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École affiliée à l'Université de Montréal

Essays on the CDS-bond Basis

par

Sahar Guesmi

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Présentée par:

Sahar Guesmi

a été évaluée par un jury composé des personnes suivantes:

Jean-Guy Simonato

HEC Montréal

Président-rapporteur

Michèle Breton

HEC Montréal

Co-directrice de recherche

Georges Dionne

HEC Montréal

Co-directeur de recherche

Frédéric Godin

Université Concordia

Membre du jury

Van Son Lai

Université Laval

Examinateur externe

Résumé

Cette thèse traite de la différence entre les écarts de crédit des obligations corporatives et les primes des dérivés sur événements de crédit (CDS) associés, appelée communément la base CDS-obligation.

Le premier essai décrit les deux instruments, obligations et CDS, le fonctionnement de chacun des marchés où ils sont transigés et en souligne les similitudes et les différences. Cet essai présente également la méthodologie que nous utilisons dans cette thèse pour calculer la base CDS-obligation, c'est-à-dire la construction d'un CDS synthétique.

Le deuxième essai examine la persistance de la discordance entre le marché obligataire et celui des CDS. Cette discordance surprenante a été qualifiée d'énigme de la négativité de la base CDS-obligation par la communauté financière. Dans un premier temps, nous fournissons une démonstration empirique de la persistance de cette discordance. Nous montrons que les deux premiers moments de la base sont décrits par trois régimes distincts qui peuvent être identifiés à des périodes en rapport avec la crise financière de 2008. Nous observons que les régimes durant les périodes de crise et post crise sont significativement différents du régime durant la période d'avant la crise. Dans un deuxième temps, nous explorons la variation transversale de la base CDS-obligation. Notre modèle, qui fait intervenir plusieurs limites à l'arbitrage, permet de constater que la négativité de la base est expliquée par le risque de liquidité et de contrepartie ainsi que par les contraintes de financement affectant les instruments correspondants. Ce résultat indique qu'une partie

significative de la base constitue une compensation pour les risques et les coûts supportés par les arbitragistes qui transigent la base, alors que la partie restante constitue le profit d'arbitrage. Enfin, nous nous concentrons sur la persistance de la négativité de la base durant la période post crise. Nous montrons que cette anomalie est liée à une diminution considérable de l'activité d'arbitrage de la base, qui en constitue le mécanisme de correction et tend à la ramener vers une valeur nulle. Nous constatons que la détérioration de l'activité d'arbitrage de la base a suivi les réformes réglementaires associées à la période post crise.

Le troisième essai étudie l'impact des événements de modification de cotes de crédit sur les marchés sensibles au risque de crédit, à savoir le marché des CDS et celui des obligations. Nous montrons que les deux instruments réagissent de manière significative aux modifications des notations de crédit. Nous constatons cependant que les CDS et les obligations réagissent de façon différente à un même événement de crédit. Par conséquent, de tels événements ont un impact sur l'équilibre entre le marché des obligations et celui des CDS, tel que mesuré par la base. Nous montrons que l'ampleur du comportement anormal de la base CDS-obligation autour des événements de modification de cotes de crédit est principalement liée au type et à la période de l'événement ainsi qu'à l'illiquidité des obligations correspondantes. Finalement, nous montrons que la détérioration de la base à la suite d'un événement risqué est plus prononcée à l'ère des nouvelles réglementations.

Mots clés: base CDS-obligation, limites à l'arbitrage, post crise, négativité persistante, activité d'arbitrage de la base, modification de cote de crédit, réformes réglementaires.

Méthodes de recherche: économétrie, régression Fama-MacBeth, étude d'événement

Abstract

This thesis deals with the difference between the corporate bond spread and its related Credit Default Swap (CDS) premium, defined as the CDS-bond basis.

The first essay describes the function of bonds and CDS contracts and highlights the similarities and differences between their markets. This essay also presents the methodology used to compute the CDS-bond basis, which involves the construction of a synthetic CDS.

The second essay investigates the unexpected persistence of the dislocation between bond and CDS markets, which has been termed the CDS-bond basis negativity puzzle. We first provide empirical evidence of the existence of this puzzle. We show that the first two moments of the basis are described by three distinct regimes that can be identified with periods related to the 2008 financial crisis. We observe that the crisis and post-crisis regimes differ significantly from the pre-crisis regime. We then explore the cross-sectional variation of the CDS-bond basis. Using a model involving several limit-to-arbitrage factors, we find that the negative basis can be explained by liquidity risk, counterparty risk, and funding constraints affecting the corresponding instruments. This result indicates that a significant part of the basis constitutes a compensation for the risks and costs incurred by arbitrageurs involved in the basis trade, while the remaining part is an arbitrage profit. Finally, we focus on the basis negativity persistence during the post-crisis period. We show that this anomaly is related to a considerable decrease of the basis arbitrage activity, which is the correction mechanism responsible for bringing back the basis to zero. We

find that this deterioration in arbitrage activity was concurrent with the post-crisis regulatory reforms.

The third essay studies the impact of credit-rating events on credit-sensitive markets, that is, the CDS and cash-bond markets. We show that both instruments react significantly to changes in credit ratings. More importantly, we find that CDS and bonds react differently to a change in credit ratings. Consequently, such events have an adverse impact on the CDS and bond markets equilibrium, as measured by the basis. We show that the magnitude of the CDS-bond basis abnormal behavior around rating events is mainly related to the type and period of the event, as well as to the bond illiquidity. Finally, we show that the basis deterioration following a stress event is more pronounced during the regulation era.

Key words: CDS-bond basis, limits to arbitrage, post-crisis, negativity persistence, basis arbitrage activity, credit rating events, regulatory reforms

Research methods: econometrics, Fama-MacBeth regression, event study

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To my beloved mother Nabiha,

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Chapter 1

Introduction

A *basis* may appear in any market where the cash and derivative forms of the same asset are available. It is defined as the difference between the cash price of an instrument and the price of its related derivative. The term basis has multiple meanings in finance, depending on the involved instruments and markets. Traditionally, the basis is related to futures markets, where it refers to the difference between the spot price of a deliverable asset and the relative price of the shortest-duration futures contract written on the same asset. In that case, the concept of basis is crucial for the elaboration of trading and risk management strategies, since the relationship between cash and futures prices affects the value of the contracts used in hedging.

A concept closely related to the basis is *basis trading*, which is an arbitrage strategy whereas a market participant, who perceives that two related instruments are mispriced relative to each other, takes simultaneously a long position in the undervalued instrument and a short position in the overvalued one, in order to profit from the difference between them, which defines the basis. The term *basis trading* also refers to the benefits in terms of small basis point differences between related securities' prices. Arbitrageurs engaged in basis trading need large amounts of leverage in order to materialize their gain. This large degree of leverage is one of the risks involved in the basis-trading activity.

Basis trading is popular across futures commodities markets. Indeed, some of those markets offer the cash instrument and its future contract's quoted basis as negotiable instruments.

Credit risk is the risk of a financial loss resulting from a borrower's failure to fulfill its contractual obligations. Commonly, it refers to the risk that a lender may not receive the owned principal and/or interest. Credit derivatives are recently developed financial instruments whose main goal is to transfer the reference entity's credit risk, either completely or partially, between derivative contract's counterparties. Their flexibility and important liquidity provide users a number of advantages. They allow market participants to isolate credit risk and, more importantly, allow them to trade and price credit as an explicit asset class in its own right.

The introduction and development of credit derivatives for the bond market gave rise to a new concept, named the *credit basis*. The credit basis measures the divergence of a reference entity's credit risk valuation between the cash and synthetic credit markets. It is calculated as the difference between the spread of a bond and the price of its underlying credit derivative. Similarly to the futures contract basis, a non-zero credit basis constitutes an arbitrage opportunity, as it indicates a credit-risk mispricing between two credit markets.

Since the credit default swap (CDS) is the simplest and most liquid instrument among the broad class of credit derivatives, the CDS-bond basis arbitrage became the most popular credit-basis trade. Many banks and hedge funds invested great amounts of money in this arbitrage activity, generating substantial gains. However, during the last financial crisis, many financial institutions suffered huge losses in the basis trade: for instance, Deutsche Bank, Merril Lynch and Citadel lost close to 16 billions of dollars due to a bad basis bet (the CDS-bond basis trade blow up) where the basis on many credits became unexpectedly very large and very negative, and this during a long period. Since CDS and cash spreads are most of the time coupled, the magnitude and duration of this dislocation between the cash bond and CDS markets surprised both professionals and academics, defining a new financial puzzle, called the *CDS-bond basis puzzle.*

Our thesis contributes to the existing literature about the CDS-bond basis puzzle. The first essay introduces our main subject, the CDS-bond basis. We describe the involved instruments, i.e. corporate bonds and their related CDS contracts, their function, main characteristics and usefulness, in order to clarify the relation between their markets and to distinguish between their common and divergent features. We then define the CDS-bond basis, which measures the conjunction between credit cash and synthetic markets and give details on the way to compute it.

The second essay is dedicated to an investigation of the negativity persistence of the CDS-bond basis. We start by showing that basis arbitrage is a risky activity, which deviates from the traditional risk-free arbitrage concept. We then provide empirical evidence that the observation of an incomplete recovery of the basis after the 2008 crisis is corroborated by the basis' endogenous characteristics. Finally, we argue that the credit basis is not tightening because arbitrageurs are no longer active in trading the CDS-bond basis.

The third essay investigates the impact of credit events and, more precisely, credit rating changes, on the bond and CDS credit-sensitive markets and, more importantly, on the equilibrium between them, as measured by the CDS-bond basis.

The rest of the thesis is divided as follows. Chapter 2 is an introductory chapter that focuses on our main subject, the CDS-bond basis. Chapter 3 presents our essay on the basis limits to arbitrage and negativity persistence. Chapter 4 presents our investigation about the impact of credit rating changes on the basis. Finally, Chapter 5 concludes.

Chapter 2

The CDS-bond Basis

2.1 Corporate Bonds

A corporate bond is a debt security issued by a company for the purpose of raising capital. It consists of a loan agreement between the corporation (issuer) and the investor (bond holder). The terms of this legal commitment require the company to repay the principal amount lent within a specific date (the *maturity*) and to make regular interest payments (the *coupons*) on pre-specified dates. Various types of coupon amounts distinguish between different types of bonds: if the bond does not pay any periodic interest, the security is called a *zero-coupon* bond, generally traded at a deep discount. The security is a *fixed-rate* bond if it pays a fixed rate of interest, regardless of changes in market interest rates. *Floating-rate* bonds are securities that reset their coupons periodically, for instance semi-annually, adjusting their interest payments to changes in market interest rates.

Investors in the corporate bond market need to be compensated for the risks they are taking. Corporate bondholders are mainly exposed to the *default risk*, that is, the risk that the corporation will be unable to timely make the required coupon or principal payments corresponding to its debt obligations. Apart from Treasury bonds (TB), all bonds carry some level of default risk, and this is one of the reasons why corporate bonds have higher yields than government debt. Accordingly, the difference between the interest of a corporate bond and the TB interest rate, considered as risk-free, is called the *credit spread*.

Default risk is mainly gauged using credit ratings. Both corporations and their debt issues are classified by rating agencies according to their creditworthiness. These agencies evaluate the financial-risk profile of the borrower and its ability to honor payments on its debt. Rating agencies periodically review their bond ratings and may proceed to rating updates when they detect changes in a company's credit risk. Bonds' credit ratings are usually classified into two grades: *Investment grade* (IG) bonds are perceived by the rating agency to have a low default risk. *High-yield* (HY) bonds, also called junk bonds, are considered as low-quality investments and generally offer higher interest rates to compensate investors for the higher default risk.

