit risk news, that is, changes in expected loss on this bond. Discount rate news on the other hand, enters this return composition in a very similar fashion as in the equity market, but corrected for the bounded maturity. Corporate bonds differ in many aspects from equities among others because they have clearly defined cash flow patterns and a fixed time to maturity. These features of corporate bonds are very convenient, since an analysis based on the corporate bond market, by virtue of its structure, accommodates several criticisms made in Chen and Zhao (2009). The limited maturity of corporate bonds addresses the concerns Chen and Zhao (2009) have about the use of very persistent variables that have a disproportionally large weight in the sum of a geometric series. Moreover, the theoretical derivation also tells how to derive cash flow news directly, thus addressing the concern that due to omitted state variables in the predictive regression, indirect (i.e. residual based) cash flow news can still contain discount rate news.

The use of corporate bonds indeed has its benefits. The predictive regressions have a substantially higher R^2 than is the case for stocks, which should lead to

more accurate estimates of discount rate news. Variance decompositions show that a high percentage of the corporate bond returns are due to discount rate news. However, despite the higher predictive R^2, the simpler structure, and the limited maturity, issues relating to persistence still play up. Large negative covariance contributions in variance decompositions indicate the presence of these issues. When the exposure to overly persistent variables (in this case the 10 year smoothed P/E ratio) is moderate or small, the use of shorter maturity corporate bonds can mitigate this problem. When exposure is large, indices with a maturity that is short enough are not available to me and the problem can only be solved by choosing a less persistent, but economically less well motivated state variable, the 3 month treasury rate. When I do this, the implausible results due to persistence disappear.

The insight that cash flow news for corporate bonds is basically default risk news, allows to do several other types of relevant analyses. For example, one can study how corporate debt prices evolve relative to stock prices. Merton (1974) states that the value of the debt is linked to the value of the equity and the contemporaneous correlation between the two should even be equal to one since the underlying asset value is the only risk factor driving both equity and debt values. However, cash flow news for stocks and corporate bonds can also be negatively correlated when some of the assumptions of the Merton (1974) model are relaxed. An increase in company risk will lead to lower expected cash flows for corporate bond holders, but higher expected cash flows for stock holders due to limited liability for stockholders and limited upside for corporate bond holders. On an aggregated basis, I do indeed find high correlations between stock and corporate bond returns, but this commonality seems to be driven largely by commonality in discount rate news rather than cash-flow news. Indirect cash flow news for stocks and corporate bonds also tends to be positively correlated. In cases that suffer from an excessively persistent state variable in the VAR, I find a negative correlation that disappears when I correct for the over-persistence by replacing the overly persistent state variable. Thus, I do not find any evidence against market wide risk shifting.

To address some of the concerns stated in Chen and Zhao (2009), I also model cash flow risk directly using a similar VAR approach for default rates rather than returns. The direct cash flow news correlates rather highly to stock and corporate bond returns. For stocks, both cash flow news and discount rate news correlate highly to direct cash flow news. Again I show the strong of a persistent state variable. For the specifications in which corporate bonds suffer from exposure

to an excessively persistent state variable, direct cash flow news correlates very highly with discount rate news and hardly or negatively with indirect cash flow news. When I replace the persistent variable with a highly correlated but less persistent variable or when I consider shorter term bonds, indirect cash flow news correlates positively with direct cash flow news.

In a variance decomposition with discount rate news, direct cash flow news and misspecification noise, I show that I can explain up to 35% of unexpected corporate bond returns with direct cash flow news and can get misspecification noise as low as 20% of unexpected return variance.

The remainder of the chapter is organized as follows. Section 2 gives a literature review and highlights the contribution of this chapter. Section 3 introduces the derivations necessary to conduct the return decomposition. Section 4 describes the empirical approach. Section 5 describes the data that have been used. Section 6 presents the empirical results and section 7 concludes.

4.2 Literature review and contribution

This chapter contributes to several strands of the academic literature on asset pricing and risk management.

First and foremost, it relates to the literature on return decompositions into an expected cash flow news and a discount rate news part. The cornerstone of this literature is the paper by Campbell (1991). This paper shows, using the derivations from Campbell and Shiller (1988), that unexpected stock returns can be decomposed into expected cash flow news and discount rate news. He also gives a variance decomposition of unexpected stock returns. Another paper by Campbell and Ammer (1993) uses the Campbell (1991) methodology for jointly decomposing excess stock and treasury bond returns into a discount rate and an expected cash flow part. Their results also shed more light on the sources of correlation between stock and bond returns. The Campbell (1991) approach is also used in later a later paper by Campbell and Mei (1993) to break up betas into an expected cash flow and a discount rate component. Campbell and Vuolteenaho (2004) use the results from Campbell and Mei (1993) to argue that there are two types of beta, a good (discount rate beta with a low risk premium) and a bad one (cash flow beta with a high risk premium). This allows them to explain the size and value anomalies (small and value stocks have high cash flow betas) as well as the poor performance of the CAPM since 1963 (large discount rate betas for growth stocks). In a follow up-paper, Campbell, Polk and Vuolteenaho (2010) decompose market

as well as individual excess returns into discount rate and cash flow news. This allows them to decompose the good and the bad beta further. They find that for value stocks, firm specific cash flow news correlates highly with market wide cash flow news. On the other hand, for growth stocks, the discount rate beta mainly stems from correlation of stock level cash flow news with market wide discount rate news. These results provide evidence that for both growth and value stocks, the main source of risk enters through firm specific cash flow news. However, for growth firms cash flow shocks are more transient because market wide discount rate shocks are also more transient. Consequently, value stocks have higher risk premia.

In a recent paper, Chen and Zhao (2009) criticize the traditional approach of estimating discount rate news explicitly and backing out expected cash flow news as the residual by imposing a present value condition. They show that discount rate news cannot be estimated accurately due to low predictive R^2 and high sensitivity to the inclusion of persistent state variables. Therefore also the expected cash flow measure is seriously flawed. The results reported by Campbell and Vuolteenaho (2004) they find to be not robust. In addition, they explore several solutions to the problem. These include modeling cash flow news directly as well as a Bayesian averaging approach. This paper develops the theoretical framework for this type of return decomposition for corporate bonds and investigates to which extent the issues noticed by Chen and Zhao (2009) are present. I find that the problems they describe also play up in the corporate bond market. Especially issues relating to overly persistent variables have an effect that is even more disruptive than what Chen and Zhao (2009) describe for the stock market. I also come up with a mechanism to detect disrupting effects of persistent variables by looking at covariances in the variance decomposition of corporate bond returns. Moreover, I suggest using short maturity assets as a remedy not explored in Chen and Zhao (2009) yet.

The second strand of literature this chapter relates to is the literature on the estimation of present value models. Whereas the return decomposition literature looks at price changes or returns, this literature estimates the mechanics behind price levels or equivalent measures. As the return decomposition literature, this literature also starts from Campbell and Shiller (1988) but develops into a different direction. As the starting point for both strands of literature is the same, by construction they are linked. For a full exploration of the links between state space and VAR models, refer to Cochrane (2008). Papers in this field take the relationship that the dividend-price ratio is a discounted infinite sum of future returns and dividend growth rate plus a constant. As a recent example, Van Bins-

bergen, Brandt and Koijen (2009) impose extra structure on this framework by modeling expected returns and dividend growth rates explicitly and estimate the model using maximum likelihood. This allows them to study predictability in expected returns and dividend growth rates. Another example is a paper by Lettau and Van Nieuwerburgh (2008) who set up a similar structure, but restrict the persistence of price dividend ratios and dividend growth rates to be the same. This allows them to back out structural parameters from reduced form estimates, which allows for simpler estimation techniques. This chapter shows that a Campbell and Shiller (1988) log-linearization gives an expression for log coupon yields that is very similar in nature to the expression for log dividend-price ratio in Campbell and Shiller (1988), because the boundary condition of a know price at maturity conditional on no default in combination with a convenient structure for default losses serves as an alternative to the convergence boundary condition for discounted dividend-price ratios in Campbell and Shiller (1988). Consequently, theoretical insights from this literature carry over automatically to the corporate bond market and estimation techniques from this literature can directly be applied as well.

Another strand of literature this chapter relates to is the literature on what drives changes in credit spreads. Two papers in particular are of interest. Those are by Collin-Dufresne et al. (2001) and Berndt, Lookman and Obreja (2007). Common to both papers is a decomposition of the changes in credit spreads. Collin-Dufresne et al. (2001) find that when they correct changes in credit spreads for changes in credit quality and financial market business conditions, they are left with a strong common factor in the residuals. Berndt et al. (2007) focus on estimating a systematic jump risk premium from credit spreads. They impose a parametric structure on real world and risk neutral default intensities and decomposes changes in credit spreads into a default only, a default risk premium only and a large residual part that they interpret as a jump risk premium. This chapter decomposes corporate bond returns that are largely due to changes in credit spreads, but has a different focus. It strongly links to the cash flow and discount rate news literature in the equity market and also links its results to the results found in equity markets. Contrary to both studies, this study investigates the corporate bond market as a whole rather than at individual company level. Moroever, as opposed to Berndt et al. (2007), I impose hardly any specific structure for risk premia. In line with Collin-Dufresne et al. (2001), I also find that changes in credit risk only account for a relatively small portion of the corporate bond return variance (about 35% maximum).

4.3 Cash flow and discount rate news in corporate bonds

4.3.1 Campbell-Shiller approximation for corporate bonds

In this section, I derive a log-linerization for corporate bond returns in the same spirit as Campbell and Shiller (1988). Later I will use these results to derive expressions for a return decomposition in a similar spirit as Campbell and Vuolteenaho (2004). Let me start from the holding return h_{t+1} from time t to time $t+1$ on a corporate bond with infinite maturity. This is given by:

$$h_{t+1} = \log(P_{t+1} + C_{t+1}) - \log(P_t) \tag{4.1}$$

where P_t is the price of the bond at time t and $C_t + 1$ is the coupon paid between t and $t+1$. Analogous to Campbell and Shiller (1988), I can approximate h_{t+1} with a Taylor approximation ξ:

$$\xi = k + \rho \log(P_{t+1}) + (1-\rho)\log(C_{t+1}) - \log(P_t) \tag{4.2}$$

where ρ is the average ratio of price over price plus coupon and k is a constant. Writing $p_t = \log(P_t), c_t = \log(C_t), \delta_t = c_t - p_t$ and $\Delta c_t = c_t - c_{t-1}$, I get

$$h_{t+1} \simeq k + \delta_t - \rho\delta_{t+1} + \Delta c_{t+1}. \tag{4.3}$$

Now to avoid problems relating to approximation accuracy and tractability, I make an assumption about what happens at default. I write for every (uncertain) coupon $C_t = C\exp(-\gamma_t)$, where C is the coupon rate of the bond. That is, the uncertain coupon is equal to the coupon times a loss function and default before maturity is possible. The loss function is an exponential function of a random variable, the loss rate, which is equal to zero if no default has taken place and larger than zero in case of default. The parameter γ_t then measures the Loss-Given-Default (LGD). Analogous, I impose $P_T = \exp(-\gamma_T)$[3]. Also imposing the boundary condition that $\lim_{i\to\infty} \rho^i \delta_{t+i} = 0$, rearranging and solving forward, (4.3) reduces to

$$\delta_t = \sum_{j=0}^{\infty} \rho^j (h_{t+1+j} + \Delta\gamma_{t+1+j}) - \frac{k}{1-\rho}. \tag{4.4}$$

[3]Notice that without loss of generality, I have normalized the face value of the corporate bond to 1 for tractability reasons.