It was originally, and for a long time, believed that the corporate bonds' credit spreads depended only on the default risk. However, credit spreads were shown to be much wider than what would be implied by default risk alone, suggesting the existence of other risks in the corporate bond market. Among those, one of the most important identified factors is the *liquidity risk,* defined as the inability to easily purchase or sell the bond, which may cause drastic changes in its price. Indeed, when corporate bonds are illiquid, investors seeking to sell them may offer a premium in order to attract buyers and compensate them for holding non-liquid securities. Liquidity risk is measured and described more precisely in Chapter 3.

2.2 Credit Default Swaps

Credit Default Swaps are financial derivatives designed to short credit risk. As suggested by its name, a CDS is an agreement between two parties to swap the credit risk of a reference entity, from an investor exposed to this risk (protection buyer) to another party accepting to bear it (protection seller). The buyer makes periodic payments to the seller as a compensation for his risk exposure. These payments, generally quarterly, are called the CDS *spread* or *premium*. In exchange for this premium, the protection seller agrees to compensate the buyer if a credit event occurs before the bond maturity date. This compensation can take different forms. In a *physical settlement*, the seller receives the defaulted bond, and pays its par value to the buyer. In a *cash settlement*, the seller pays the difference between the bond's par and recovery values.

Credit default swaps were initially designed by the JP Morgan bank. Since its inception in 1994, the CDS market has grown considerably, reaching a notional principal of $60 trillion by the start of the 2008 financial crisis, making credit default swaps one of the most important financial instruments in the last decades. However, since 2008, the market has shrunk greatly as the notional amount outstanding has been declining continuously.

Credit default swaps allow financial institutions and investors to manage efficiently their exposure to credit risk. For instance, they enable banks to provide corporations with debt without bearing the full risk, which improves credit availability and, consequently, increases investment opportunities. In addition, thanks to their contractual feature and to the fact that they do not need large amounts of funding capital, credit default swaps offer an easier and less costly way to trade credit risk than corporate bonds. As a consequence, the CDS market may adversely impact the liquidity and efficiency of the bond cash market.

While proponents consider the CDS to be a useful instrument to transfer credit exposure and to allow risk sharing between market participants, opponents have a completely different point of view.[1] While in a regular insurance contract, the buyer is usually exposed to the insured risk, one can buy CDS protection without being exposed to the debtor default risk. Such a *naked position* is a way to speculate on the creditworthiness and the health of a reference entity. The CDS market allowed

[1] For instance, Warren Buffet called the CDS a "weapon of mass destruction" and CBS denounced it to be the "bet that blew up Wall Street" during the last financial crisis.

speculators to bet against some companies, or even countries. Moreover, in the event of default, the CDS seller may not have sufficient funds to cover the CDS buyer's compensation, resulting in the default of the insurance provider and leading to a contagion effect. This phenomenon is even more dangerous considering the huge size of the CDS market and the interrelation between CDS positions. In that sense, opponents consider that the CDS can create a systemic risk and represent a serious threat to the financial system stability. Specifically, some market observers believe that the CDS contributed substantially to the last financial crisis. Finally, there were real concerns about the lack of regulation, lack of transparency and opaqueness of the CDS market[2]. This environment enabled some market participants to manipulate the market and adversely affect some financial institutions.[3]

These considerations highlight the importance of the CDS market and the reasons why this credit instrument has received significant attention recently.

2.3 The bond and CDS markets

While related on several levels, the markets for the CDS and for its underlying bonds have different characteristics, specifically with respect to liquidity, participants, and efficiency.

Unlike in the corporate bond market, where an investor needs to finance his position, CDS transactions do not involve much funding. In addition, shorting credit risk is usually difficult in the cash market. Moreover, the secondary bond market is not very liquid, with investors generally holding bonds until maturity. This makes the CDS market interesting for investors who want to trade the credit risk of a reference entity and explains the tremendous success of this instrument, which appeared as a liquid substitute to bonds for managing corporations' credit risk. The

[2] Central clearing for OTC credit default swaps was introduced in 2009 to control counterparty risk

[3] Such manipulations were argued to be in part responsible for the collapse of Bear Stearns and Lehman Brothers.

CDS market became the investors' preferred instrument to trade default risk, while the bond market remained less liquid and less popular. Some empirical studies provide evidence that CDS spreads have lower liquidity premium than corporate bonds (Cossin and Lu (2005) Zhu (2006), Kim (2017)).

The higher liquidity and lower funding costs associated with the CDS market, as compared to the bond market, have a significant impact on the determination of the leading market in the price discovery process. Indeed, informed traders prefer to trade on the more liquid and less costly CDS market, so that new information is incorporated into CDS prices before bond spreads (Blanco, Brennan and Marsh 2005). As a result, the bond market's efficiency was adversely affected by the introduction of the CDS instrument. The difference in efficiency and price discovery between the cash and CDS markets is also caused by a difference in their participants. Financial institutions, which are likely to be well informed, trade on both CDS and corporate bond markets, while uninformed retail investors are mainly active on the cash market.

The introduction of the CDS also had an impact on the bond pricing mechanism. The CDS market allows investors to trade the CDS-bond basis, that is, the difference between the CDS and bond spreads. A *negative basis trade* consists of buying a CDS and holding a long position in the bond, which results in pushing up the bond price. In case of an economic downturn or of funding or liquidity difficulties, arbitrageurs can find themselves unable to hold their portfolios and be forced to liquidate their positions in both instruments, which may put a downward pressure on the bond prices. Kim, Li and Zhang (2017) provide empirical evidence that the CDS-bond basis arbitrageurs' activity introduced sources of risk in the bond market, affecting bonds' returns.

2.4 The CDS-bond basis definition and computation

As mentioned in Chapter 1, the concept of basis is generally used to evaluate the connection between cash and synthetic markets. Precisely, the CDS-bond basis is defined as the difference between the CDS premium and the bond spread of the same reference entity. Duffie (1999) shows that the spread of a floating-rate note over a risk-free rate is equivalent to the price of a corresponding CDS with the same maturity. Accordingly, to accurately measure the CDS-bond basis, one would need to pick a floating-rate bond among the firm's debt securities. Unfortunately, floating-rate bonds are much less commonly traded than fixed-rate bonds. While CDS prices are readily available, the way the bond spread is computed distinguishes various methods used to compute the basis, the three most common being the Z-spread, the Par Asset Swap Spread (ASW) and the Par Equivalent CDS Spread (PECDS).

The *Z-spread* is a parallel shift applied to a spot-rate curve so that the theoretical price of a bond equals its market price; the ASW is the spread of an asset swap transaction involving the bond's coupons. Both the Z-spread and the ASW are frequently used in the CDS-bond basis literature. However, neither the Z-spread nor the ASW account for default risk characteristics, which are key factors of the CDS premium. In addition, the CDS-bond basis trade implies uncertain future cash flows; the default probability term structure is essential to determine the realization likelihood of these cash flows, and therefore the basis trade return.

The PECDS is the only method that explicitly considers default-risk factors, that is, the term structure of default probabilities and the recovery rate (see, e.g., Bai & Collin-Dufresne 2013 and Nashikkar, Subrahmanyam & Mahanti 2011). The *PECDS* is the premium of a synthetic CDS, which default probability term structure allows the bond's discounted cash flows to be as close as possible to its observed price. The computation of the PECDS involves extracting the firm's default probability term structure from its corresponding CDS curve. This term structure is then shifted by a value minimizing the distance between the market price and the theoretical price of the bond. The last step consists of reversing the process by transforming the shifted default term structure into the premium of a synthetic CDS. The CDS-bond basis is then the difference between the observed CDS price and the synthetic CDS premium, so that

$$Basis_i(T) = CDS_i(T) - PECDS_i(T),$$

where i and T index respectively the reference entity and the maturity.

Besides incorporating default characteristics, another advantage of the PECDS is that it involves the comparison of two CDS prices.

2.5 Data

Our empirical investigation of the CDS-bond basis is based on a data sample that contains observations of 447 reference entities over the period 02/01/2006 to 30/09/2014, further divided into three sub-samples pertaining to three different sub-periods: pre-crisis (02/01/2006 to 30/06/2007), crisis (01/07/2007 to 31/03/2009) and post-crisis (01/04/2009 to 30/09/2014).

The first step in the construction of our database is the computation of the CDS-bond basis. We start by collecting CDS data from Markit Company, a reliable information provider for credit derivative instruments, that collects and aggregates quotes from principal market participants. We choose single name, senior CDS contracts with a "Modified Structuring" (MR)[4] documentation clause and US dollar price. CDS premiums are quoted in basis point. We use CDS contracts with maturities ranging from 1 to 10 years for the construction of the default probability term structure of a given reference entity. Daily CDS spread quotes are also used

[4]MR clause limits the deliverable bonds to be within 30 months of the CDS contract maturity.

to compute the abnormal CDS spreads used in Chapter 4. Markit also provides bid-ask spreads, used as a proxy for CDS illiquidity.

The next step is to match a 5-year-maturity CDS with its underlying bond, in order to be able to compare their spreads and compute the basis. To each reference entity corresponds a set of issued bonds and only one CDS. Ideally, the CDS should be matched with the bond that appears on the protection contract, but this is not possible when dealing with a large sample. We choose instead the most "classical" bond with a maturity providing the best fit with the CDS MR clause.

Our first selection criterion is based on bond characteristics. We only keep straight bonds. We exclude securities denominated in foreign currencies or that have foreign issuer, variable coupons, or any special features such as put, call, conversion and exchange embedded options. We also exclude floating-rate bonds and bonds with sinking funds, in order to accurately compute the bonds' discounted cash flows. Our second criterion is maturity: since we need to compare the bond spread to a 5-year CDS premium, we select bonds having between 3 to 7.5 years left to maturity. The criteria for selecting the bonds are obtained from the FISD (Fixed Investment Security Database).

Detailed bond transaction data is obtained from TRACE (Trade Reporting and Compliance Engine). For each selected bond, we extract the price, date, time and volume of every transaction during each of the three sub-periods. We use the Dick-Nielson (2009) code to clean the TRACE database by removing transaction reporting errors.

Matching Trace and FISD data is relatively easy, since bonds are identified by their CUSIP (Committee on Uniform Securities Identification) in both databases. This is not the case for Markit where CDSs are identified by their RedCode, that needs to be matched with CUSIPs. In order to do so, we use two additional tables from Markit: *Entities XML file* and *Obligations XML file*.

As suggested by Longstaff, Mithal and Neis (2005) and Nashikkar, Subrahmanyam and Mahanti (2011), we use the Libor-swap curve downloaded from the

Federal Reserve Board website for the risk-free rate used to discount cash flows in the PECDS computation.

2.6 CDS-bond basis summary statistics

Table 2.1 provides summary statistics on the daily CDS-bond basis values, averaged across each sub-period of the sample and across different rating categories. We observe that, prior to the financial market crisis, the theoretical well-established relationship between CDS and bond spreads is confirmed by the basis observed average level, which is close to zero. During the crisis, the average basis drops to -111 bps, with a significant increase in volatility. The average basis level during the post-crisis period is higher than during the crisis; post-crisis values are however still far from the pre-crisis level and volatility.

Another striking observation is the pronounced cross-sectional differences in basis values between rating classes. Figure 2-1 depicts the evolution of the average CDS-bond basis of investment grade (Moody's ratings from Aaa to Baa) and high yield (Ba and lower) issuers over the three sub-periods of the study. We observe that the dynamics of the basis for HY and IG bonds differ significantly over the entire period. Before the crisis, while the HY basis is slightly above zero, that of IG bonds is null; at the onset of the financial crisis, the decline in the basis is much more pronounced for HY than for IG bonds, with a minimum value of -800 bps for HY bonds at the height of the crisis, while the IG basis does not fall beyond -250 bps. Figure 2-1 also shows that the serious departure from equilibrium in credit risk markets for HY and IG firms becomes striking with the Lehman Brothers bankruptcy in September 2008. In the post-crisis period, the HY basis remains significantly lower than that of IG bonds, and significantly lower than the pre-crisis level. Basis volatility also differs across ratings: the basis of HY firms is much more volatile than that of IG firms, even more so during the crisis period.

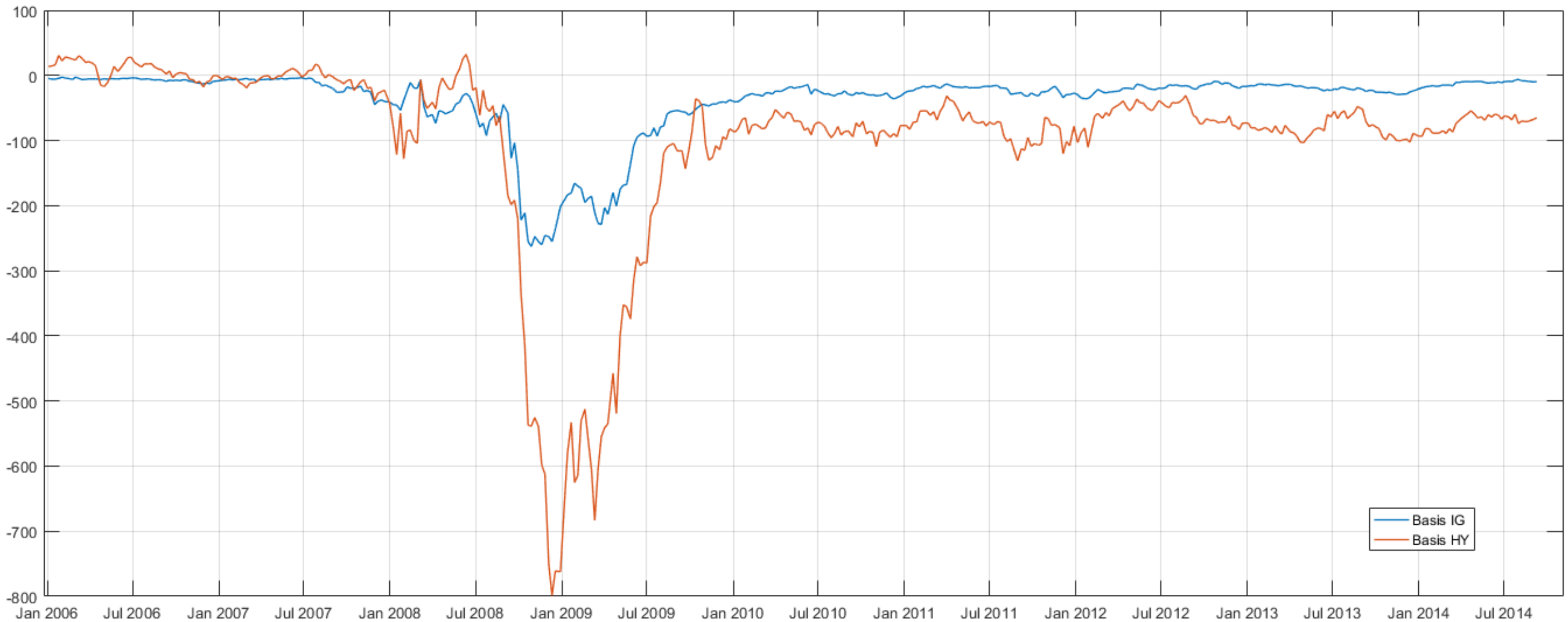
Table 2.1: Basis summary statistics

This table provides summary statistics for the CDS-bond basis in basis points for different Moody's rating categories and during three different periods: pre-crisis period (02/01/2006 to 30/06/2007), crisis period (01/07/2007 to 31/03/2009) and post-crisis period (01/04/2009 to 30/09/2014).

	pre-crisis				crisis				post-crisis			
	mean	σ	min	max	mean	σ	min	max	mean	σ	min	max
All	-5.56	3.17	-15.53	1.79	-110.82	113.65	-372.66	3.53	-45.04	38.20	-233.94	3.98
IG	-6.71	2.19	-15.53	-2.12	-78.26	70.67	-231.46	-0.61	-29.39	24.14	-146.40	3.98
HY	-0.44	10.51	-32.62	32.92	-202.70	248.54	-792.61	31.50	-93.61	83.74	-535.29	-16.99
Aaa/Aa	-3.23	1.93	-11.51	0.67	-20.20	30.80	-115.19	28.74	-5.06	7.18	-24.31	29.36
A	-4.87	2.07	-14.08	-0.85	-56.72	50.33	-184.28	8.62	-18.29	17.86	-105.49	3.98
Baa	-11.53	3.34	-29.41	-4.36	-143.75	111.31	-365.65	-4.55	-42.90	37.23	-234.53	-9.04
Ba	-8.84	8.96	-36.43	22.38	-171.20	178.28	-633.00	24.52	-81.89	55.38	-355.10	-5.50
B	4.75	16.04	-29.76	43.28	-161.14	246.60	-641.64	58.46	-62.92	54.52	-387.85	4.32
Caa	-8.52	57.11	-186.49	66.30	-272.94	242.89	-761.49	37.60	-166.10	146.15	-680.47	4.15

Figure 2-1: The CDS-Bond basis of IG and HY firms

This figure plots the two-weeks time series of the CDS-bond basis' mean value for two groups of firms according to their Moody's rating: investment grade (IG) and high yield (HY), from 02-01-2006 to 30-09-2014.



Chapter 3

Basis Limits to Arbitrage & Negativity Persistence

3.1 Introduction

During the last decades, credit default swaps have become a significant part of the financial markets. CDS are currently the most liquid and popular instruments among traded credit derivatives. A CDS and its underlying corporate bond are perceived as reliable gauges of the market perception about the credit risk of a given obligor. As a consequence, there exists a strong theoretical relationship between the valuations of these two instruments. The *CDS-bond basis*, defined as the difference between the CDS premium of a reference entity and the spread of a bond issued by the entity and having the same maturity, is the common way to quantify this relationship.

In a frictionless market, a corporate bond and its protection, being different instruments involving the same type of risk, are expected to price this risk equally, so that the basis should not significantly differ from zero. However, in normal conditions, market irregularities may cause the CDS-bond link to deviate slightly from parity and the basis to become non-null, raising the possibility of riskless profits. When this happens, arbitrageurs would normally take advantage of this pricing mismatch, which should make the spread difference between the cash and synthetic markets vanish.

When financial markets were hit by a crisis in 2008, the well-established connection between CDS premium and bond spread broke down, and the basis became sizably negative. This departure from equilibrium persisted over several months and across several companies belonging to different industries and rating classes. The consequences of this situation were severe for many market participants, namely, Citadel, Deutsche Bank, and Merrill Lynch, who wrongly assumed that a negative CDS-bond basis was a genuine arbitrage opportunity, short-lived and riskless. Although the basis has tightened after the financial crisis, it did not return to its pre-crisis level and remained persistently and conspicuously negative (JP Morgan[1]). Given the puzzling basis fluctuations observed during the last decade, the link between the corporate bond and its protection, as measured by the basis, has become an intriguing research subject.

The aim of this chapter is to explain the persistent negativity of the CDS-bond basis. We contend that this persistence is due to a dysfunction in the markets' habitual correction mechanism, namely arbitrage activity. Our argumentation develops in three steps. We first show that the evolution of the basis over time shows three distinct regimes and that the post-crisis regime differs from the regime that prevailed before the onset of the financial crisis. We then explore the cross-sectional variations of the CDS-bond basis, documenting that a considerable part of price inconsistencies reflect the various risks and costs associated with the basis arbitrage activity. We consider three distinct periods (before, during, and after the crisis) and find that the impact of risk factors on basis trading is the most pronounced during the crisis sub-period, but is also observed outside the crisis period. In a third step,

[1] https://libertystreeteconomics.newyorkfed.org/2017/06/market-liquidity-after-the-financial-crisis.html

we provide evidence of a decrease in the arbitrage activity following changes in the regulatory framework after the 2008 financial crisis. This is done by tracing, through different periods, the effect of arbitrage on two major aspects of the corporate bond market: transactions volume and pricing.

Despite the abundant literature on the CDS-bond basis fluctuations, this chapter is one of the rare works explaining these variations in a risk-return framework. A first contribution to the literature is the way we model risk factors. In fact, despite strong empirical proof of a liquidity basis between the CDS and bond markets (Kim 2017), bond liquidity risk was never appropriately measured in the existing basis literature as it was mostly reduced to a single dimension. We opt for an aggregate measure in order to capture the multidimensional aspect of liquidity risk, as in Dick-Nielsen, Feldhutter and Lando (2012), Dionne and Maalaoui (2013), and Maalaoui, Dionne and Francois (2014). Moreover, while most of the literature considers bond illiquidity as sufficient indicators of liquidity risk (Kryukova and Copeland 2015), recent empirical evidence (Arakelyan and Serrano 2016) shows that CDS spreads include a relevant liquidity premium. We therefore consider both bond and CDS illiquidity as potential determinants of the basis. Our results compare favorably to those in the existing literature, and notably to the seminal paper of Bai and Collin-Dufresne (2014), explaining a higher portion of the basis cross-sectional variation, with an R^2 reaching 55%. Moreover, while in Bai and Collin-Dufresne (2014) the explanatory power and significance of the risk factors decrease substantially outside of the crisis sub-period, our model remains highly effective across periods, showing a significant impact in the expected direction for most of the risk factors.

A second contribution is our analysis of the negativity persistence in the post-crisis period. While there is a rich literature dealing with the determinants of the basis before and during the recent financial crisis, to the best of our knowledge our thesis is the first to propose an explanation to why the basis did not return to its pre-crisis level after the recovery of the financial markets and, presumably, the disappearance of constraints on arbitrage activity. We argue that this phenomenon is explained by a considerable deterioration in investors' implication in basis arbitrage activity. This assumption is motivated by the growing literature on the adverse impact of the new, post-crisis, regulatory framework on the financial markets and on its major participants (Anderson and Stulz 2017, Dick-Nielsen and Rossi 2017, Bao, O'Hara and Zhou (2018), Boyarchenko, Gupta, Steele and Yen 2016). More specifically, Boyarchenko et al. (2016) argue that the new leverage ratio constraint made arbitrage trade more expensive for dealers. Our results, showing a decrease in arbitrage activity after the crisis, links our study to the recent and growing literature exploring the financial market structure and operation in the new regulation era. It also contributes to limits-to-arbitrage research by providing a new proxy for arbitrage activity, which facilitates the measurement of an unobservable variable.

The rest of the chapter is organized as follows. We start by an overview of the literature pertaining to the CDS-bond basis in Section 3.2. Section 3.3 describes the arbitrage activity and the risks inherent to negative basis trading. Section 3.4 provides an overview of the most important post crisis regulatory reforms. Section 3.5 provides details on the empirical methodology used to explore the basis cross sectional variation and to explain the negativity persistence during the post-crisis period. Our data set is described in Section 3.6 and our results are discussed in Section 3.7. Section 3.8 is a conclusion.