Thus, for a credit risky console bond, one can write the log coupon yield as the discounted sum of all future returns and default loss rates plus a constant. However, when I consider the more usual case where a corporate bond has a limited maturity T, (4.4) changes to

$$\delta_t = \sum_{j=0}^{T-t-1} \rho^j (h_{t+1+j} + \Delta\gamma_{t+1+j}) + \rho^{T-t}\delta_T - kAF(\rho, T-t), \tag{4.5}$$

where $AF(r, s)$ is an annuity factor with discount rate r and maturity s. Working out δ_T, I get

$$\delta_t = \sum_{j=0}^{T-t-1} \rho^j (h_{t+1+j} + \Delta\gamma_{t+1+j}) + \rho^{T-t}c - kAF(\rho, T-t), \tag{4.6}$$

where $c = \log(C)$. This expression is important as it shows that the log coupon yield can be written as a sum of future returns and log default rates and a constant, without the need of the boundary condition $\lim_{i\to\infty} \rho^i \delta_{t+i} = 0$. This will allow for advanced estimation procedures as are know in the equity market literature (see for example Van Binsbergen and Koijen (Forthcoming)). Notice that if I have a dividend or coupon paying security with limited maturity whose terminal value is stochastic in a different way than its last coupon/dividend payment, an additional stochastic term would end up in the expression preventing the results from the equity market to carry over directly[4].

As it turns out, if one solves (4.3) forward with respect to p_t rather than δ_t, a more intuitive solution is obtained. I write

$$p_t = \rho p_{t+1} + (1-\rho)c_{t+1} - h_{t+1} + k \tag{4.7}$$

[4]As an example, one could think of an equity stake in a project paying fixed dividends that will be liquidated after a limited time. The uncertainty of the terminal value of the project will not cancel (in logs) against the uncertainty in the last dividend payment (since there is none) and creates an extra stochastic term. The stochastic component of the last coupon payment cancels (in logs) exactly against the stochastic component of the notional, thereby leaving only a constant which is subsumed in the (constant) annuity factor already present.

Solving forward and imposing a boundary condition, I get:

$$p_t = \sum_{i=0}^{T-t-1} -\rho^i h_{t+1+i} + \rho^i(1-\rho)c_{t+1+i} + \rho^{T-t}p_T + AF(\rho, T-t)k \tag{4.8}$$

$$= E_t\left(\sum_{i=0}^{T-t-1} -\rho^i h_{t+1+i} + \rho^i(1-\rho)c_{t+1+i} + \rho^{T-t}p_T\right) + AF(\rho, T-t)k \tag{4.9}$$

(4.9) is obtained by taking contemporaneous expectations of (4.8) on both sides. Imposing again that $C_t = C\exp(-\gamma_t)$ and that $P_T = \exp(-\gamma_T)$, I get

$$p_t = E_t\left(\sum_{i=0}^{T-t-1} -\rho^i h_{t+1+i} - \rho^i(1-\rho)\gamma_{t+1+i} - \rho^{T-t}\gamma_T\right) + AF(\rho, T-t)(k + (1-\rho)c) \tag{4.10}$$

Thus, the log price of a corporate bond[5] is given by a the present value of expected losses and expected future returns corrected for the time value of coupons that are realized earlier than the notional (the $c(1-\rho)$ part of the annuity) and a linearization correction (the k part of the annuity). To see that this expression makes sense, one can set the coupon rate to zero, in which case $\rho = 1, k = 0$ and the annuity factor drops out. The discount from par in this case is equal to the cumulated expected return plus the expected loss of notional as one would expect.

4.3.2 Unexpected return decomposition

If one conditions (4.10) on information at time $t+1$ rather than time t and subtracts p_t conditional on time t information, one obtains after some rearranging the unexpected return:

$$h_{t+1} - E_t(h_{t+1}) = (E_{t+1} - E_t)\left(\sum_{i=0}^{T-t-1} \rho^i(1-\rho)(-\gamma_{t+1+i}) + \rho^{T-t}(-\gamma_T)\right) - (E_{t+1} - E_t)\left(\sum_{i=1}^{T-t-1} \rho^i h_{t+1+i}\right) \tag{4.11}$$

Thus, as one can see, the cash-flow news for a corporate bond is equal to the changes in expected loss on the bond.

For the discount rate news, I can use the results from Campbell (1991) and

[5] Which essentially is the discount from par.

modify these slightly. When expected returns follow an AR(1) process

$$E_{t+1}(h_{t+2}) = \phi E_t(h_{t+1}) + u_{t+1}, \tag{4.12}$$

then with infinite horizon, the discount rate news follows from the formula for the sum of a geometric series, analogous to the value of a perpetuity:

$$(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j h_{t+1+j} = \frac{\rho u_{t+1}}{1 - \phi\rho}. \tag{4.13}$$

Similar to constructing annuity factors from a console and a forward console, I can construct the finite sum of discount rate terms as the difference between two infinite sums of discount rate news starting at different times. Thus, I have:

$$(E_{t+1} - E_t) \sum_{j=1}^{T-t-1} \rho^j h_{t+1+j} = \frac{\rho u_{t+1}}{1 - \phi\rho}(1 - (\phi\rho)^{T-t-1}). \tag{4.14}$$

4.3.3 Excess returns

In the section above, interest rates have been ignored. However, interest rate movements account for an important portion of the price movements in corporate bond prices. To align with the literature on return decompositions for stocks, I start by taking the short rate as a benchmark rate, analogous to how I construct excess returns for stocks. One can extend the model to also correct for unexpected term structure movements by subtracting the holding return on a treasury. The only news for a treasury is discount rate news. Thus, the excess returns defined as the return on a corporate bond minus that of a treasury, can be decomposed into the original cash flow news and the original discount rate news minus the interest rate news as far as it would affect the treasury. The question is which treasury to take as a benchmark. Therefore, I realize that investors typically have different investment horizons for example due to asset liability management. The yield on a treasury with a duration corresponding to the investor's horizon is for him or her the true risk-free rate. Moreover, I assume that an investor is most likely to invest in a corporate bond with a duration close to his horizon. Therefore, as an alternative, I construct excess holding returns as the total return on a corporate bond index minus the total return on a treasury index with matching duration. Finally, Collin-Dufresne et al. (2001) show the existence of a strong latent corporate bond factor. If one finds a large discount rate factor, it may be hard to identify the (indirect) cash flow news properly, because it is very sensitive

to small misspecifications in the discount rate news. Therefore, I also do the same analysis with the return on a Aaa corporate bond index with matching maturity as a benchmark.

4.4 Empirical approach

4.4.1 Discount rate news

I first estimate discount rate news using a VAR approach as in Campbell and Vuolteenaho (2004). This I do for stocks and corporate bonds jointly. However, in the interest of stability, I restrict the coefficients in my VAR drastically. Thus, I define a first order VAR

$$z_{t+1} = Az_t + \omega_{t+1}, \tag{4.15}$$

where z_t is a vector containing m elements, the first of which is the stockmarket excess return and the second of which is the bond (index) excess return. m is the total number of endogenous variables in my VAR. As Campbell (1991) shows, the discount rate news N_{t+1}^{DR} for the stock market is defined as

$$N_{t+1}^{S,DR} = \lambda_S' \omega_{t+1}, \tag{4.16}$$

$$\lambda_S = e1'\rho_S A(I - \rho_S A)^{-1}, \tag{4.17}$$

where e_j is a vector of length m with all zeros except for a one at element j and ρ_S is a constant close to one that results from a similar log-linearization as in the previous section. The (indirect) cash flow news for the stockmarket $N_{t+1}^{S,CF}$ is defined as the residual of the total unexpected return minus the discount rate news

$$N_{t+1}^{S,CF} = (e1' + \lambda_S')\omega_{t+1}. \tag{4.18}$$

For corporate bonds, the multivariate extension of (4.14) implies for discount rate news $N_{t+1}^{CB,DR}$ and (indirect) cash flow news $N_{t+1}^{CB,CF}$

$$N_{t+1}^{CB,DR} = \lambda_{CB}' \omega_{t+1}, \tag{4.19}$$

$$N_{t+1}^{CB,CF} = (e2' + \lambda_{CB}')\omega_{t+1} \tag{4.20}$$

$$\lambda_{CB} = e2'\rho_{CB}A(I - \rho_{CB}A)^{-1}(I - (\rho_{CB}A)^T), \tag{4.21}$$

where T is the (average) maturity of the corporate bond (index). The cash flow news measures for stocks and corporate bonds as defined above are indirect in nature. They are not directly measured by their fundamental drivers, dividend growth rates and default rates, but rather backed out as a residual due to a present value restriction. Since I will also estimate cash flow news directly, whenever I refer to indirect cash flow news, I refer to $N_{t+1}^{S,CF}$ or $N_{t+1}^{CB,CF}$ as defined above.

For the implementation of my VAR, I use stock index excess returns, whereas for corporate bonds, I use excess holding returns on corporate bond indices as described in the previous section. The other endogenous variables in my VAR are 10 year smoothed P/E ratio, slope of the term structure, and the small value spread (all following Campbell and Vuolteenaho (2004)) as well as the short rate and the level of credit spreads. The short rate will capture business cycle related aspects and availability and cost of credit for refinancing. The level of credit spreads is an important component of the ex-ante expected return on corporate bonds, and is therefore a natural candidate to be included in my VAR. The analysis is done on quarterly data. To construct $N_{t+1}^{S,DR}, N_{t+1}^{CB,DR}, N_{t+1}^{CB,CF}$ and $N_{t+1}^{S,CF}$, I use $\rho_S = 0.95$ for stocks and $\rho_{CB} = 1 - YTM$ where YTM is the average yield-to-maturity for the corporate bond index under investigation[6]. To get the time to maturity left, I transform the duration of the corporate bond index as explained in Appendix 4.9.1.

As mentioned before, in the interest of stability, I restrict the coefficients in my VAR. To maintain maximum compatibility with previous research on this topic, I only allow the smoothed P/E ratio, the term yield and the small-value-spread as state variables for the stock returns. For the corporate bond returns, I use the 10 year smoothed P/E ratio, the term yield and the credit spread level as state variables. When the 1 month treasury rate is the benchmark return, I also include the short rate as an extra state variable, because in this case, the shape of the term structure is likely to be more important to predict the corporate bond returns. For all the other variables, I set the coefficients on lagged corporate bond and stock

[6]One may wonder why always the yield-to-maturity rather than the credit spread is used here, since in the empirical section in some cases the returns on a risk-free or Aaa benchmark index are subtracted. The reason is that the ρ parameter indicates the relative importance of each cash flow for both cash flow and discount rate news. Since the full coupon of the corporate bond is exposed to default risk, one can easily see that the coupon yield rather than the credit spread should be used. Technically, the right way to correct for the effect of returns on treasuries, is to estimate a separate VAR for them and subtract the indirect cash flow and discount rate news from the decomposition of the total(not excess) returns on the corporate bond. However, Chen and Zhao (2009) show that although theoretically, in such a decomposition, cash flow news should be zero, this is typically not the case. For this reason, I use the excess return as state variable in my VAR.

returns to zero.