3.2 Literature review

Our work is mainly related to the literature analyzing the empirical relation between the bond and CDS markets. Contributions to this topic and research interests can be classified according to three consecutive periods: before, during and after the 2008 financial crisis. Initially, research focused on finding empirical evidence for the theoretical parity relationship and on explaining the fact that the basis was generally slightly positive. During the crisis, the link between the CDS and bond markets was clearly violated, which made researchers move their interest into exploring the determinants of a negative basis. Finally, despite a remarkable change in the basis levels compared to the pre-crisis period, literature dealing with the post-crisis period is scarce.

Long before the financial crisis, Duffie (1999) argued that, under simplifying assumptions, there is a theoretical equivalence between the CDS premium and the floating-rate spread of a corporate bond having similar maturity and issued by the same entity. This theoretical link is empirically verified by Blanco, Brennan and Marsh (2005), who document a stable equilibrium equating credit prices on cash and synthetic markets for most of the considered entities. However, these authors find that this relation does not hold in the short run, for a limited number of companies where the CDS spread is an upper bound for the credit-risk price, corresponding to a slightly positive basis. This is explained by the cheapest-to-deliver (CTD) option in CDS contracts, which, in case of a credit event, allows the CDS holder to deliver to the protection seller the cheapest among all traded bonds. The value of this option is expected to raise the CDS price, so that it should trade at a higher premium than the corresponding bond spread. This argument is also supported by De Wit (2006), who shows that technical constraints related to the difficulty to short corporate bonds, along with the CTD option, can explain positive deviations in the basis. By studying cointegration of bond and CDS time series, De Wit (2006) also shows that prices may deviate slightly from fundamental values in the short run, but generally move in unison and do converge to a long-run equilibrium.

A first thourough study of the CDS-bond basis drivers is provided by Trapp (2009), who establishes a comovement between CDS prices and asset swap spreads using a vector error correction analysis. Trapp (2009) documents that factors related to general market conditions and to the firm liquidity and credit risk have a significant impact on basis levels. Nashikkar, Subrahmanyam and Mahanti (2011) propose a corporate bond liquidity measure that overcomes the problem of infrequent transaction prices and volumes in the bond market. They find that this liquidity measure has an important explanatory power for the CDS-bond basis, exceeding other bond characteristics and traditional liquidity metrics, such as observed trading volume. They also find that liquid bonds are more expensive than their corresponding CDS when compared to less liquid bonds.

The onset of the financial crisis challenged these earlier results. During the crisis, the basis reached unexpected and substantially negative levels that lasted several months, which is inconsistent with the cointegration feature observed during the previous period. Many researchers focused on this phenomenon in order to determine factors explaining these unusual levels. Fontana (2011) concentrates on the role of funding cost variables and argues that, during the financial crisis, the lack of funding sources, combined with capital shortage due to huge losses incurred by market participants, impeded basis trading and, consequently, made the convergence to equilibrium levels more difficult. Moreover, the increase in funding costs may have made basis traders unable to fund and maintain their arbitrage positions and may have compelled them to close them by selling corporate bonds at a discount, which pulled the basis further down.

In the same vein, Mitchell, Pulvino and Mahanti (2011) suggest that the debt financing risk is one of the main causes of basis negativity. Hedge funds, who were among the most important players in the CDS-bond arbitrage operation, used to fund this trade through prime brokers. During the financial crisis, this activity was constrained by the inability of prime brokers to provide the needed capital and, as a result, the operation mechanism broke down. Garleanu and Pederson (2011) develop a theoretical general-equilibrium asset-pricing model that takes into account margin constraints. Applying their model to the CDS-bond basis, they conclude that deviations from equilibrium are caused by a difference in margin requirements of funded assets (such as corporate bonds) with respect to their unfunded derivatives (CDS). Bhanot and Guo (2012) examine the role of liquidity as a potential factor of basis deviations from parity. They distinguish two different types of liquidity: arbitrageurs' funding liquidity, and asset-specific liquidity. They find that the latter accounted for a considerable part of basis variability during the crisis. Augustin (2012) also insists on the importance of considering idiosyncratic, market, and funding liquidity risks separately. He concludes that, while all liquidity types have an impact on the amplitude of the basis variations, funding liquidity is the most relevant. In a more recent study, Bai and Collin Dufresne (2014) point to limits to arbitrage factors to explain the decline in the basis. They attribute the cross-sectional variation of the basis during the crisis to risks that were inherent to the arbitrage operation during that period.

Despite the puzzling fact that basis negativity still persists, long after the end of the recession, very few studies focus on the post-crisis period. Bai and Collin Dufresne (2014) find a considerable deterioration in the explanatory power of their model when applied to the post-crisis period. Kim, Li and Zhang (2017) do not focus on the basis determinants, but rather analyze the CDS-bond basis under a different angle, exploring the implications of the arbitrage trades on the corporate bonds' future returns. Using a regression model of the basis on the risk factors inherent to the arbitrage activity, they split the basis into two parts; the first part is called the *predicted basis*, and its variation is explained by the risk factors, while the variations in the second *residual* part are not explained by variation in the risk factors. These authors provide evidence that the residual part, which is exempt from all arbitrage risks, is a strong predictor of bond excess returns.

To the best of our knowledge, no explanation has been provided yet for the lasting departure from equilibrium between the CDS and bond markets in recent years. In that sense, our study complements the existing literature by focusing on a period spanning January 2006 to September 2014, the longer and the most recent to date, and by proposing an explanation for the persistence of a negative CDS-bond basis in the post-crisis period.

3.3 Arbitrage activity and limits to arbitrage

Arbitrage activity

One of the key concepts in our thesis is the market arbitrage activity, which is closely related to the important financial theory of *market efficiency* (Fama 1970). This theory states that current market prices fully reflect all currently available information, so that no investment strategy can consistently outperform the market and produce a positive excess return. However, several studies (see, e.g., Grossman and Stiglitz 1980 and Dimson and Mussavian 2000) challenge the market efficiency assumption and provide evidence of mispricing and arbitrage opportunities.

Arbitrage activity consists of trading theoretically equivalent assets having different prices in different markets in order to earn a riskless profit (Sharpe and Alexander 1990). Arbitrage involves a wide range of markets and applications, spanning from betting on sports results to trading financial securities. In financial markets, arbitrage activity constitutes a stabilizing force, as it helps maintain the *law of one price*, ensuring that similar assets in related markets trade at similar prices. Arbitrageurs in financial markets seek temporary price discrepancies. These distortions are generally very small, so that arbitrageurs have to invest important amounts to generate profits. Such large-scale trades put pressure on markets and reduce the magnitude of pricing mismatch. Arbitrageurs maintain their activity until it is no longer interesting, thus contributing to the elimination of market distortions. The impressive paradox is that, while arbitrage activity is a violation of the price efficiency assumption, it is also the mechanism that ensures the market return to equilibrium.

In the specific case of credit derivatives, arbitrage opportunities arise when the prices in the CDS and bond markets diverge, so that the basis becomes positive or negative. The basis is positive when the bond spread is lower than its CDS premium, so that the bond is relatively more expensive than its protection. An appropriate arbitrage strategy involves short-selling the bond through a reverse repo and selling the corresponding CDS contract. Conversely, a negative basis indicates that the bond spread is too high compared to its CDS premium. An arbitrageur can initiate a theoretically risk-free position by holding the bond and buying a protection against its default. By doing so, the arbitrageur hedges away the reference entity's default risk and simultaneously realizes a positive return equal to the basis value. Given that short selling a bond is generally more difficult than purchasing it, negative-basis trading is by far more popular among arbitrageurs than the reverse.

Limits to arbitrage

According to the textbook definition, arbitrage is free money on the table. Smart eagle-eyed arbitrageurs would spot any out of line prices and push them back towards their fundamental values, making easy profits without bearing any risk or incurring any cost. This perspective is challenged by Shleifer and Vishny (1997), who point out that noise traders can cause price deviations to widen, so that arbitrageurs may need to invest additional funds to maintain their positions. Since keeping this capital flow for a long period is unrealistic, especially for highly levered arbitrageurs, such a situation may cause their collapse. A well-known instance of such a case is the collapse of the Long Term Capital Management (LTCM) hedge fund in 1998, where the managers were unable to fund their position and saw their capital destroyed in a few days, confirming that arbitrage activity does involve risks.

Since the LTCM demise, a growing body of literature has addressed limits to arbitrage that may deter arbitrageurs from correcting mispricing (Mitchell, Pulvino and Mahanti 2011, Vayanos and Gromb 2010, Brunnermeier and Pedersen 2009). In practice, arbitraging away price distortions can be difficult, risky and costly; implementation costs and capital availability have been identified as the main issues hindering the ability to exploit price deviations. When funding is constrained and the access to debt is limited, arbitrageurs may be unable to raise capital to implement or maintain an arbitrage position. Borrowing and transactions costs may also be so high as to exceed potential benefits, making the arbitrage activity less attractive. In a nutshell, arbitrageurs are crucial for the well-functioning of financial markets, but various risks and costs weaken the possibility and willingness to take advantage of price distorsions, allowing these anomalies to persist.

Negative-basis trading risks

In this section, we thoroughly describe the negative CDS-bond basis trading steps in order to identify the various limitations that may preclude this arbitrage activity and consequently hinder the price correction mechanism.

A negative-basis arbitrage strategy involves purchasing a bond and buying a protection on the CDS market. The bond purchase is often funded with borrowed money through the repo market, where the bond has to be posted as collateral. The interest rate applied to this transaction is the repo rate, which varies across assets and may differ significantly from the risk-free rate, resulting in arbitrage costs. Repo transactions generally have short maturities, and extending the holding period requires rolling over the position, which may be executed at a higher repo rate. The roll-over risk depends on both asset quality and capital availability. Typically, the bond's market value cannot be entirely borrowed through the repo market and the remaining *haircut* needs to be funded by other means. The size of the haircut depends on the credit and liquidity risks of the collateral: when the ability to sell the collateral is adversely affected, or when the bond is less valuable, the haircut increases. Accordingly, a lower collateral quality on the repo market results in a higher haircut, which may reduce the profitability of the trade.

On the other hand, taking position on the CDS market requires an initial margin and is subject to margin calls, which are triggered when the credit quality of one of the two parties, CDS seller or buyer, changes. Like haircut, margin calls are habitually financed at high interest rates. Thus, the ability of the arbitrageur to fund his position depends not only on the bond's quality, but on funding liquidity and capital availability and cost, which are subject to market conditions. Any worsening in funding conditions may considerably reduce the arbitrageur's return. Even worse, during the financial crisis, funding cost has not only reached critical values, but funding itself became unavailable.

Negative-basis trading involves holding CDS and bond positions for an unspecified period of time. Empirical evidence shows that corporate bonds (Longstaff, Mithal and Neis 2005) and their protections (Arakelyan and Serrano 2016) are both subject to liquidity frictions which may hinder transactions and increase their cost. Moreover, the arbitrageur may need to unwind his position for some reason, such as the need for cash or to stop the loss caused by a depreciation of his portfolio. In order to do so, the arbitrageur needs to find an investor eager to take the opposite position. This could be a particularly difficult, expensive and long process for an illiquid bond or CDS. Such a situation can get even worse during a crisis period, where liquidity constraints are binding. Thus, the arbitrageur can find himself stuck with a portfolio that is loosing value every day, without being able to limit the damage and get rid of it. In that sense, liquidity specific to either bond and/or CDS can highly affect arbitrageurs' willingness to exploit price distortions.

Finally, the negative-basis arbitrage strategy is based on the assumption that, by holding both bond and CDS intruments, the arbitrageur is perfectly hedged against the reference entity's default risk, meaning that, in case of default, the CDS seller will undoubtedly compensate the bond holder for his loss. However, this premise ignores counterparty risk in the CDS market, which is the risk that the CDS seller defaults simultaneously with the debt and, consequently, is unable to honor his part of the contract, leaving the arbitrageur's long credit position uncovered. Simultaneous default of the instrument and of its protection can happen, and these two events can even exhibit positive correlation (wrong-way risk), particularly during financial crises.

These observations indicate that negative-basis trading is not a riskless operation.

In practice, basis traders are subject to significant risks, namely, funding difficulties, illiquidity on both the bond and CDS markets, protection seller's counterparty risk, and collateral quality deterioration. Even if the arbitrageur is able to hedge the default risk through the CDS protection, it is difficult, if not impossible, to eliminate all risks inherent to negative-basis trading, which can therefore be considered as any investment strategy, with its own risks and returns. Hence, before initiating the trade, the basis arbitrageur should find, like any other investor, the best risk-return tradeoff by choosing the best trade that grants him the maximum return with the minimum risk.

3.4 The post-crisis regulatory environment

During the global financial crisis of 2007-2009, a significant number of financial institutions experienced liquidity, funding and solvency difficulties, causing significant losses and severely distressing the financial system. The crisis unveiled many shorcomings of the financial system's regulatory framework, and important changes in regulations and laws were elaborated and gradually adopted during the post-crisis period.

A centerpiece of the regulatory reforms is the Basel III accord, which aims at improving the liquidity and solvency of the banking system. This reform involves increased capital requirements and the implementation of a leverage ratio. Banks are required to hold more capital, and of higher quality, against both their risky assets and their total exposure. Moreover, the Basel III reform requires the bank to hold an adequate stock of liquid instruments and to limit funding risk by relying on stable, long-term sources of funding. Each of these restrictive reforms increases the banks' capital cost.

Another important regulatory reform is the Volcker rule of the Dodd–Frank Wall Street Reform and Consumer Protection Act, which prohibits depositary institutions from engaging in proprietary trading, except for market-making activities, and forbids banks from owning, investing in or sponsoring hedge funds and private equity funds.

While the aim of these regulatory reforms was to strengthen the health and resilience of the financial system, many market participants and researchers argue that these new regulations may have caused more harm than good (Bao, O'Hara and Zhou 2018, Bessembinder, Jackson, Maxwell and Venkataraman 2016). Actually, the higher capital and liquidity requirements, combined with new leverage ratios, reduced the dealers' willingness to hold risky positions and, more importantly, increased their cost of capital. In particular, these requirements made funding through the repo market much more expensive. Furthermore, Duffie (2012) explains that market making is inherently a form of proprietary trading. The Volcker rule is thus blamed for reducing the banks' market-making capacity and, consequently, for deteriorating the liquidity provision in the corporate bond market (Dick-Nielsen and Rossi 2017, Bao, O'Hara and Zhou 2018).

In that sense, the new regulatory framework seems to be a hostile environment for CDS-bond basis arbitrageurs, where they find it more difficult and costly to hedge their risks and manage their positions. To perform a negative-basis trade, an arbitrageur needs to finance both the bond and CDS purchases, and, to avoid huge losses, he also has to be able to close his arbitrage position as soon as the basis starts to deteriorate. However, in an environment where market-making activity is hindered, liquidity is constrained, and capital cost is high, entering, holding or exiting the basis trade becomes difficult and expensive. This may dissuade market participants from engaging in the basis arbitrage activity.

3.5 Methodology and variables

3.5.1 Regime analysis

One of our working hypothesis is that changes in the financial market environment may be responsible for an alteration in the behavior of the CDS-bond basis. To support the anecdotic observation of an uncomplete recovery from the non-zero basis anomaly after the crisis for all rating categories, we propose to investigate the evolution of the basis variable in a Markov regime-switching framework. We assume that changes in the basis level and variability are described by a Hidden Markov-switching model (HMM) (Hamilton 1990). For a case with three distinct regimes, we apply the HMM model to the averaged basis monthly data and obtain the regime transition matrix along with the mean and variance of the basis variable in each regime. We then check the robustness of the three-regime assumption by performing the same analysis in a four-regime model.

3.5.2 Basis cross-sectional variation

We then evaluate the impact of various frictions and constraints related to the negative-basis trade on the basis cross-sectional variations. To do so, for each reference entity in our data base, we quantify arbitrage-risk variables, namely CDS and bond illiquidity, counterparty risk and funding risk. We perform a multivariate Fama-Macbeth regression of the negative basis on these various sources of risk according to the following equation:

$$\begin{aligned} NB_{it} &= \alpha_t + \gamma_{1t} ILB_{it} + \gamma_{2t}\beta_{ILB,i} + \gamma_{3t} ILC_{it} + \gamma_{4t}\beta_{CNT,i} \\ &\quad + \gamma_{5t}\beta_{LIB,i} + \gamma_{6t}\beta_{REP,i} + \gamma_{7t} RAT_{it} + \varepsilon_{it}, \end{aligned} \tag{3.1}$$

where i and t index respectively the reference entity and the date and NB_{it} is a negative-basis observation. Table 3.1 provides a list of the regression's variables with their symbol, definition and expected sign in the regression. This regression is performed for each of the three distinct periods of our sample with respect to the 2008 financial markets crisis. These periods are analyzed separately because of the considerable difference in market conditions during the pre-crisis, crisis and post-crisis periods. In addition, we also examine the impact of the risk factors on the basis within an endogenously defined Markov regime-switching framework, performing the regression (3.1) for the three basis-regime periods identified by our HMM analysis.

These regressions are used to test, in each sub-period, whether variations in arbitrage-risk variables are able to explain the basis cross-sectional variation. If this were the case, then it would indicate that negative-basis trading is risky, so that arbitrage risks may prevent the CDS-bond basis of the more constrained arbitrage trades to converge to its fundamental level.

Indeed, if a rational arbitrageur had to choose between two trades on two different reference entities that have the same return, but not the same exposure to, say, funding risk, he would choose the less risky trade. All rational arbitrageurs would do the same, gradually reducing the return of the less risky trade and its basis until equilibrium is reached, while this correction mechanism would be absent for the more risky arbitrage operations.

Bond illiquidity risk

In a negative-basis trade, bond liquidity affects the market value of the arbitrage position, and its variation according to market conditions may have an impact on the trade attractiveness. In particular, liquidity constraints may prevent an arbitrageur from exiting a position. Two variables are used to describe the bond illiquidity risk: ILB, which is a bond-illiquidity factor based on eight different liquidity measures, and β_{ILB}, which represents the co-movement of specific and market illiquidity.

Bond illiquidity factor Bond liquidity is a multidimensional concept, and there is no consensus on how to characterize it using a single measure. As in Dick-Nielsen, Feldhutter and Lando (2012), we opt for a multi-dimensional methodology that consists of computing various liquidity measures and performing a principal component analysis (PCA) in order to choose a single component summarizing the pertinent information contained in these measures in order to construct our illiquidity proxy ILB. We use eight distinct bond liquidity measures, described in Appendix 3.9. A PCA is then performed in order to identify the best factor summarizing these eight measures. The PCA results indicate that five variables are retained in the factor with the largest explanatory power. We then create the illiquidity proxy ILB using these five variables. This proxy is defined by

$$ILB_{it} = \sum_{j=1}^{5} \omega_j \overline{V}_{it}^{j},$$

where $\overline{V}_{it}^{j}$ is the normalized value of liquidity measure j and ω_j is its loading on the first principal component.

A bond's poor liquidity implies a higher liquidity premium, which increases the credit spread and consequently pushes the basis toward negative values. Moreover, additional costs are borne by the arbitrageurs when bond transactions gets complicated by liquidity issues. Bond illiquidity should have an adverse impact on the negative-basis trade, and we therefore expect the coefficient of ILB to be negative.

Bond illiquidity beta The bond illiquidity beta β_{ILB} contextualizes the bond liquidity by describing the dependence between the bond and the market illiquidity. The market illiquidity, denoted by $ILBM$, is measured as the mean of the liquidity variable ILB over the whole sample. β_{ILB} is then defined as

$$\beta_{ILB,i} = \frac{cov\left(ILB_i, ILBM\right)}{var\left(ILBM\right)}.$$

When market conditions are poor and liquidity decreases, an arbitrageur intending to perform a negative-basis trade would choose the bond with liquidity risk that is less correlated with market liquidity. We expect that an increase in specific and market liquidity dependence dissuades arbitrageurs from investing in a bond, which has an adverse impact on the negative-basis trade, and we therefore expect the regression coefficient of β_{ILB} to be negative.

CDS illiquidity risk

To measure CDS illiquidity, we opt for one of the most used proxy in literature, that is, the bid-ask spread, denoted by ILC. Since negative-basis trading requires the arbitrageur to hold a long position in the CDS, illiquidity in this instrument should have an adverse impact on the investor's position and reduce the arbitrage return. In addition, the CDS illiquidity can increase the cost and the difficulty of closing the arbitrage position. An arbitrageur choosing between two negative-basis trades, all other things being equal, would select the one with the more liquid CDS, pushing its basis toward zero. Since a more liquid CDS should be associated with a less negative basis, we expect the sign of the coefficient of ILC to be negative.

Counterparty risk

Counterparty risk resides in the possibility that both the bond and its protection seller default simultaneously. As in Bai and Collin-Dufresne (2014), in order to characterize counterparty risk, we evaluate the correlation between the reference entity and the CDS seller stock returns. However, since the CDS market is over-the-counter (OTC), it is very difficult to accurately identify protection sellers. Accordingly, we identify the CDS sellers with the market primary dealers. The counterparty-risk variable is then defined by

$$\beta_{CNT,i} = \frac{cov\left(R_i, RD\right)}{var\left(RD\right)}$$

where R_i is the stock return of the reference entity and RD is the excess return of the market primary dealers.

Through a CDS purchase, the arbitrageur seeks to eliminate a part of the negative basis trade risks, namely the firm's default risk. However, the worse scenario is when the protection provider becomes insolvent at nearly the same time as the bond's default. The CDS contract turns out to be worthless, which may deter the arbitrageur from investing in this trade and consequently pull down the basis. So, the higher the counterparty risk, the lower the eagerness of market participants to engage in the basis trade and the lower is the negative basis level. Thus, we expect the coefficient of this variable to be negative.

Funding risk

One of the major issues for any investor is funding. The arbitrageur, who is operating with borrowed money to finance his basis trade, is exposed to funding risk. One of the worst scenarios for an arbitrageur is when the basis decreases, which implies additional costs, simultaneously with a deterioration of funding conditions. Funding risk refers to the risk that the cost of borrowing to finance a negative-basis trade increases simultaneously with a decrease in the basis. The variables β_{LIB} and β_{REP} are used to characterize this risk.

Libor beta This variable uses the difference LIB between the LIBOR and OIS rates as a proxy for the funding cost on the uncollateralized debt market. The variable β_{LIB} quantifies the dependence between the basis and uncollateralized funding cost variations and is computed by

$$\beta_{LIB,i} = \frac{cov\left(basis_i, LIB\right)}{var\left(LIB\right)}.$$

Repo spread beta This variable uses the Repo spread REP, that is, the difference between the General Collateral repo rate and the Treasury Bills (T-Bills) rate.