4.4.2 Direct cash flow news

Since Chen and Zhao (2009) show that the residual based approach for cash flow news is problematic for stocks, I also model cash flow news explicitly. To this end, I estimate a separate unrestricted VAR for quarterly default rates. This VAR has as state variables the 10 year smoothed P/E ratio, the slope of the term structure and the 3 month treasury rate. From this VAR, I construct the default risk news for the base case bond portfolio following (4.11). To this end, I write

$$\Delta\gamma_t = \psi\Delta\gamma_{t-1} + \eta_t, \tag{4.22}$$

$$E_t(\gamma_T) = \gamma_t + \Delta\gamma_t \sum_{i=1}^{T-t-1} \psi^i, \tag{4.23}$$

$$E_{t+1}(\gamma_T) = \gamma_t + (\Delta\gamma_t + \eta_{t+1}) \sum_{i=1}^{T-t-1} \psi^i, \tag{4.24}$$

$$(E_{t+1} - E_t)(\gamma_T) = u_{t+1}(1-\psi)^{-1}(1-\psi^{T-t-1}), \tag{4.25}$$

where $\Delta\gamma_t$ is the per period default rate[7]. The univariate setup with only one lag is thus very similar to an intensity model with a Vasicek process driving the default intensity. In the VAR I have

$$v_{t+1} = \Psi v_t + \zeta_{t+1}, \tag{4.26}$$

$$\gamma_s = e1'(I-\Psi)^{-1}(I-\Psi^{s-t-1}), \tag{4.27}$$

$$-N_{t+1}^{CB,CF,direct} = \sum_{i=1}^{T-t} \rho_{CB}^{i-1}(1-\rho_{CB})(-\gamma_{t+i}) + \rho_{CB}^{T-t}(-\gamma_T), \tag{4.28}$$

where v_t is the matrix of state variables with the default rate in the first column and thus γ_s is the cumulative default rate from time t up to time s. These direct cash flow news measures are used later in specification tests.

[7]Thus, empirically I abstract from changes in LGD. The reason for this is that the ultimate LGD is not known at the moment an issuer defaults. Therefore, it is hard to get the timing right. Since I will not directly subtract credit risk news from corporate bond returns (due to data limitations, in particular the lack of default observations within each rating class), this is equivalent to assuming that the changes in LGD orthogonal to changes in default rates are white noise.

4.5 Data

The data for my empirical tests are constructed as follows. Equity market return data and the data required to construct the small stock value spread as well as the 1 month treasury benchmark rate are obtained from Ken French's website. The small stock value spread, I construct analogous to Campbell and Vuolteenaho (2004). The short rate (three month treasury constant maturity) as well as the slope of the term structure (10 year minus 3 month treasury constant maturity) are obtained from Federal Reserve banking reports. The 10 year smoothed P/E ratio is obtained from Bob Shiller's website and is defined as the inflation adjusted level of the S&P index divided by the average of cyclically and inflation adjusted earnings of its constituents over the 10 past ten years. The corporate bond index data as well as the treasury index data are downloaded from Datastream and are provided by the former Lehman Brothers (nowadays Barclays Capital). There are corporate bond indices for the ratings Aaa to Baa and a general IG index for intermediate and long maturities for the full sample. There are two treasury indices, an intermediate and a long maturity one. All intermediate maturity corporate bond indices are matched with the intermediate treasury index and all long maturity corporate bond indices are matched with the long treasury index[8]. Credit spreads for each corporate bond index are formed by taking the average yield-to-maturity on that index and subtracting the yield-to-maturity of the matched treasury index. For the 1 month treasury (1MT) case, excess total returns are constructed by taking the total returns on the corporate bond index and subtracting the 1 month treasury rate. For the matched maturity treasury (MMT) case, excess total returns are constructed by taking the total returns on the corporate bond index and subtracting the matched treasury total returns. For the matched maturity Aaa (MMA) case, excess total returns are constructed by taking the total returns on the corporate bond index and subtracting the matched maturity Aaa benchmark total returns. Rating and default data are obtained from Moody's Default Risk Services Corporate. This is a database in which all defaults and rating transitions for Moody's rated bonds and issuers are recorded. I obtain the number of issuer defaults, downgrades and upgrades for every quarter, as well as the total number of issuers rated during that period. The quarterly default rate is the ratio of the two.

[8]The average durations of the corporate bond and benchmark indices matched quite well, but not perfect. The advantage of this approach however, is that methodologies for index construction and timing of rebalancing of all indices is likely to be very similar since all data comes from the same provider

The base case will be to use total returns on the intermediate Baa portfolio, since Baa bonds cover a large part of the market, are relatively liquid and have substantial exposure to credit risk, but at the same time due to their relatively short maturity suffer less from several problems described in Chen and Zhao (2009). The advantage of portfolio data is that despite the skewed nature of individual corporate bond returns, the distribution of corporate bond portfolio returns is closer to a normal distribution. The sample period runs from Jan 1st 1973 to June 1st 2007. Data for the rest of 2007, 2008 and 2009 is also available, but I feel that the crisis might have brought about regime shifts, for example for my VAR parameters.

Table 4.1 contains summary statistics of the VAR inputs. The P/E ratio and value spread summary stats are much in line with Campbell and Vuolteenaho (2004), although the standard deviation of the P/E ratio is much higher in my sample. The term yield is on average much higher in my sample than in theirs. Baa bonds have a credit spread of 184 bps per year on average, which seems reasonable.

4.6 Results

4.6.1 VAR results

The results of the restricted VAR regression can be found in Table 4.2. As in Campbell and Vuolteenaho (2004), the R^2 for the stock market equation is rather low, comparable to their implementation. The signs of the coefficients on these state variables are roughly in line with Campbell and Vuolteenaho (2004), but particularly the smoothed P/E ratio lacks in significance, possibly due to the shorter sample period and lower frequency that I consider.

For the corporate bond return equation, the predictive power is much higher, given the R^2s of 12.8% to over 16%. As expected, credit spreads are an important predictor for corporate bond returns as well the term yield in all specifications. The short rate is important in the 1MT case. The sign and significance on the P/E ratio differs for the three implementations. The credit spread, short rate and the 10 year smoothed P/E ratio are most persistent and therefore likely to be important determinants for discount rate news over longer horizons.

VAR based decompositions

Once I have estimated my VAR, I can construct and analyze $N_{t+1}^{S,DR}$, $N_{t+1}^{CB,DR}$, $N_{t+1}^{CB,CF}$ and $N_{t+1}^{S,CF}$.

First, Table 4.3 shows a variance decompositions of unexpected stock and bond returns. For stocks, discount rate news explains about 21% of the unexpected excess return variance and indirect cash flow news dominates. The covariance terms also explain a sizeable part of the realized variance[9]. These results are in line with the results by Campbell (1991) for his full sample. For corporate bonds, discount rate news explains a more sizeable portion of total return variance and is often the dominant part. The discount rate news explains a particularly large part in the 1MT case, since a large part of the excess return will be due to changes in the risk-free term structure as also shown empirically in Cornell and Green (1991). I often get negative covariances between $N^{CB,CF}$ and $-N^{CB,DR}$. Depending on the specification those covariance terms are smaller or larger. In the 1MT case, this effect is similar for all corporate bond indices. However, in the MMT case, the effect is observed mainly for long maturity and high rating indices. While in general it is possible that $N^{CB,CF}$ and $-N^{CB,DR}$ correlate negatively, for example due to flight-to-quality effects, this would be less plausible in the MMA and the long MMT case, since the return on either a treasury or a Aaa index is subtracted which should be most exposed to flight-to-quality effects. Moreover, evidence on default clustering (see for example Lando and Stenbo Nielsen (2008)) suggests that default risk becomes more systematic in adverse economic scenarios, even correcting for common driving factors. Therefore, risk premia on default risk are expected to go up as default risk increases. Another possible explanation for this phenomenon could be that the state variables used in the VAR are too persistent. This would lead to discount rate news that is too large. The over-correction terms ends up in the indirect cash flow news, thereby creating a large negative covariance between the two components, mainly in the long maturity indices. In the MMA case, the presence of negative covariances is even stronger. Also this could be due to too persistent variables in the VAR, since Table 4.2 shows that corporate bond returns in this specification load highly on the very persistent P/E ratio.

Table 4.4 presents the correlations between unexpected stock and corporate bond returns as well as the indirect cash flow and discount rate news portions of stocks and intermediate and long term Baa corporate bonds. As one would

[9]Notice that I often use $-N^{DR}$. This is because $e1'u = N^{S,CF} - N^{S,DR}$ and $e2'u = N^{CB,CF} - N^{CB,DR}$ and thus a positive shock in $-N^{DR}$ corresponds to a positive unexpected return.

expect based on a Merton (1974) model, stock and corporate bond unexpected excess returns are positively correlated, in line with existing empirical results by for example Kwan (1996). When looking at discount rate news between stocks and corporate bonds, the correlation is always positive, but the strength of this correlation differs substantially across the different specifications. In the 1MT case, correlations are small, presumably since the very persistent P/E ratio loads with opposite signs. Indeed for the other two specifications where the P/E ratio loads with the same sign, correlations between stock and corporate bond discount rate news are very high. The indirect cash flow news for stocks and corporate bonds is sometimes correlated positively in line with a Merton (1974) style model, but sometimes negatively. The cases in which the correlation is negative are exactly those where the persistence of state variables could be an issue because of the long maturity (long MMT case) or high exposure to the P/E ratio (MMA case). With 54%, the correlation of $N^{S,CF}$ and $-N^{S,DR}$ is large for stocks. For corporate bonds, this correlation is often negative, and this effect is stronger for longer maturities.

Comparisons across maturities

To investigate the structure of indirect cash flow and discount rate news and assess performance of the decomposition, I compare the decompositions of long and intermediate maturity indices of the same rating. If the decomposition works properly, the different components of the long and intermediate indices should be highly correlated[10]. Table 4.5 shows these correlations between the several cases. Since the vast majority of the unexpected returns in the 1MT cases is discount rate news resulting from changes in the risk-free term structure, the discount rate news of long and intermediate portfolios is highly correlated. The correlations for indirect cash flow news are also high and similar for all rating categories. The interesting case here is the MMT case. While discount rate news across different maturities is generally positively correlated, indirect cash flow news is often negatively correlated. This again is a pattern that would fit the over-correction due to too persistent variables. In the MMA case, indirect cash flow news indeed correlates positively again. But since in these cases the exposure to the P/E ratio is very high, this might also be due to common misspecification.