T-Bills are considered to be as one of the safest investments on the market. In case of adverse market conditions, investors would prefer less risky investments, namely T-Bills, which would decrease their return compared to the repo rate. The variable REP is then a good indicator of the flight-to-quality phenomenon. The variable β_{REP} captures the link between the basis and collaterized debt cost variations and is computed by

$$\beta_{REP,i} = \frac{cov\left(basis_i, REP\right)}{var\left(REP\right)}.$$

When basis variations are highly correlated with funding conditions, an arbitrageur could be subject to a sudden and important increase in trading costs, which he would have to fund at higher price. Higher correlations thus deter arbitrageurs from investing in basis trades, which results in basis deterioration. The two variables β_{LIB} and β_{REP} are therefore expected to have negative regression coefficients.

Collateral quality

We use the Moody's ratings, which we convert into numbers where Aaa$=1$,AA$=2$ and so on, as a proxy of collateral quality denoted by RAT. While using ratings as a measure of bond credit worthiness can be criticized, in our case we are rather interested in the market's willingness to accept the bond as a collateral and the resulting haircut, which is known to depend heavily on the bond's rating. On the repo market, a decrease in collateral quality results in a higher haircut and repo rate, which can reduce significantly the arbitrage return. Everything being equal, an arbitrageur would then be more attracted by a basis trade with a better collateral quality, resulting in a basis improvement. We therefore expect the regression coefficient of the variable RAT to be negative.

Table 3.1: List of variables

This table provides the list of variables, symbols and definitions along with the predicted coeffcients signs for the regression 3.1

Variable	Symbol	Definition	Data source	Predicted sign for the regression coeffcient
Bond illiquidity	ILB	Linear combination of five bond illiquidity proxies	Trace	Negative
Bond illiquidity beta	β_{ILB}	Dependence between the bond and the market illiquidity	Trace	Negative
CDS illiquidity	ILC	CDS bid-ask spread	Markit	Negative
Counterparty risk	β_{CNT}	Dependence between the reference entity and the primary dealers stock return	CRSP, Federal Reserve Bank of New York	Negative
Libor beta	β_{LIB}	Dependance between the basis and the Libor-OIS	Federal Reserve Bank of New York, Bloomberg	Negative
Repo spread beta	β_{REP}	Dependance between the basis and the Repo spread	Federal Reserve Bank of New York, Bloomberg	Negative
Collateral quality	RAT	Reference entity's rating	FISD	Negative

3.5.3 Residual and predicted basis analysis

Prior to the financial crisis of 2008, a period with very small market frictions and risks, arbitrageurs were able to lean against the negative basis until they made it disappear. Figure 2-1 clearly indicates that, before the financial crisis, the CDS-bond basis was very close to zero, or slightly positive for high yield firms.

With the advent of the crisis, market conditions became difficult, with funding becoming rare and expensive and markets becoming illiquid. Consequently, arbitrage activities became difficult to execute, and we can observe the basis reaching very negative values in all categories, and for a long period of more than a year (Figure 2-1).

After the end of the turmoil, given the considerable improvement of the financial market conditions, one would expect arbitrageurs to regain their ability to perform correcting trades, and consequently the basis to return to its previous levels. However, contrary to expectations, CDS and bond spreads did not fully converge, as illustrated in Figure 2-1. Our main assumption is that the mechanism responsible for bringing back the basis to its fundamental value, i.e. negative-basis arbitrage, is not fully functional during the post-crisis period.

This assumption is motivated by the growing concerns about the unintended negative impacts of the post-crisis regulations on financial markets, especially on liquidity provision, market making and cost of capital. Using a stylized example, Boyarchenko, Gupta, Steele and Yen (2016) show that the new capital regulations and, in particular, the supplementary leverage ratio, considerably increases the cost of basis trading. This results in a decrease in arbitrage profitability, which adversely affects arbitrageurs' incentives to initiate this type of trade.

These arguments hint at a lower arbitrage activity, which would explain the persistence of basis negativity after the end of the crisis. It is a fact that, at the current basis levels, arbitrageurs would have performed negative-basis trade in the pre-crisis period, and as a result would have closed the existing gap between the two markets. However, it is not the case and the basis continues to be negative.

To show that the arbitrage mechanism is defective in the post-crisis period, causing the basis' constant departure from equilibrium, we need a reliable measure for this activity. However, this is a challenging task, since the identity of arbitrageurs is unknown and arbitrage is not observable (Lou and Polk 2012).

To circumvent this problem, we opt for a popular methodology among financial and accounting researchers, based on the separation of a variable into its predicted and residual components (Chen, Hribar and Melessa 2018). To do so, we exploit results of regression 3.1. This regression aimed to show that the CDS-bond basis arbitrage is not "free money on the table" and that arbitrageurs face a wide range of constraints. If this is the case, then it is not realistic to consider that the entire basis is a pure gain for arbitrageurs. On the contrary, a part of the basis would be a compensation for arbitrage risks, and only the portion that remains unexplained by the arbitrage risk factors would represent the price discrepancy that arbitrageurs are able to correct through their arbitrage activity.

Accordingly, we divide the observed basis into two parts:

- **The predicted basis**, denoted PB, is the part of the basis explained by the arbitrage risk factors, namely funding, counterparty and liquidity risks. This portion evaluates all the difficulties and frictions related to the basis trade which may hamper this activity and reduce its return.

- **The residual basis**, denoted RB, is the part of the basis exempt from the described risks. Only this portion represents the real mispricing or, in other words, the real pure gain of an arbitrage trade. Although the residual basis may not be fully devoided of market frictions or risk factors that are not specified in our empirical model, it is expected to be less noisy in capturing mispricing after removing the well-known risks and measurable market frictions (Kim, Li and Zhang 2016).

These two components of the basis allow us to show a decrease in the potency of arbitrage. We trace, through different periods, the effect of this activity on two major aspects of the corporate bond market: transaction volume and pricing mechanism.

3.5.3.1 Impact of the basis arbitrage activity on the bonds' purchase volume

Assumption 1 *The sensitivity of the bonds' purchase volume to the potential arbitrage gain has decreased after the crisis.*

Given that a negative-basis arbitrage strategy involves purchasing a bond and its CDS, then a larger potential profit being more appealing to arbitrageurs will lead to a larger amount of purchased bonds. In other words, a large basis trading activity should mark transaction volumes. This suggests that a regression of the amount of purchased bonds on the potential arbitrage gain, proxied by the residual basis, would have a positive coefficient.

In each period, we run mutivariate cross-sectional regressions of the bond's bought volume on the residual basis, controlling for the usual factors (Woodley 2010):

$$BV_{it} = \alpha_t + \gamma_{1t} RB_{it} + \sum_{k=2}^{K} \gamma_{kt} C_{kit} + \varepsilon_{it}, \tag{3.2}$$

where i and t index respectively the reference entity and the date, BV is the bond purchased volume, and the variables C_k are control variables. The regressors used as control variables are the bond's one-day lagged purchased volume, age, amount outstanding, illiquidity measure, and rating on date t.

We use the coefficient γ_1, reflecting the sensitivity of the bonds' trade volume to the potential pure arbitrage profit, as a proxy of the intensity of the negative-basis arbitrage activity. We expect the regression coefficient γ_1, an indicator of the strength of the negative-basis trade activity, to be significantly positive before the crisis, reflecting a prevailing and efficient practice, while we expect γ_1 to be insignificant and small after the crisis, reflecting a dysfunction in the correction mechanism.

We focus our study on the bond market, instead of the CDS market, for three reasons. First, detailed daily data with buy/sell marks are only available for bond transactions. Second, before the CDS introduction and the initiation of the basis arbitrage activity, the bond market was dominated by buy-and-hold investors, which are not very active. Third, since basis deviations are generally small, arbitrageurs usually invest large amounts of money. As a consequence, we believe that large transactions driven by arbitrage incentives should be easier to detect in the passive bond market than in the larger and more liquid CDS market.

3.5.3.2 Impact of the basis arbitrage activity on the bonds' return

Assumption 2 *The impact of arbitrage risks on bonds' return has decreased after the crisis*

During the crisis, difficult funding conditions compelled arbitrageurs to close their positions. This deleveraging phenomenon impacted the bond market, by putting an unusual pressure on bond prices, driving them down. Moreover, a decrease in negative-arbitrage activity reduces the demand for bonds. It is then logical to assume that the negative-basis arbitrage activity and, more specifically, risks related to this trade, may influence the bond-pricing mechanism. In fact, before the negative-basis trade became a popular activity, most of the bond market transactions were performed by passive buy-and-hold investors, who care less about the risks described in Section 3.3, than arbitrageurs.

The predicted basis variable PB can be used as a proxy of the global risk involved in the negative-basis arbitrage trade, as in Kim, Li and Zhang (2017). These authors use the predicted basis as the main explanatory variable to analyze the impact of negative-basis arbitrage on the price of corporate bonds. Using data from the pre-crisis period, they show the existence of an "arbitraging channel" through which the risks involved in negative-basis trades are transferred to bond returns, and find that this arbitraging channel exists only for IG bonds. The authors explain this result by the fact that HY bonds are rarely traded by arbitrageurs, so that the negative-basis trade risks are not transferred to HY bonds' returns, that is, arbitraging channel is inexistent for this type of bonds.

In the same way, we study the relation between arbitrage risks and bond returns in the post-crisis period in order to check whether it is still relevant. Our concern is to support our assumption that arbitrage-trading activity has significantly decreased after the crisis. If we show that risks linked to the basis trade, proxied by the predicted basis, are no more affecting bond pricing as they used to do in the pre-crisis period, this means that the so-called arbitraging channel is destroyed or at least weakened, indicating a decrease in the basis-arbitrage force. To confirm this, we regress the bond excess returns during a $20-$day holding period on the predicted basis,

$$BR_{it} = \alpha_t + \gamma_{1t} PB_{it} + \sum_{k=2}^{K} \gamma_{kt} C_{kit} + \varepsilon_{it}, \tag{3.3}$$

where i and t index respectively the reference entity and the date, BR is the bond's $20-$day holding period excess return and PB is the predicted basis. The additional regressors C_k used as control variables are the bond's age, credit rating, coupon, illiquidity and issuance amount, defined as the par value of the debt initially issued.

A coefficient γ_1 that is significant indicates that the arbitrage risks, proxied by the predicted basis PB, do affect the bond returns BR, or that the arbitrage activity is well functioning. On the other hand, a non-significant coefficient γ_1 indicates a weak or inexistant arbitrage activity. We expect the coefficient γ_1 to be non significant during the post-crisis period.

3.5.3.3 Impact of the basis arbitrage activity on the bond market during the regulation era

Assumption 3 *The sensitivity of the bonds' purchase volume to the potential arbitrage gain has decreased after the introduction of new regulations*

Assumption 4 *The impact of arbitrage risks on bonds' return has decreased after the introduction of new regulations*

As mentioned in Section 3.4, there are serious suspicions that the new post-crisis regulations hampered the arbitrageurs' activity and prevented them from bringing back CDS and bond markets to equilibrium (Boyarchenko, Gupta, Steele and Yen 2016). However, directly relating the changes in arbitrageurs' behavior to the new regulatory framework is not an easy task (Dick-Nielsen, Feldhutter and Lando 2012, Bessembinder, Jackson, Maxwell and Venkataraman 2016, Bao, O'Hara and Zhou 2018). We choose to approach this problem by comparing the impact of the arbitrage trades on the bond market before and after each reform.