[10]Notice that the opposite is not the case; high correlations of the components between long and intermediate portfolios can also be due to common misspecification

4.6.2 Direct cash flow news

As indicated before, Chen and Zhao (2009) found stability problems with the VAR approach, in particular for interpreting the residual as cash flow news. Therefore, in line with their paper, I model cash flow news directly. To this end, I estimate again a first order VAR. I use expression (4.28) to construct the default risk news. For long term portfolios I use the maturity and ρ_{CB} corresponding to the Baa long index and for the intermediate portfolios, use the maturity and ρ_{CB} corresponding to the Baa intermediate index. Table 4.6 shows the VAR coefficients of the default rate VAR. A higher level and slope of the term structure lead to higher default rates since funding is more expensive. A high P/E ratio leads to lower default rates, most likely since this offers a cheap way to pay off debt by raising equity.

Table 4.7 shows how direct cash flow news relates to several return components of stock and corporate bond portfolios. In panel A, the results for the 1MT case are shown. Correlations with index returns increase as the rating decreases as one would expect, which is also the case for the discount rate news. Taken together, the results for discount rate news suggest a flight-to-quality effect. An unexpected worsening of default rates has a strong negative correlation with the cash flow news component of corporate bond returns as one would expect.

In panel B, a different picture emerges. First of all, corporate bond returns show a stronger correlation to direct cash flow news, probably since the effect of changes in the term structure is taken out by taking a matched maturity treasury index as benchmark, for long maturities even stronger than for intermediate maturities. Yet, while still with the right sign, the correlations for the cash flow news component are small for the long maturity portfolio. As it turns out, this is caused by the very strong positive correlation in the discount rate news, in particular for the long maturity portfolios. The fact that this mainly plays up for the long maturity portfolios is another indication that there may be an issue with respect to the persistence of state variables.

In panel C, one can see an effect similar to the long MMT case for all indices. Remember that these portfolios load strongly on the P/E ratio, so the issue of persistence is likely to show up in all portfolios.

In panel D, the correlations of direct cash flow news with stock returns (components) are shown. Interestingly, stock returns correlate strongly with market wide direct cash flow news in the predicted direction with a correlation of 69%. Correlations of indirect cash flow and discount rate news hardly differ. Campbell et al. (2010) show that the cash flow and discount rate beta in Campbell and

Vuolteenaho (2004) arise typically because for individual companies, their cash flow news correlates highly with market wide cash flow or discount rate news respectively. My observation here is consistent with their findings in that if the market wide default rates constitutes partially of firms with cash flow news linked to market wide cash flow news and partially of firms with cash flow news linked to market wide discount rate news, the market wide default risk news should correlate to both equity return components. One question that remains is why stock returns correlate higher to direct cash flow news. There are several possible explanations for this. First, the CRSP value weighted index consists of more low credit quality companies than the IG indices. Second, in case of a default, a stock has a higher loss given default than a corporate bond due to its lower seniority. Finally, for stocks the upside is not capped. Therefore, even for a safe firm, substantial positive company cash flow news would translate into substantial positive stock cash flow news because (expected) dividends will go up. For its bonds that are rated Aaa, the cash flow effect will be small.

4.6.3 Accounting for persistent variables

The MMT and MMA specifications consistently show effects of over-correcting for discount rate news due to excessive persistence of the P/E ratio. Therefore, instead of including the extremely persistent P/E ratio, I include the 3 month treasury rate which shows a 60% correlation with the P/E ratio, but is substantially less persistent. Table 4.8 shows the variance decompositions. Indeed, in panel B, the degree of negative covariance is reduced substantially. For the long portfolios however, it is hard to get discount rate news up to levels reported in earlier studies (Collin-Dufresne et al. (2001) for example only manage to explain 25% of credit spread changes by changes in default probability and recovery rates and therefore leave the other 75% for discount rate news). In Table 4.9, I now get positive across maturity correlations for indirect cash flow news in all cases. Correlations are increasing as credit quality decreases, as one would expect. Table 4.10 shows correlations of direct cash flow news with the different return components and the correlations for cash flow news now seem rather aligned. Thus, in the presence of VAR state variables that are rather persistent for assets that are known to have a large component of their returns due to discount rates, strong negative correlations between cash flow and discount rate news indicate over-correcting of discount rate news due to persistence. When exposure to a persistent factor is rather mild, short maturity assets, possibly artificially created with derivatives as

in for example Van Binsbergen et al. (2009), will keep the impact of the persistent variable contained.

4.6.4 The case with a 1 month treasury

In view of the concluding remarks of the previous section, also the results for the case where the 1 month treasury is the benchmark would look suspicious. There is substantial exposure to the P/E ratio and indeed, the covariance in the variance decompositions is consistently negative suggesting over-estimation of discount rate news due to persistence. Yet, in Table 4.7, the indirect cash flow news is in line with the direct cash flow news for all indices, whereas that was not the case for the other specifications. To understand this, one has to go back to the VAR coefficients in Table 4.2 and 4.6. Corporate bond returns load positively on the P/E ratio, whereas default rates load negatively on the P/E ratio. Thus, the effect of a too persistent P/E ratio will increase rather than reduce the cash flow news effect due to over-correction. Now the reason that the P/E ratio shows up positively in this specification is that also the short rate is included as a state variable and those two exhibit a 60% correlation. If the short rate is excluded, the P/E ratio shows up negatively as in the other specifications. This will however come at the expense of a disruptively reduced fit, mainly in the part of the returns due to changes in term structure.

4.6.5 Alternative variance decomposition

Inspired by Chen and Zhao (2009), I investigate the variance decomposition of corporate bond returns when I explicitly account for noise due to misspecification. To this end, I use my direct rather than indirect cash flow measure. Since I estimate this measure for the market as a whole and leave out any effects of unexpected changes in loss given default, I first regress the unexpected corporate bond return on the direct cash flow measure and regress the residual on the discount rate news:

$$y = e2'u \tag{4.29}$$

$$y = \beta_{CF} N^{CB,CF,direct} + \nu \tag{4.30}$$

$$\nu = \beta_{DR} N^{CB,DR} + \epsilon. \tag{4.31}$$

For constructing the discount rate news, I use the short rate instead of the P/E ratio as a state variable in the VAR for reasons described above. Moreover I define the fitted values of these regressions as $\tilde{y} = \tilde{\beta}_{CF} N^{CB,CF,direct}, \tilde{\nu} = \tilde{\beta}_{DR} N^{CB,DR}$

where $\tilde{\beta}_{CF}, \tilde{\beta}_{DR}$ are the OLS estimates of β_{CF}, β_{DR} respectively. Now I present the fractions of unexpected return variance explained by direct cash flow news, discount rate news and noise by $\frac{\tilde{y}'\tilde{y}}{y'y}$, $\frac{\tilde{\nu}'\tilde{\nu}}{y'y}$ and $\frac{\epsilon'\epsilon}{y'y}$ respectively in Table 4.11. Note that the fraction for direct cash flow news will be an upper bound since this is the first variable in line used for this decomposition. Due to the sequential regression procedure, covariance term are zero. As expected, in the 1MT case, the vast majority of return variance is discount rate news since also unexpected changes in the risk-free term structure are included. In this case I obtain a fraction due to misspecification noise as low as 20%. When going to the MMT case, I can explain at most 35% of the unexpected return variance by direct cash flow news, more or less in line with the results in Collin-Dufresne et al. (2001). For intermediate term bonds discount rate news also explains a sizeable fraction, but for long term bonds hardly, possibly due to the state variables in the VAR that are now not persistent enough. Explanatory power for bonds with a lower rating is substantially better than for those with a Aaa rating. For the MMA case, the cash flow part is relatively unchanged, but the discount rate part is very low. In this case, the noise part is clearly dominant for all indices. Notice that the fraction for discount rate news is downward biased when the pricing kernel is a function of (a factor driving) credit risk.

4.7 Conclusion

In this chapter, I present the theoretical derivation and performance results of a return decomposition for corporate bonds extending Campbell and Vuolteenaho (2004). On the theoretical side, using an appropriate structure for a boundary condition, I extend the results in Campbell and Shiller (1988) such that they completely carry over to the corporate bond market. Extending this result, I show that cash flow news in the corporate bond market is equivalent to unexpected changes in (discounted) expected loss rates. By taking corporate bonds, I can exploit several properties of those assets, among others, the simple pre-defined cash flow structure, the limited maturity and higher predictive R^2. I show that the decomposition performs rather well in general. The decomposition is however very sensitive to the inclusion of excessively persistent variables. Issues of this nature lead to counter intuitive results and can be identified from covariances between indirect cash flow news and discount rate news. The use of short maturity assets or less persistent state variables, if available, can be used as a remedy. Possible extensions include jointly modeling cash flow and discount rate news in a structural

firm value model, cross-section asset pricing tests to verify the Campbell and Vuolteenaho (2004) results as well as investigating the impact of cash flow and discount rate news in the 2007-2009 financial crisis. In view of the theoretical results, the use of techniques and insights from the literature on present value models in stock markets can now directly be applied to corporate bond markets to study for example persistence of expected returns and default rates.

4.8 Tables

Table 4.1: Summary statistics of VAR inputs

The table presents the mean, median, maximum, minimum, standard deviation, skewness and kurtosis of the state variables used in the base case return and default rate VAR. *Stockret* measures the quarterly excess return on the value weighted CRSP index in percentage points, $BaaI1MT, BaaIMMT$ and $BaaIMMA$ measure the quarterly holding return on the Lehman Brothers Baa Intermediate US corporate bond index in excess of the 1 month treasury rate, the holding return on the Lehman Brothers US intermediary treasury index and the holding return on the Lehman Brothers US intermediary Aaa index, respectively in percentage points. $P/E10$ measures the value of the inflation adjusted S&P index divided by the averaged inflation adjusted earnings of its constituents over the past 10 years; this figure is divided by 10 for improved readability. $TSSLOPE$ measures the slope of the term structure as the the yield-to-maturity on a 10 year minus that on a the 3 month treasury in percentage points, $VALSPR$ measures the small stock value spread as computed by Campbell and Vuolteenaho (2004), $SHRATE$ measures the yield-to-maturity on a 3 month treasury and CS measures the credit spread as the yield-to-maturity on the Lehman Brothers Baa Intermediate US corporate bond index minus that on the Lehman Brothers US intermediary treasury index in percentage points. $DEFRATE$ measures the quarterly market-wide default rate defined as number of Moody's rated issuers defaulting that quarter divided by the total number of Moody's rated issuers that quarter. Observations are on a quarterly frequency and run from the end of quarter 1 1973 to the end of quarter 2 2007.

Variable	Mean	Median	Max.	Min.	Std. Dev.	Skew.	Kurt.
Stockret	1.48	2.63	21.60	-28.95	8.69	-0.60	3.84
$BaaI1MT$	0.70	0.64	14.52	-10.40	3.12	0.18	6.71
$BaaIMMT$	0.29	0.21	5.26	-8.72	1.56	-0.94	11.29
$BaaIMTA$	0.19	0.20	4.33	-4.47	1.04	-0.28	7.51
$P/E10$	1.92	1.77	4.42	0.67	0.96	0.77	2.80
$TSSLOPE$	1.57	1.74	4.42	-2.65	1.38	-0.52	2.86
$VALSPR$	1.56	1.53	2.60	1.20	0.24	1.78	7.96
$SHRATE$	6.04	5.55	15.49	0.90	2.97	0.86	4.21
CS	1.84	1.72	4.46	0.77	0.77	1.11	4.18
$DEFRATE$	0.27	0.17	1.14	0.00	0.28	1.22	3.56

Table 4.2: VAR results on data from Jan 1973 to June 2007

The table shows the coefficients of the restricted first order VAR containing stock market excess returns, 10 year smoothed P/E ratio, slope of the term structure, value spread, 3 months treasury rate and Baa Intermediate term credit spread and Baa intermediate term corporate bond returns in excess of either the 1 month treasury rate, a duration matched treasury index or a duration matched Aaa index. Variable definitions can be found in Table 4.1. Coefficients on lagged stock or corporate bond returns are restricted to be zero. Stocks are restricted to have a zero coefficient on credit spreads and the short rate. Corporate bond returns are restricted to have a zero coefficient on the value spread and the short rate, except for when the benchmark is the 1 month treasury rate. Observations are on a quarterly frequency and run from first quarter 1973 up to second quarter 2007. t-statistics are in square brackets.

End. Var	$Stockret_t$	$BaaI1MT_t$	$P/E10_t$	$TSSLOPE_t$	$VALSPR_t$	$SHRATE_t$	CS_t	$BaaIMMT_t$	$BaaiMMA_t$
$PE10_{t-1}$	-0.057	0.666	0.986	-0.023	0.122	-0.260	0.085	-0.096	-0.185
	[-0.06]	[1.72]	[43.1]	[-0.18]	[4.82]	[-1.48]	[1.45]	[-0.73]	[-2.0]
$TSSLOPE_{t-1}$	0.929	0.909	0.009	0.752	0.029	0.052	-0.017	0.238	0.124
	[1.70]	[3.72]	[0.63]	[10.3]	[1.94]	[0.50]	[-0.48]	[2.52]	[1.92]
$VALSPREAD_{t-1}$	-4.778	0.000	-0.069	0.713	0.474	-0.286	0.081	0.000	0.000
	[-1.42]	.	[-1.07]	[2.04]	[6.62]	[-0.58]	[0.49]	.	.
$SHRATE_{t-1}$	0.000	0.362	-0.004	0.032	0.034	0.859	0.043	0.000	0.000
	.	[2.57]	[-0.55]	[0.77]	[3.89]	[14.4]	[2.17]	.	.
CS_{t-1}	0.000	0.994	-0.017	0.257	0.051	-0.374	0.893	0.556	0.262
	.	[2.85]	[-0.90]	[2.45]	[2.37]	[-2.52]	[18.0]	[3.25]	[2.24]
Const.	7.668	-6.019	0.187	-1.349	0.241	2.392	-0.325	-0.942	-0.135
	[1.55]	[-3.08]	[1.61]	[-2.15]	[1.86]	[2.69]	[-1.09]	[-2.12]	[-0.44]
R^2	0.034	0.167	0.975	0.650	0.493	0.849	0.745	0.166	0.128
Adj. R^2	0.012	0.142	0.975	0.637	0.474	0.843	0.735	0.147	0.109

Table 4.3: Variance decomposition of unexpected returns
This table presents variance decompositions of unexpected return variance into cash flow and discount rate news variance and their covariance. Figures are given as a proportion of total variance of unexpected excess returns. Results for stocks are presented in Panel A. Corporate bond returns are in excess of either the 1 month treasury rate (Panel B), returns on a maturity matched treasury index (Panel C) or returns on a maturity matched Aaa index (Panel D). Corporate bond indices have either an intermediate or long maturity. Ratings run from Aaa to Baa. The Corp index is a general US IG corporate bond index. Cov refers to the covariance between (N^{CF} and $-N^{DR}$).

Panel A: Stocks			
	Var(N^{CF})	Var(N^{DR})	2Cov
Stocks	0.46	0.21	0.34

Panel B: Benchmark is 3 month treasury						
	Intermediate maturity			Long maturity		
	Var(N^{CF})	Var(N^{DR})	2Cov	Var(N^{CF})	Var(N^{DR})	2Cov
Aaa	0.39	0.85	-0.24	0.36	0.89	-0.24
Aa	0.34	0.76	-0.10	0.36	0.86	-0.22
A	0.30	0.80	-0.10	0.30	0.83	-0.13
Baa	0.28	0.96	-0.24	0.27	1.00	-0.27
Corp	0.24	0.92	-0.16	0.37	0.88	-0.25

Panel C: Benchmark is matched maturity treasury index						
	Intermediate maturity			Long maturity		
	Var(N^{CF})	Var(N^{DR})	2Cov	Var(N^{CF})	Var(N^{DR})	2Cov
Aaa	1.26	0.60	-0.85	0.62	0.57	-0.19
Aa	0.91	0.53	-0.44	0.82	0.45	-0.27
A	0.52	0.56	-0.08	0.69	0.59	-0.29
Baa	0.23	0.73	0.04	0.69	0.73	-0.42
Corp	0.41	0.53	0.05	0.66	0.50	-0.16

Panel D: Benchmark is matched maturity Aaa index						
	Intermediate maturity			Long maturity		
	Var(N^{CF})	Var(N^{DR})	2Cov	Var(N^{CF})	Var(N^{DR})	2Cov
Aa	0.99	0.20	-0.20	1.03	0.20	-0.23
A	0.72	0.26	0.02	0.94	0.30	-0.24
Baa	0.56	0.68	-0.23	0.79	0.63	-0.43
Corp	0.89	0.78	-0.67	0.81	0.21	-0.02

Table 4.4: Correlation matrices of unexpected returns

This table presents correlations between stock and Baa rated corporate bond index returns and their cash flow and discount rate components. Correlations between unexpected returns on stocks and corporate bonds are presented in Panel A. Corporate bond returns are in excess of either the 1 month treasury rate (Panel B), returns on a duration matched treasury index (Panel C) or returns on a duration matched Aaa index (Panel D). Corporate bond indices have either an intermediate or long maturity.

Panel A: Correlations of unexpected stock and bond returns

	Intermediate maturity			Long maturity		
	$Baa1MT$	$BaaMMT$	$BaaMMA$	$Baa1MT$	$BaaMMT$	$BaaMMA$
$Stockret$	0.36	0.54	0.40	0.43	0.39	0.40

Panel B: Benchmark is 1 month treasury rate

	Intermediate maturity				Long maturity			
	$N^{S,CF}$	$N^{CB,CF}$	$-N^{S,DR}$	$-N^{CB,DR}$	$N^{S,CF}$	$N^{CB,CF}$	$-N^{S,DR}$	$-N^{CB,DR}$
$Stockret$	0.92	0.29	0.82	0.22	0.93	0.33	0.81	0.26
$Baa1MT$	0.35	0.30	0.28	0.86	0.38	0.26	0.38	0.87
$N^{S,CF}$	1.00	0.31	0.54	0.19	1.00	0.34	0.54	0.20
$N^{CB,CF}$	0.31	1.00	0.17	-0.23	0.34	1.00	0.22	-0.26
$-N^{S,DR}$	0.54	0.17	1.00	0.19	0.54	0.22	1.00	0.27
$-N^{CB,DR}$	0.19	-0.23	0.19	1.00	0.20	-0.26	0.27	1.00

Panel C: Benchmark is matched maturity treasury index

	Intermediate maturity				Long maturity			
	$N^{S,CF}$	$N^{CB,CF}$	$-N^{S,DR}$	$-N^{CB,DR}$	$N^{S,CF}$	$N^{CB,CF}$	$-N^{S,DR}$	$-N^{CB,DR}$
$Stockret$	0.92	0.21	0.82	0.51	0.93	-0.15	0.81	0.60
$BaaMMT$	0.40	0.52	0.58	0.88	0.25	0.58	0.48	0.61
$N^{S,CF}$	1.00	0.22	0.54	0.34	1.00	-0.19	0.54	0.49
$N^{CB,CF}$	0.22	1.00	0.13	0.04	-0.19	1.00	-0.03	-0.30
$-N^{S,DR}$	0.54	0.13	1.00	0.61	0.54	-0.03	1.00	0.59
$-N^{CB,DR}$	0.34	0.04	0.61	1.00	0.49	-0.30	0.59	1.00

Panel D: Benchmark is matched maturity Aaa index

	Intermediate maturity				Long maturity			
	$N^{S,CF}$	$N^{CB,CF}$	$-N^{S,DR}$	$-N^{CB,DR}$	$N^{S,CF}$	$N^{CB,CF}$	$-N^{S,DR}$	$-N^{CB,DR}$
$Stockret$	0.92	-0.26	0.82	0.72	0.93	-0.19	0.81	0.68
$BaaMMA$	0.24	0.59	0.52	0.68	0.25	0.65	0.44	0.53
$N^{S,CF}$	1.00	-0.26	0.54	0.53	1.00	-0.21	0.54	0.54
$N^{CB,CF}$	-0.26	1.00	-0.17	-0.19	-0.21	1.00	-0.11	-0.30
$-N^{S,DR}$	0.54	-0.17	1.00	0.79	0.54	-0.11	1.00	0.68
$-N^{CB,DR}$	0.53	-0.19	0.79	1.00	0.54	-0.30	0.68	1.00

Table 4.5: Correlations between long and short maturity portfolios
This table presents correlations of cash flow and discount rate news between intermediate and long maturity corporate bond portfolios of the same rating. Corporate bond returns are in excess of either the 1 month treasury rate (1MT), returns on a duration matched treasury index (MMT) or returns on a duration matched Aaa index (MMA). Ratings run from Aaa to Baa. The Corp index is a general US IG corporate bond index.

	Benchmark is 1MT		Benchmark is MMT		Benchmark is MMA	
Rating	N^{DR}	N^{CF}	N^{DR}	N^{CF}	N^{DR}	N^{CF}
Aaa	0.91	0.75	-0.03	-0.23		
Aa	0.93	0.78	0.11	-0.28	0.32	0.07
A	0.93	0.75	0.38	-0.30	0.73	0.42
Baa	0.94	0.69	0.71	0.21	0.84	0.72
Corp	0.94	0.72	0.50	-0.12	0.82	0.48

Table 4.6: Direct cash flow news VAR on data from Jan 1973 to June 2007
The table shows the coefficients of the unrestricted first order VAR containing quarterly default rates, 10 year smoothed P/E ratio, slope of the term structure and 3 months treasury rate. Variable definitions can be found in Table 4.1. Observations are on a quarterly frequency and run from first quarter 1973 up to second quarter 2007. t-statistics are in square brackets.

End. Var.	$DEFRATE_t$	$P/E10_t$	$TSSLOPE_t$	$SHRATE_t$
$DEFRATE_{t-1}$	0.272	0.668	-0.560	1.003
	[3.39]	[1.18]	[-1.77]	[2.31]
$P/E10_{t-1}$	-0.002	0.983	-0.001	-0.017
	[-0.61]	[48.9]	[-0.05]	[-1.12]
$TSSLOPE_{t-1}$	0.071	-0.030	0.866	-0.084
	[3.61]	[-0.21]	[11.2]	[-0.79]
$SHRATE_{t-1}$	0.041	-0.083	0.062	0.829
	[3.62]	[-1.05]	[1.41]	[13.7]
Const.	-0.122	0.763	0.001	1.214
	[-0.92]	[0.82]	[0.00]	[1.70]
R^2	0.407	0.975	0.620	0.846
Adj. R^2	0.389	0.974	0.609	0.841

Table 4.7: Correlations of return components with direct cash flow news
The table shows correlations between direct cash flow news and corporate bond and stock excess returns, indirect cash flow news and discount rate news. Corporate bond returns are in excess of either the 1 month treasury rate (Panel A), returns on a maturity matched treasury index (Panel B) or returns on a maturity matched Aaa index (Panel C). Results for stocks are presented in Panel D. Corporate bond indices have either an intermediate (I) or long (L) maturity. Ratings run from Aaa to Baa. The Corp index is a general US IG corporate bond index.