The two main regulatory changes we consider are the Dodd-Frank Act, signed in July 2010, and the implementation of the Basel III accord in July 2013. We therefore divide the post-crisis period into three subperiods, according to the dates of the advent of these regulations, to check whether the impact of the arbitrage activity on bonds' transaction volume and/or return was altered.

3.6 Data

Risk factors are measured using a wide variety of data sources. Bond illiquidity proxies are computed using bond transaction data from TRACE. Correlation values for these proxies are presented in Table 3.2. As expected, some of the eight illiquidity measures are highly correlated. The results of the PCA used to construct the bond illiquidity variable are provided in Table 3.3. Based on these results, the first five liquidity measures (Amihud, IRC and their variability, and Roll) and their loadings are retained to compute the bond illiquidity variable.

The CDS liquidity variable is computed using the bid-ask spread measure provided by two different data sources: CMA datastream covers the period from 2006 to 2010, while the remaining values are obtained from Markit liquidity reports.

To compute the counterparty risk variable, we use the value-weighted stock market return, market capitalizations and equity returns obtained from CRSP. The list of primary dealers is downloaded from the Federal Reserve Bank of New York website.

The funding risk variables are computed using the Overnight index Swap (OIS) and the 3-month general collateral repo rate, both obtained from Bloomberg.

The correlation matrix of the variables used to measure the negative-basis arbitrage risk factors is presented in Table 3.4.

Table 3.2: Correlation matrix of the illiquidity variables

This table provides correlation values for the eight corporate bond liquidity measures. These measures are computed daily for the period 02/01/2006 to 30/09/2014. Bond transaction data is obtained from TRACE and bond information is obtained from FISD.

	AMI	σ_{AMI}	IRC	σ_{IRC}	ROL	BHT	$B0$	$F0$
AMI	1							
σ_{AMI}	0.54	1						
IRC	0.49	0.26	1					
σ_{IRC}	0.37	0.45	0.50	1				
ROL	0.30	0.37	0.38	0.44	1			
BHT	0.26	0.16	0.02	0.05	0.05	1		
$B0$	-0.19	-0.11	-0.13	-0.06	0.08	0.14	1	
$F0$	-0.16	-0.10	-0.13	-0.07	0.05	0.13	0.85	1

3.7 Empirical results

3.7.1 Regime analysis

Table 3.5 reports the estimation results obtained using a three-regime Markov switching model for the monthly series of the average CDS-bond basis. We report the mean and standard deviation of the basis in each regime, along with the conditional probabilities of switching from one regime to another. All estimated values are highly

Table 3.3: Results of the principal component analysis for the liquidity measures
This table provides the PCA loadings for each of the eight corporate bond liquidity measures and the cumulative explanatory contribution of the components. The measures are computed daily for the period 02/01/2006 to 30/09/2014. The bond transaction data is obtained from TRACE and bond information from FISD.

	$PC1$	$PC2$	$PC3$	$PC4$	$PC5$	$PC6$	$PC7$	$PC8$
AMI	0.41	0.09	0.41	0.24	0.49	0.27	-0.51	0.02
σ_{AMI}	0.42	0.17	-0.02	-0.46	0.50	-0.12	0.55	0.12
IRC	0.37	0.01	0.03	0.75	-0.18	-0.13	0.46	0.01
σ_{IRC}	0.44	0.19	-0.28	-0.11	-0.23	-0.63	-0.45	-0.01
ROL	0.37	0.26	-0.36	-0.16	-0.38	0.69	-0.02	-0.03
BHT	0.08	0.21	0.78	-0.28	-0.49	-0.06	0.09	-0.01
$B0$	-0.26	0.63	-0.05	0.09	0.07	-0.01	-0.01	0.70
$F0$	-0.27	0.63	-0.02	0.11	0.12	-0.04	-0.01	-0.70
Cum. explained	30%	51%	64%	75%	84%	91%	97%	100%

significant. Figure 3-1 shows the monthly evolution of the basis over time, simultaneously with the endogenously defined basis Markov switching regimes, the crisis sub-periods and the Lehman bankruptcy date.

According to our results in table 3.5 and figure 3-1, the third regime, where the basis' variability and mean (in absolute value) are the highest, starts in the middle of the period that is commonly associated with the financial crisis which reflects the absence of a basis regimes' predictive power on crisis. It is worth noting that this regime starts a few months before the peak of the crisis, corresponding to the Lehman Brothers bankruptcy, and lasts until almost one year after the official date associated with the end of the crisis, indicating the presence of a persistence aspect in basis regimes.

The first regime, identified with a slightly negative mean (-5.24 bps) and a low standard deviation (0.21 bps), spreads over the pre-crisis period and lasts until the first months of the crisis, confirming the non-predictive power on crisis of the basis regimes.

A second regime is identified by a significantly negative basis mean of -33.09 bps

Table 3.4: Correlation matrix of the negative basis arbitrage risk factors

This table is the correlation matrix of arbitrage risk factor variables for three distinct sub-periods. Panel A pertains to the pre-crisis period (02/01/2006 to 30/06/2007), Panel B to the crisis period (01/07/2007 to 31/03/2009), and Panel C to the post crisis period (01/04/2009 to 30/09/2014).

Panel A: Pre-crisis							
	ILB	β_{ILB}	ILC	β_{CNT}	β_{LIB}	β_{REP}	RAT
ILB	1.0000						
β_{LIB}	0.1478	1.0000					
ILC	0.0494	0.0558	1.000				
β_{CNT}	-0.0095	-0.1254	-0.3562	1.0000			
β_{LIB}	0.1121	-0.0039	0.1133	-0.0035	1.0000		
β_{REP}	-0.0934	0.0353	-0.1459	0.0205	-0.8784	1.0000	
RAT	0.0225	0.0963	0.6228	-0.5554	0.2140	-0.2135	1.0000
Panel B: Crisis							
	ILB	β_{ILB}	ILC	β_{CNT}	β_{LIB}	β_{REP}	RAT
ILB	1.0000						
β_{LIB}	0.3245	1.0000					
ILC	0.1139	0.0478	1.0000				
β_{CNT}	0.2172	0.3776	-0.0138	1.0000			
β_{LIB}	-0.1296	-0.1716	-0.1120	-0.1582	1.0000		
β_{REP}	0.0596	0.0825	0.0607	0.0311	-0.8710	1.0000	
RAT	0.0627	-0.0841	0.2014	-0.4027	-0.1719	0.1371	1.0000
Panel C: Post-crisis							
	ILB	β_{ILB}	ILC	β_{CNT}	β_{LIB}	β_{REP}	RAT
ILB	1.0000						
β_{LIB}	0.2735	1.0000					
ILC	0.0352	-0.0099	1.0000				
β_{CNT}	0.0817	0.2241	-0.0152	1.0000			
β_{LIB}	-0.1433	-0.1185	-0.0042	-0.0482	1.0000		
β_{REP}	-0.2449	-0.2216	-0.0212	-0.1410	0.2973	1.0000	
RAT	0.1712	0.0190		-0.0557	-0.0811	-0.2097	1.0000

with a relatively low standard deviation of 1.52 bps. Surprisingly, the post-crisis period, expected to be a return-to-normal period, shares the same regime as the tumultuous first months of the crisis, which is the second regime.

According to these observations, we first detect a persistence aspect of basis regimes toward crisis while the predictive power is absent. More importantly, the persistent departure from equilibrium in the post-crisis period is confirmed by the endogenous basis dynamics.

Table 3.5: Basis regimes parameters

The first panel provides the basis regimes parameters. We report the mean and standard deviation of the basis, along with their p-values in each regime. The second panel provides the conditional probabilities $p_{ij}$of the process switching from Regime R_i to Regime R_j.

	R1	R2	R3
Mean	-5.24	-33.09	-219.39
p-value	0.00	0.00	0.00
Standard dev.	0.21	1.52	123.79
p-value	0.00	0.00	0.00

	R1	R2	R3
R1	0.84	0.01	0.16
R2	0.16	0.96	0.00
R3	0.00	0.03	0.84
Log Likelihood : -446.71			

Figure 3-1: Basis regimes, crisis sub-periods and Lehman Brothers collapse date

The figure plots the monthly average basis, the three regimes identified by the Markov regime-switching Model, the crisis sub-periods and the Lehman Brothers bankruptcy date.

3.7.2 Basis cross-sectional variation

Results of the multivariate Fama-Macbeth regression of the basis on arbitrage risk measures, during pre-crisis, crisis and post crisis periods, are summarized in Table 3.6.

The first factor of interest is bond illiquidity. As expected, the coefficient of the bond illiquidity variable ILB is significantly negative across the three sub-periods. The highest impact of ILB on the basis is observed during the crisis sub-period, where the liquidity constraints in the corporate bond market were particularly severe (Dick-Nielsen, Feldhutter and Lando 2012). It is worth noting that the impact of the ILB decreases after the crisis, but remains significantly higher than in the pre-crisis sub-period. There is a growing and controversial literature arguing that regulatory changes following the financial crisis had an adverse impact on bond market liquidity (Anderson and Stulz 2017, Bao et al. 2018), which, according to our results, further affects the negativity of the basis.

To check that our bond illiquidity factor summarizes the best the pertinent information in the eight illiquidity proxies, we conduct the same previous regression and add one of the illiquidity proxies not included in the illiquidity factor, the bond holding time (BHT), to check for better or different results. When we compare the obtained results, available in Appendix 3.10., to the ones of the table 3.6, we notice that the addition of the BHT variable as a bond illiquidity proxy does not ameliorate the results: BHT coefficient is not significant, the remaining variables coefficients' are unchanged and the R^2 does not ameliorate.

A second risk factor is CDS illiquidity, as measured by the variable ILC. We find that CDS illiquidity also plays an important role in explaining variations in the negative basis. The coefficient of ILC is significantly negative in all sub-periods, indicating that the difficulty of executing negative-basis arbitrage trades when the CDS market is not liquid enough is a significant arbirage-risk factor.

Our counterparty risk variable β_{CNT} reflects the risk of a simultaneous default of a reference entity and its protection seller. The coefficient of β_{CNT} has the expected negative sign in all sub-periods. Interestingly, the impact of this variable is significantly smaller in the pre-crisis period. CDS sellers are large financial institutions with a well established reputation. Before the crisis, there was a general belief that these institutions were too solid to default. Arbitrageurs trusted them and, consequently, did not attribute much importance to their default risk, which was perceived to be improbable. This could explain the value of the coefficient of β_{CNT} in the pre-crisis period. However, during the crisis, firms that were believed to be "too big to fail" (e.g. Lehman Brothers) went bankrupt. Investors then became more aware of the importance of counterparty-default risk, even when large institutions are involved. This is reflected in a considerable increase in the coefficient of β_{CNT} during the crisis period. Our results indicate that this loss of confidence persists during the post-crisis period, as reflected by a significantly negative coefficient, which is not as high as for the crisis period sample, but higher than its pre-crisis level.