Panel A: Benchmark is 1 month treasury rate						
	Ret		N^{CF}		$-N^{DR}$	
	I	L	I	L	I	L
Aaa	0.01	0.04	0.44	0.51	-0.25	-0.22
Aa	0.02	0.05	0.49	0.55	-0.24	-0.23
A	0.07	0.11	0.48	0.51	-0.15	-0.12
Baa	0.17	0.22	0.41	0.40	0.01	0.07
Corp	0.08	0.12	0.39	0.55	-0.06	-0.16

Panel B: Benchmark is matched maturity treasury index						
	Ret		N^{CF}		$-N^{DR}$	
	I	L	I	L	I	L
Aaa	0.30	0.45	0.26	0.25	0.00	0.37
Aa	0.34	0.43	0.39	0.31	-0.01	0.30
A	0.43	0.51	0.42	0.16	0.21	0.53
Baa	0.50	0.56	0.33	0.11	0.44	0.58
Corp	0.45	0.54	0.43	0.31	0.28	0.46

Panel C: Benchmark is matched maturity Aaa index						
	Ret		N^{CF}		$-N^{DR}$	
	I	L	I	L	I	L
Aa	0.16	0.12	0.05	0.21	0.24	-0.13
A	0.37	0.37	0.09	-0.03	0.60	0.73
Baa	0.49	0.50	-0.01	0.03	0.65	0.63
Corp	0.46	0.48	-0.18	0.23	0.73	0.63

Panel D: Stocks			
	Ret	N^{CF}	$-N^{DR}$
Stock	-0.69	-0.55	0.71

Table 4.8: Persistence corrected variance decomposition of unexpected returns
This table is analogous to table 4.3 except for the fact that in the VAR, the coefficient for corporate bond excess returns on the lagged 3 month treasury is now unrestricted and the coefficient of corporate bond excess returns on the 10 year smoothed P/E ratio is now restricted to zero. Results are presented for corporate bond returns in excess of the returns on a matched treasury index (Panel A) or a Aaa index (Panel B).

Panel A: Benchmark is matched maturity treasury index						
	Intermediate maturity			Long maturity		
	Var(N^{CF})	Var(N^{DR})	2Cov	Var(N^{CF})	Var(N^{DR})	2Cov
Aaa	0.89	0.55	-0.44	0.99	0.31	-0.30
Aa	0.76	0.50	-0.26	1.13	0.30	-0.43
A	0.47	0.57	-0.03	0.84	0.25	-0.08
Baa	0.27	0.69	0.03	0.55	0.43	0.02
Corp	0.39	0.54	0.06	0.88	0.21	-0.09

Panel B: Benchmark is matched maturity Aaa index						
	Intermediate maturity			Long maturity		
	Var(N^{CF})	Var(N^{DR})	2Cov	Var(N^{CF})	Var(N^{DR})	2Cov
Aa	0.98	0.21	-0.19	1.03	0.19	-0.22
A	0.79	0.18	0.03	0.99	0.05	-0.04
Baa	0.69	0.46	-0.15	0.70	0.33	-0.04
Corp	0.85	0.24	-0.09	1.01	0.04	-0.05

Table 4.9: Persistence corrected correlations between long and short maturity portfolios
This table is analogous to table 4.5 except for the fact that in the VAR, the coefficient for corporate bond excess returns on the lagged 3 month treasury is now unrestricted and that the coefficient of corporate bond excess returns on the 10 year smoothed P/E ratio is now restricted to zero. Results are presented for corporate bond returns in excess of the returns on a matched treasury index (MMT) or a Aaa index (MMA).

	Benchmark is MMT		Benchmark is MMA	
Rating	N^{DR}	N^{CF}	N^{DR}	N^{CF}
Aaa	0.12	0.12		
Aa	0.19	0.10	0.32	0.11
A	0.40	0.15	0.65	0.50
Baa	0.68	0.49	0.79	0.77
Corp	0.52	0.37	0.64	0.65

Table 4.10: Persistence corrected correlations of return components with direct cash flow news
This table is analogous to table 4.5 except for the fact that in the VAR, the coefficient for corporate bond excess returns on the lagged 3 month treasury is now unrestricted and that the coefficient of corporate bond excess returns on the 10 year smoothed P/E ratio is now restricted to zero. Results are presented for corporate bond returns in excess of the returns on a maturity matched treasury index (Panel A) or a Aaa index (Panel B).

Panel A: Benchmark is MMT				
	N^{CF}		$-N^{DR}$	
	I	L	I	L
Aaa	0.22	0.64	0.13	-0.29
Aa	0.28	0.67	0.16	-0.45
A	0.40	0.66	0.25	-0.14
Baa	0.49	0.53	0.35	0.28
Corp	0.55	0.61	0.20	-0.03

Panel B: Benchmark is MMA				
	N^{CF}		$-N^{DR}$	
	I	L	I	L
Aa	0.02	0.29	0.31	-0.33
A	0.29	0.32	0.29	0.29
Baa	0.33	0.37	0.38	0.37
Corp	0.34	0.48	0.34	0.01

Table 4.11: Orthogonalized variance decompositions of unexpected returns allowing for misspecification
The table shows an orthogonalized variance decompositions of unexpected corporate bond excess returns, with respect to direct cash flow news, discount rate news and misspecification noise. Returns are orthogonalized first with respect to direct cash flow news. Corporate bond returns are in excess of either the 1 month treasury rate (Panel A), returns on a maturity matched treasury index (Panel B) or returns on a maturity matched Aaa index (Panel C). Corporate bond indices have either an intermediate or long maturity. Ratings run from Aaa to Baa. The Corp index is a general US IG corporate bond index. The 3 month treasury rate has been used in the VAR instead of the 10 year smoothed P/E ratio.

Panel A: Benchmark is 1 month treasury rate

	Intermediate maturity			Long Maturity		
Rating	Var(N^{CF})	Var(N^{DR})	Var(noise)	Var(N^{CF})	Var(N^{DR})	Var(noise)
Aaa	0.003	0.648	0.349	0.009	0.696	0.294
Aa	0.006	0.690	0.304	0.013	0.696	0.291
A	0.015	0.736	0.249	0.028	0.743	0.229
Baa	0.052	0.731	0.217	0.077	0.718	0.205
Corp	0.017	0.782	0.200	0.033	0.695	0.272

Panel B: Benchmark is matched maturity treasury index

	Intermediate maturity			Long Maturity		
Rating	Var(N^{CF})	Var(N^{DR})	Var(noise)	Var(N^{CF})	Var(N^{DR})	Var(noise)
Aaa	0.082	0.049	0.870	0.230	0.200	0.570
Aa	0.129	0.186	0.685	0.233	0.103	0.663
A	0.211	0.358	0.431	0.297	0.088	0.615
Baa	0.290	0.407	0.303	0.345	0.071	0.584
Corp	0.233	0.400	0.367	0.328	0.108	0.564

Panel C: Benchmark is matched maturity Aaa index

	Intermediate maturity			Long Maturity		
Rating	Var(N^{CF})	Var(N^{DR})	Var(noise)	Var(N^{CF})	Var(N^{DR})	Var(noise)
Aa	0.025	0.037	0.938	0.024	0.044	0.932
A	0.144	0.090	0.766	0.141	0.003	0.855
Baa	0.272	0.119	0.609	0.276	0.039	0.685
Corp	0.228	0.024	0.747	0.242	0.015	0.742

4.9 Appendix

4.9.1 Derivation of continuous compounded par coupon duration

Suppose I have a bond that pays a continuous coupon c. Its duration at time 0 is defined as

$$D = (\int_0^T ct \exp(-yt)dt + 100T \exp(-yT))/P_0 \tag{4.32}$$

where y is the yield-to-maturity, T is the maturity of the bond, D is its duration and P is its price. One can solve the integral in this expression by integrating by parts:

$$F'(t) = -c/y(-yt \exp(-yt) - \exp(-yt) + \exp(-yt)) \tag{4.33}$$

$$F(t) = -c/y(-t \exp(-yt) - 1/y \exp(-yt)) \tag{4.34}$$

which gives me

$$\int_0^T ct \exp(-yt)dt = F(t)|_0^T \tag{4.35}$$

$$= -c/y(-T \exp(-yT) - 1/y \exp(-yT) + 1/y). \tag{4.36}$$

Thus, I have derived a analytic formula for the duration when coupons are paid continuously. However, this analytic formula is typically not invertible with respect to T because it involves a product of T and an exponent of T (although it is possible to find T numerically when D is known). However, in the special case that the bond is priced at par, $c = 100y$ and the two terms involving the product of T and an exponent of T cancel and I am left with:

$$D = 1/y(1 - exp(-yT)) \tag{4.37}$$

which is invertible as long as $Dy < 1$:

$$T = -1/y \log(1 - Dy) \tag{4.38}$$

Chapter 5

Conclusion

This thesis studied several phenomena and trends in credit markets during the build up and during the onset of the financial crisis of 2007-2009. While the different chapters study different trends, two conclusion are common to all chapters. The first one is that the pricing of credit risky securities depends on much more than just the exposure to credit risk. Aspects like for example liquidity and regulation drive a wedge between the theoretical price if the only risk were credit risk and the realized price. Time variation in these non credit risk related factors can also lead to extra return volatility on credit risky instruments. If regulators are unaware of these effects when designing financial regulation, they may find themselves facing unexpected adverse effects in turbulent times of the regulation that was designed during quiet times. This immediately links to the second common conclusion, which is that financial regulation, while intended to compensate the effect of externalities, is likely to lead to other frictions that in turn lead again to other externalities.

The next section will give a short summary of the main findings of the three chapters followed by implications and associated suggestions for further research.

5.1 Summary of the main findings

Chapter 2 investigates the pricing mechanism of liquidity on asset prices when there is a substantial degree of short selling in a market. This research is most relevant for derivatives markets, since derivatives are typically in zero net supply and therefore the number of short positions should be equal to the number of long positions. The theoretical results however also apply to positive net supply markets with substantial amounts of short selling. One of the main theoretical

results is that a lower risk aversion, higher wealth or shorter horizon leads to a steeper demand or supply curve, making the side with less risk aversion, more wealth or a shorter horizon more sensitive to the liquidity costs. Empirically the most important result is that for CDSs there is a strong and significant positive effect of expected liquidity costs on expected returns, suggesting that protection sellers have lower risk aversion, more wealth or a shorter trading horizon than protection buyers.

Chapter 3 aims to explain why different corporate bond issuers apply for credit ratings from different credit rating agencies. Of the three suggested explanations, information production, rating shopping and certification, only evidence is found in favor of certification. Another important result is that this observation is consistent with a setting in which a regulatory boundary coincides with a boundary that separates information sensitive and insensitive assets in equilibrium. Additional results support the validity of this setting.

Chapter 4 investigates the composition of unexpected corporate bond returns in terms of cash flow and discount rate news. On the theoretical side, there are two key results. The first one is that cash flow news for corporate bonds is equivalent to news about expected loss rates. The other theoretical result is that a finite version of the results in Campbell and Shiller (1988) holds for corporate bonds without having to resort to a boundary condition. On the empirical side, the chapter shows that a substantial part of the unexpected corporate bond return is due to discount rate news. Moreover, the return decomposition gives reasonable results, but shows problematic behavior when the exposure of returns to a persistent factor in the VAR is large. When exposure to the persistent factor is moderate, the use of short term bonds limits the disruptive effect of the persistent variable.

5.2 Implications of the findings

The findings in Chapter 2 are important in several aspects. First, the theoretical results imply that in positive net supply markets with substantial short-selling, illiquid securities can have a lower expected return than liquid securities, which goes against the traditional paradigm. The empirical results suggest that it may be worthwhile for corporations with substantial exposure to bank loans or with a substantial volume of illiquid bonds outstanding to facilitate a liquid CDS market. When investors are likely to hedge a loan they provide with a CDS, the credit spread they will charge on the loan will be linked to the CDS spread. Since the CDS spread for liquid CDSs is lower than that for illiquid CDSs, the underlying

issuer has a direct benefit from a liquid CDS market. This could also provide extra support for the initiative to institutionalize the CDS market and bring all the trading to an exchange.

On first sight, the findings in Chapter 3 would suggest that a discrete regulatory boundary leads to perverse incentives and should be abolished to be replaced with regulation that leads to a more gradual decrease in demand as credit quality worsens. However, in view of the results at the end of the chapter relating to information sensitive and insensitive securities, such a regulatory design could resolve a non-trading region. What a regulator could do to limit shopping around the boundary is to make introduce a 'vesting period' for a new rating. That is, with respect to regulation, a newly added rating only takes effect after a a certain vesting period. This reduces the possibility for an issuer to game the regulation substantially, while the aspirant rating can still be available to investors as a signal of research opportunities during this vesting period.

Chapter 4 shows that discount rate news is a very substantial part of unexpected corporate bond returns. Especially from a regulatory standpoint it is important to understand what the effect could be of large unexpected movements in discount rates, in particular when it is to be expected that these movements are only temporary. One of the considerations is when and for which assets capital should be held as a buffer for discount rate shocks. Taking discount rate risk into account makes sense for assets that are also used to cover liquidity risk and only for the scenarios in which no cheaper sources of freeing up liquidity are available. For assets with a buy-and-hold motive, typically only fundamentals matter, since the terminal value is what is ultimately realized. The only reason to model discount rate news for buy-and-hold securities is earnings risk management when these securities have a long maturity and are short-term funded. In that case, adverse changes in discount rates that are also common to short term funding costs can lead to a negative shock in profitability. This discussion also shows from a theoretical perspective why, when and to which extent shocks to discount rates should eat into available (Tier 1 and/or 2) capital. Only for assets that are required to free up liquidity and for earnings risk management part should shocks to discount rates affect available capital since those are the only shocks relevant to the solvency of a bank. Otherwise, volatility in capital ratios will cause unnecessary panic, dead weight losses due to fire sales required to de-lever and unnecessary dilution of equity capital.

5.3 Suggestions for future research

This dissertation has brought forward new insights to the credit markets in the turbulent times in which it was written. Moreover, it brings up new questions and highlights areas in which more research is required.

One of the major new challenges for future research is to connect the results in Chapter 2 with the research in the field of market microstructure. In the model, variations in liquidity, both cross-sectionally and over time are exogenous. Understanding how demand and supply for liquidity are formed and which players are the liquidity providers and which the liquidity consumers in an OTC market like the CDS market is the next logical step in this strand of literature.

Regarding credit ratings, a next logical step for further research would be to test the setting with information-sensitive and insensitive investors more formally. To this end, holding and trading information of both types of investors would be crucial. Incorporating the strategic behavior of CRAs more explicitly could also create more understanding on this issue.

The theoretical side result in Chapter 4 immediately gives directions for further research on present value models in credit markets. Applying one of the estimation techniques for present value models in equity markets to the credit market can allow to extract information optimally from current and past returns, prices and default loss rates in a fairly general setting with only weak assumptions. Moreover, one could, using the discussion in the previous section, derive for a bank the real and optimal funding cost for different assets.

Chapter 6

Samenvatting (Summary in Dutch)

Dit hoofdstuk bevat Nederlandstalige samenvattingen van de hoofdstukken 2 t/m 4 van dit proefschrift.

Hoofdstuk 2 behandelt het effect van liquiditeit op de prijs van assets met substantiële mate van short-selling en test deze theorie empirisch op de markt voor Credit Default Swaps (CDSs). In de theoretische sectie van het hoofdstuk wordt een prijzingsmodel afgeleid waarin investeerders in verschillende mate risico lopen op niet-verhandelbare bezittingen (denk in de context van de latere toepassing op de CDS markt bijvoorbeeld aan banken die niet-verhandelbare leningen op hun balans hebben staan). Om dit risico af te dekken nemen investeerders posities in standaard instrumenten (dit noem ik base assets, denk hierbij aan bijvoorbeeld aandelen) en voor het deel dat niet met base assets kan worden afgedekt worden posities genomen in zogenaamde hedge assets waarvoor investeerders bij het handelen transactiekosten betalen. Deze transactiekosten zijn tijdsvariërend en verschillen tussen de verschillende hedge assets. In het algemeen heeft iedereen de voorkeur voor zo klein mogelijke transactiekosten. Het effect van hogere transactiekosten op de prijs hangt echter af van hoe gevoelig beide kanten van de transactie zijn voor de hoogte van de transactiekosten. De vraag-, danwel aanbodscurve ten opzichte van de hoogte van de transactiekosten is steiler voor investeerders met veel vermogen, lagere risico-aversie en kortere beleggingshorizon. Daarnaast speelt in het effect van het risico door fluctuaties in transactiekosten over tijd ook de grootte van het niet-verhandelbare risico een rol. Empirisch is er in de CDS markt een sterk effect van verwachte transactiekosten op verwacht rendement, waarbij de partij die bescherming aanbiedt een hogere premie krijgt voor een CDS met lagere

liquiditeit. Dit is consistent met meer vermogen, lagere risico-aversie en/of een kortere horizon van aanbieders in vergelijking met kopers van kredietbescherming.

Hoofdstuk 3 probeert te verklaren waarom sommige bedrijfsobligaties door meer kredietbeoordelaars (credit rating agencies, CRAs) worden beoordeeld dan andere. Hiervoor worden eerst empirische implicaties voor drie theorieëen bekeken. De eerste theorie, informatie productie stelt dat bedrijven een extra CRA vragen omdat deze onzekerheid voor investeerders wegneemt, daardoor een obligatie aantrekkelijker maakt en leidt tot een betere prijs. De tweede, rating shopping, stelt dat bedrijven alleen een extra rating aanvragen als ze het idee hebben dat eerdere ratings te laag waren. De derde theorie stelt dat financiële regelgeving rond discrete grens in het ratingspectrum voor grote verschuivingen in vraag naar obligaties kan leiden en dat extra ratings gebruikt worden om in het gunstige gebied terecht te komen of om het risico om naar het ongunstige gebied af te glijden te minimaliseren. Verschillende empirische tests op zowel rating compositie als obligatie prijzen vinden alleen bewijs voor de regelgeving theorie. Deze theorie blijkt theoretisch en empirisch consistent te zijn met een raamwerk met informatiegevoelige en informatie-ongevoelige investeerders waarin een extra rating helpt om de markt in het middenstuk van het rating spectrum vlot te trekken.

Hoofdstuk 4 past een methode uit de literatuur over aandelenmarkten toe op de markt voor bedrijfsobligaties om onverwachte rendementen op te splitsen in schokken in verwachte kasstromen en schokken in verdisconteringsvoeten. De theoretische afleiding laat zien dat schokken in verwachte kasstromen gelijk zijn aan schokken in verwachte krediet verliezen. Een ander belangrijk, maar voor de rest van dit hoofdstuk minder relevant theoretisch resultaat is dat het log couponrendement van bedrijfsobligaties geschreven kan worden als een eindige som van toekomstige verwachte rendementen en kredietverliesratios. Een empirische test van deze methode op de bedrijfsobligatiemarkt laat zien dat schokken in verdisconteringsvoeten een belangrijke component zijn van onverwachte rendementen op bedrijfsobligaties. Verdere analyse van de resultaten laat zien dat deze methode overwegend goed werkt, maar wel gevoelig is voor erg persistente variabelen. Bij relatief zwakke invloed van deze persistente variabelen geeft het gebruik van obligaties met een korte looptijd een aanzienlijk beter resultaat omdat het effect van persistentie minder groot is.

Bibliography

Acharya, V. V. and Pedersen, L. H.: 2005, Asset pricing with liquidity risk, *Journal of Financial Economics* **77**, 375–410.

Acharya, V. V., Schaefer, S. M. and Zhang, Y.: 2008, Liquidity risk and correlation risk: A clinical study of the General Motors and Ford downgrade of 2005. Working Paper.

Amihud, Y.: 2002, Illiquidity and stock returns: Cross-section and time series effects, *Journal of Financial Markets* **5**, 31–56.

Amihud, Y. and Mendelson, H.: 1986, Asset pricing and the bid-ask spread, *Journal of Finance* **17**, 223–249.

Bailey, M. J., Muth, R. F. and Nourse, H. O.: 1963, A regression method for real estate price construction, *Journal of the American Statistical Association* **58**, 933–942.

Bannier, C., Behr, P. and Güttler, A.: 2009, Rating opaque borrowers: why are unsolicited ratings lower? Working Paper.

Bannier, C. and Tyrell, M.: 2006, Modeling the role of credit rating agencies- do they spark of virtuous circle? Working Paper.

Basel Committee on Banking Supervision: 2000, Credit ratings and complementary sources of credit quality information. Basel Committee on Banking Supervision Working Papers No. 3.

Becker, B. and Milbourn, T.: 2008, Reputation and competition: evidence from the credit rating industry. Working Paper.

Bekaert, G., Harvey, C. R. and Lundblad, C. T.: 2007, Liquidity and expected returns: Lessons from emerging markets, *Review of Financial Studies* **20**(5), 1783–1831.

Berndt, A., Lookman, A. and Obreja, I.: 2007, Default risk premia and asset returns. Working paper.

Blanco, R., Brennan, S. and Marsh, I. W.: 2005, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *Journal of Finance* **60**(5), 2255–2281.

Bolton, P., Freixas, X. and Shapiro, J.: 2009, The credit ratings game. Working Paper.

Bongaerts, D., Cremers, K. and Goetzmann, W.: 2009, Tiebreaker: Certification and multiple credit ratings. Working Paper.

Bongaerts, D., De Jong, F. and Driessen, J.: 2010, Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance* **forthcoming**.

Boot, A., Milbourn, T. and Schmeits, A.: 2006, Credit ratings as coordination mechanisms, *Review of Financial Studies* **19**(1), 81–118.

Boot, A. and Thakor, A.: 1993, Security design, *Journal of Finance* **48**(4), 349–1378.

Brenner, M., Eldor, R. and Hauser, S.: 2001, The price of options illiquidity, *Journal of Finance* **56**(2), 789–805.

Brister, B., Kennedy, R. and Liu, P.: 1994, The regulation effect of credit ratings on bond interest yield: The case of junk bonds, *Journal of Business Finance and Accounting* **21**(4), 511 – 531.

Bühler, W. and Trapp, M.: 2009, Time-varying credit risk and liquidity premia in bond and CDS markets. Working Paper.

Campbell, J.: 1991, A variance decomposition for stock returns, *Economic Journal* **101**(405), 157–179.

Campbell, J. and Ammer, J.: 1993, What moves the stock and bond markets? a variance decomposition for long-term asset returns, *Journal of Finance* **48**(1), 3–37.

Campbell, J. and Mei, J.: 1993, Where do betas come from? asset price dynamics and the sources of systematic risk, *Review of Financial Studies* **6**(3), 567–592.

Campbell, J., Polk, C. and Vuolteenaho, T.: 2010, Growth or glamour?, *Review of Financial Studies* **23**(1), 305–344.

Campbell, J. and Shiller, R.: 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* **1**(3), 195–228.

Campbell, J. and Taksler, G.: 2003, Volatility and corporate bond yields, *Journal of Finance* **58**(6), 2321–2349.

Campbell, J. and Vuolteenaho, T.: 2004, Good beta, bad beta, *American Economic Review* **94**(5), 1249–1275.

Campbell, J. Y. and Viceira, L. M.: 2002, *Strategic Asset Allocation*, Clarendon Lectures in Economics, Oxford University Press.

Campello, M., Chen, L. and Zhang, L.: 2008, Expected returns, yield spreads, and asset pricing tests, *Review of Financial Studies* **21**(3), 1297–1338.

Cantor, R. and Packer, F.: 1997, Differences in opinion and selection bias in the credit rating industry, *Journal of Banking and Finance* **21**, 1395–1417.

Case, K. E. and Shiller, R. J.: 1987, Prices of single-family homes since 1970: New indexes for four cities, *New England Economic Review* pp. 45–56.

Çetin, U., Jarrow, R. A., Protter, P. E. and Warachka, M.: 2006, Pricing options in an extended Black-Scholes economy with illiquidity: Theory and empirical evidence, *Review of Financial Studies* **19**(2), 494–529.

Chen, L., Lesmond, D. and Wei, J.: 2007, Corporate yield spreads and bond liquidity, *Journal of Finance* **62**(1), 119–149.

Chen, L. and Zhao, X.: 2009, Return decomposition, *Review of Financial Studies* .

Chen, R.-R., Cheng, X. and Wu, L.: 2005, Dynamic interactions between interest rate, credit, and liquidity risks: Theory and evidence from the termstructure of credit default swap spreads. Working Paper.

Chordia, T., Roll, R. and Subrahmanyam, A.: 2000, Commonality in liquidity, *Journal of Financial Economics* **56**, 3–28.

Cochrane, J. H.: 2005, *Asset Pricing*, Princeton University Press.

Cochrane, J. H.: 2008, State-space vs. VAR models for stock returns. Working Paper.

Collin-Dufresne, P., Goldstein, R. and Martin, S.: 2001, The determinants of credit sperad changes, *Journal of Finance* **56**(6), 2177–2207.

Cornell, B. and Green, K.: 1991, The investment performance of low-grade bond funds, *Journal of Finance* **46**(1), 29–48.

Covitz, D. and Harrison, P.: 2003, Testing conflicts of interest at bond rating agencies with market anticipation: Evidence that reputation incentives dominate. Working Paper.

Das, S. R. and Hanouna, P.: 2009, Hedging credit: Equity liquidity matters, *Journal of Financial Intermediation* **18**(1), 112–123.

De Jong, F. and Driessen, J.: 2005, Liquidity risk premia in corporate bond markets. Working Paper.

De Jong, F. and Driessen, J.: 2007, Liquidity risk premia in corporate bond markets. Working Paper.

De Roon, F., Nijman, T. and Veld, C.: 2000, Hedging pressure effects in futures markets, *Journal of Finance* **55**(3), 1437–1456.

Deuskar, P., Gupta, A. and Subrahmanyam, M. G.: 2009, Liquidity effects in interest rate options markets: Premium or discount? Working Paper.

Doherty, N., Kartasheva, A. and Phillips, R.: 2009, Competition among ratings agencies and information disclosure. Wharton working paper.

Downing, C., Underwood, S. and Xing, Y.: 2005, Is liquidity risk priced in the corporate bond market? Working Paper.

Duffie, J. D., Gârleanu, N. B. and Pedersen, L. H.: 2005, Over-the-counter markets, *Econometrica* **73**(6), 1815–1847.

Duffie, J. D. and Singleton, K. J.: 2003, *Credit Risk: Pricing, Measurement and Management*, Princeton Series in Finance, Princeton University Press, Princeton.

Elton, E. J., Gruber, M. J., Agrawal, D. and Mann, C.: 2001, Explaining the rate spread on corporate bonds, *Journal of Finance* **56**, 247–277.

Fama, E. and French, K.: 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* **51**(1), 55–84.

Gârleanu, N. B. and Pedersen, L. H.: 2009, Margin-Based Asset Pricing and Deviations from the Law of One Price. Working paper.

Gârleanu, N. B., Pedersen, L. H. and Poteshman, A. M.: 2009, Demand-based option pricing, *Review of Financial Studies* **22**, 4259–4299.

Gorton, G. and Pennacchi, G.: 1990, Financial intermediaries and liquidity creation, *Journal of Finance* **45**(1), 49–72.

Guntay, L. and Hackbarth, D.: 2006, Corporate bond credit spreads and forecast dispersion. Working Paper.

Jewell, J. and Livingston, M.: 1999, A comparison of bond ratings from Moody's, S&P and Fitch, *Financial Markets, Institutions and Instruments* **8**, 1–45.

Karagozoglu, A. K., Martell, T. F. and Wang, G. H. K.: 2003, The split of the S&P 500 futures contract: Effects on liquidity and market dynamics, *Review of Quantitative Finance and Accounting* **21**(4), 323–348.

Kisgen, D. and Strahan, P.: 2009, Do regulations based on credit ratings affect a firm's cost of capital? Working Paper.

Kliger, D. and Sarig, O.: 2000, The information value of bond ratings, *Journal of Finance* **55**(6), 2879–2902.

Korajczyk, R. A. and Sadka, R.: 2008, Pricing the commonality across alternative measures of liquidity, *Journal of Financial Economics* **87**, 45–72.

Kwan, S. H.: 1996, Firm-specific information and the correlation between individual stocks and bonds, *Journal of Financial Economics* **40**(1), 63–80.

Lando, D. and Feldhütter, P.: 2008, Decomposing swap spreads, *Journal of Financial Economics* **88**, 375–405.

Lando, D. and Stenbo Nielsen, M.: 2008, Correlation in corporate defaults: Contagion or conditional independence? Working Paper.

Lettau, M. and Van Nieuwerburgh, S.: 2008, Reconciling the return predictability evidence, *Review of Financial Studies* **21**(4), 1607–1652.

Longstaff, F. A., Mithal, S. and Neis, E.: 2005, Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *Journal of Finance* **60**(5), 2213.

Longstaff, F. A., Pan, J., Singleton, K. J. and Pedersen, L. H.: 2009, How sovereign is sovereign credit risk? Working Paper.

Mengle, D.: 2007, Credit derivatives: An overview. Working Paper.

Merton, R.: 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* **29**(2), 449–470.

Morgan, D.: 2002, Rating banks: Risk and uncertainty in an opaque industry, *American Economic Review* **92**(4), 874–888.

Nashikkar, A. J. and Subrahmanyam, M. G.: 2006, The determinants of liquidity in the corporate bond markets: An application of latent liquidity. Working Paper.

Nashikkar, A. J., Subrahmanyam, M. G. and Mahanti, S.: 2009, Limited arbitrage and liquidity in the market for credit risk. Working Paper.

Nashikkar, A. and Pedersen, L. H.: 2007, Corporate bond specialness. Working Paper.

Partnoy, F.: 2001, The paradox of credit ratings. University of San Diego Working Paper Series.

Pastor, L. and Stambaugh, R. F.: 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* **111**(3), 642–685.

Pires, P., Pereira, J. a. and Martins, L.: 2008, The complete picture of credit default swap spreads - a quantile regression approach. Working Paper.

Poon, P. H.: 2003, Are unsolicited ratings downward biased, *Journal of Banking and Finance* **27**, 593–614.

Poon, W. P. H. and Firth, M.: 2005, Are unsolicited credit ratings lower? international evidence from bank ratings, *Journal of Business Finance and Accounting* **32**, 1741–1771.

Sangiorgi, F., Sokobin, J. and Spatt, C.: 2009, Credit-rating shopping, selection and the equilibrium structure of ratings. Working Paper.

Shanken, J.: 1992, On the estimation of beta-pricing models, *Review of Finacial Studies* **5**, 1–33.

Skreta, V. and Veldkamp, L.: 2009, Ratings shopping and asset complexity: A theory of ratings inflation, *Journal of Monetary Economics* **56**(5), 678–695.

Tang, D. and Yan, H.: 2007, Liquidity and credit default swap spreads. Working Paper.

Van Binsbergen, J. H., Brandt, M. J. and Koijen, R. S.: 2009, On the pricing and timing of cash flows. Working Paper.

Van Binsbergen, J. H. and Koijen, R. S.: Forthcoming, Predictive regressions: A present value approach, *Journal of Finance* .

Credit markets have shown a dramatic development at the start of the 21st century. Increased regulatory pressure on financial institutions has spurred the development of innovative products that allow for transfer of credit risk. These developments lay at the base of the largest financial crisis since the great depression. This dissertation contains three essays on the pricing of credit risky instruments relating to several trends in credit markets leading up to the crisis. The essays cover the pricing effect of liquidity on the pricing of Credit Default Swaps, the regulatory price impact of credit ratings on corporate bonds and the decomposition of unexpected corporate bond returns into cash flow and discount rate news components. As such, this dissertation increases the understanding of credit markets leading up to and at the onset of the crisis. Moreover, it gives an in-depth discussion of the findings against the backdrop of current and future financial regulation.

Dion Bongaerts has obtained his masters degree in econometrics from Maastricht University in 2005. Thereafter he started his PhD in finance at University of Amsterdam while working as a portfolio risk modeler at ABN-AMRO enterprise risk management. He performed part of his research while attending the International Center for Finance at Yale School of Management as a visiting researcher. His work has been presented at several major conferences including the WFA and EFA annual meetings and published in several leading academic journals among which the Journal of Finance. As of November 2009, Dion is employed as an assistant professor of finance at RSM Erasmus University.