Funding risk is captured by three variables: the first two variables, β_{LIB} and β_{REP}, are related to the co-movements of the basis with funding conditions on the interbank and repo markets respectively, while the third, RAT, is an indicator of the quality of the bond used as collateral. When the basis diverges, the arbitrageur faces additional costs (marking to market, margin calls...), which he finances with borrowed money. If this basis deterioration occurs simultaneously with a restriction on funding, arbitrage return decreases significantly. As a consequence, when basis variations are highly correlated with funding conditions, arbitrage trade becomes riskier, which may discourage arbitrageurs from investing in this activity. Our results indicate that the interbank funding risk (β_{LIB}) has a negative impact on the basis during the post-crisis period while the repo funding risk (β_{CNT}) has a negative impact during the crisis period, that is when capital became scarce and expensive (Gorton and Metrick 2012). Finally, the variable RAT, used as a proxy for collateral quality, has the expected significantly negative impact in all sub-periods. The cost and the possibility to fund an arbitrage trade are closely related to the bond's collateral worthiness in the repo market. A worse collateral quality results in a higher repo rate and a larger haircut which substantially increase the trade costs. Like for most variables, the impact of RAT on the negative basis is highest during the crisis period. Moreover, Gorton and Metrick (2012) document that repo haircuts increased dramatically during the financial crisis, to reach 50% in late 2008, where many assets were no more accepted as collaterals.

To conclude, our multivariate regressions explains a considerable part of the negative basis cross-sectional variation, with a R^2 reaching 55%, and with most variables significant and having the expected impact in the three sub-periods. During the crisis period, the explanatory power is 47%, compared to 31% for the same period in Bai and Collin-Dufresne (2014). Moreover, our model also performs well during the post-crisis period, with a R^2 of 38% and most variables significant with the intended impact.

As a robustness check, Table 3.7 reports on the result of the multivariate Fama-Macbeth regression (3.1) performed on different sub-samples, constructed on the basis of the periods corresponding with the three endogenous Markov switching regimes identified in Section 3.7.1.

Examination of Table 3.7 shows that the regression results are very similar to those obtained in Table 3.6. Indeed, during the various regime periods, all the main risk factors coefficients' are significant with the expected sign. More importantly, we find that the impact of these factors on the basis is most pronounced during the tumultuous episode corresponding to the third regime. During the second regime, which coincides with the first months of the crisis and the post-crisis period, risk factors effects have decreased, but remain higher than their impact during the first regime period, which corresponds mainly to the pre-crisis period.

Table 3.6: Multivariate Fama-MacBeth regression for the whole sample during pre-crisis, crisis and post-crisis periods.

This table provides the results of the multivariate cross-sectional Fama-Macbeth regressions of the negative CDS-bond basis on bond and CDS illiquidity, counterparty, and funding risk factors. We report the mean coefficients, standard errors and R-squared values. Results are provided for three different periods: pre-crisis (02/01/2006 to 30/06/2007), crisis (01/07/2007 to 31/03/2009) and post-crisis (01/04/2009 to 30/09/2014). The cross sectional regressions run at daily frequency. *,** and *** denote significance at the 10%, 5% and 1% levels respectively.

Variable	Pre-crisis 02/01/2006-30/06/2007	Crisis 01/07/2007-31/03/2009	Post-crisis 01/04/2009-30/09/2014
ILB	-1.38^{***}	-6.12^{***}	-2.27^{***}
	(0.12)	(0.92)	(0.26)
β_{ILB}	-0.55^{***}	-0.68	2.80^{***}
	(0.20)	(1.81)	(0.70)
ILC	-0.12^{***}	-0.05^{***}	-0.08^{***}
	(0.02)	(0.02)	(0.01)
β_{CNT}	-4.10^{***}	-68.90^{***}	-9.83^{***}
	(0.74)	(12.55)	(2.02)
β_{LIB}	0.24^{***}	0.08^{***}	-0.02^{***}
	(0.07)	(0.03)	(0.01)
β_{REP}	0.20^{***}	-0.10^{**}	0.01^{***}
	(0.05)	(0.05)	(0.01)
RAT	-1.23^{***}	-14.60^{***}	-9.24^{***}
	(0.14)	(2.20)	(0.67)
Constant	4.20^{**}	90.72^{***}	36.78^{***}
	(0.14)	(18.19)	(5.32)
R^2	0.55	0.48	0.38

Table 3.7: Multivariate Fama-MacBeth regression for the whole sample during basis endogenous regimes.

This table provides the results of the multivariate cross-sectional Fama-Macbeth regressions of the negative CDS-bond basis on bond and CDS illiquidity, counterparty, and funding risk factors. We report the mean coefficients, standard errors and R-squared values. Results are provided for three different periods that corresponds to the three endogenous basis regimes: Regime 1 (02/01/2006 to 31/10/2007), Regime 2 (01/11/2007 to 06/31/2008 & 16/12/2009 to 30/9/2014) and Regime 3 (011/08/2008 to 15/12/2009). The cross sectional regressions run at daily frequency. *,** and *** denote significance at the 10%, 5% and 1% levels respectively.

Variable	Regime 1 02/01/2006-30/06/2007	Regime 3 01/11/2007-06/31/2008 & 16/12/2009-30/9/2014	Regime 2 01/04/2009-30/09/2014
ILB	-1.48^{***}	-9.82^{***}	-1.63^{***}
	(0.11)	(0.51)	(0.07)
β_{ILB}	-0.42^{**}	-1.35	2.88^{***}
	(0.20)	(2.09)	(0.26)
ILC	-0.10^{***}	-0.07^{***}	-0.08^{***}
	(0.02)	(0.01)	(0.01)
β_{CNT}	-3.90^{***}	-98.38^{***}	-6.91^{***}
	(0.63)	(5.12)	(0.57)
β_{LIB}	0.19^{***}	0.06^{***}	-0.01^{***}
	(0.06)	(0.01)	(0.01)
β_{REP}	0.16^{***}	-0.13^{**}	0.02^{***}
	(0.04)	(0.02)	(0.01)
RAT	-1.54^{***}	-25.78^{***}	-7.20^{***}
	(0.16)	(1.04)	(0.09)
Constant	3.54^{**}	169.41^{***}	23.08^{***}
	(1.44)	(9.39)	(0.71)
R^2	0.55	0.51	0.38

3.7.3 Residual and predicted basis analysis

We now divide the basis variable observations into two components, on the basis of the results of the regression 3.1. The residual basis (RB) is identified with pure arbitrage profit, while the predicted basis (PB) evaluates basis-arbitrage risks. Table 3.8 reports on the summary statistics pertaining to variables RB and PB over the entire study period. These results show that a large portion of the basis variation is explained by the various arbitrage-risk factors, so that the standard deviation of the residual basis is very small.

In the next two sections, we report on the results of our analysis of these two variables in order to test assumptions supporting the argument that the persistence of a negative basis after the crisis is caused by a defection of the arbitrage mechanism.

Table 3.8: Summary statistics of predicted and residual basis.
This table provides summary statistics for the CDS-bond basis, predicted basis and residual basis in basis points for the period from 02/01/2006 to 30/09/2014. The predicted basis PB is the portion of the basis explained by the arbitrage risk factors using the regression equation 3.1. The residual basis RB is the remaining portion of the basis.

	mean	std. dev.	min	max
Basis	-82.52	80.93	-780.90	-7.21
PB	-82.52	80.93	-780.91	-7.21
RB	0.00	0.01	-0.14	0.53

3.7.3.1 Impact of the basis arbitrage activity on the bonds' purchase volume

Our first empirical analysis focuses on the impact that the arbitrage activity should have on transactions volumes with respect to the passive buy-and-hold bond market. We want to show that, after the crisis, an increase in the arbitrage pure potential gain, proxied by the residual basis, does not not lead to an increase in the volume of bond trades, which is the same as saying that the coeffcient γ_1 in the regression 3.2 is not significant during the post crisis period. This result would indicate that arbitrage activity is weak after the crisis.

As a first illustration, in each sub-period, we partition the data sample into four subsets according to the size of the residual basis and compute the corresponding traded volume, in order to check whether a sub-sample with higher (*resp. lower*) residual basis also presents higher (*resp. lower*) transaction volume. The results are presented in table 3.9, where a clear relationship between the residual basis and the traded volume is only observed during the pre-crisis period.

The results of the regression 3.2 performed to formally check Assumption 1 are presented in Table 3.10. We find that the coefficient γ_1 in Equation 3.2 is positive and significant in the pre-crisis period: a larger potential gain encourages arbitrageurs to invest and leads to an increase in bond purchases. This result confirms a well-established relation between arbitrage trades and the bond market before the crisis, in the sense that arbitrage activity is well reflected in bond positions, and that a more appealing negative basis trade results in an increase of traded bond amounts.

However, we find that the coefficient γ_1 in Equation 3.2 is not significantly different from 0 during the crisis. Indeed, during this period, market conditions were difficult, with rare and expensive funding sources, liquidity problems and high counterparty risk, which prevented arbitrageurs from investing in negative-basis trades. This disruption in basis arbitraging activity is well captured by our regression.

Finally, we focus on the post-crisis period, comparing the results with those of the pre-crisis period. Since market conditions improved after the crisis, we expect the arbitrage activity to resume and results to be comparable to those obtained for the pre-crisis period. This is however not the case, and the coefficient γ_1 is not significant in the post-crisis sample: an increase in potential profit, proxied by the residual basis, does not result in an increase of bond traded volume, indicating that the arbitrage trade activity decreased during the post-crisis period.

Table 3.9: Bonds purchased volumes grouped according to the value of the residual basis.
This table provides the mean volume of purchased bonds for each of four different observation sets. Portfolios 1 to 4 pool the bonds according to the value of the residual basis. Results are provided for three periods: pre-crisis (02/01/2006 to 30/06/2007), crisis (01/07/2007 to 31/03/2009) and post-crisis (01/04/2009 to 30/09/2014). Transaction data is obtained from TRACE.

	Pre-crisis 02/01/2006-30/06/2007	Crisis 01/07/2007-31/03/2009	Post-crisis 01/04/2009-30/09/2014
Portfolio 1 (lowest RB)	1 384 410	1 906 511	1 415 079
Portfolio 2	1 648 443	1 664 319	1 374 388
Portfolio 3	1 730 442	1 440 176	1 389 248
Portfolio 4 (highest RB)	1 810 907	1 482 073	1 556 415

3.7.3.2 Impact of the basis arbitrage activity on the bonds' return

Our second argument is that arbitrage risk factors, which used to have an impact on bond prices through an arbitrage channel (Kim, Li and Zhang 2017), are no longer relevant. The results of the regression 3.3 used to formally test Assumption 2 are summarized in Table 3.11.

We find that the impact of the predicted basis is significantly negative in the pre-crisis period. This result matches that of Kim, Li and Zhang (2017) and confirms their conclusion according to which arbitrage risks, as measured by the predicted basis, can predict future bond returns. A negative impact means that a more negative predicted basis, indicating a riskier arbitrage trade, leads to higher compensation through higher future bond returns. These results show that arbitrage risks do affect the bond market and that part of the arbitrage-risk premium is transferred to bond prices.

However, this is no longer the case during the post-crisis period. The predicted

Table 3.10: Regression of purchased bond volumes on the residual basis.

This table reports the results of the daily cross-sectional regressions of the bond's purchased volume on the residual basis and a set of control variables. The residual basis is the portion that is unexplained by the arbitrage risk factors in Equation 3.1. Control variables are: the bond's lagged volume, age, amount outstanding, Moody's rating (RAT) and illiquidity factor (ILB). Results are provided for three periods: pre-crisis (02/01/2006 to 30/06/2007), crisis (01/07/2007 to 31/03/2009) and post- crisis (01/04/2009 to 30/09/2014). *,** and *** denote significance at the 10%, 5% and 1% levels respectively.

Variable	Pre-crisis 02/01/2006-30/06/2007	Crisis 01/07/2007-31/03/2009	Post-crisis 01/04/2009-30/09/2014
Residual basis	0.60^{**}	-0.10	-0.00
	(0.23)	(0.08)	(0.01)
Lagged volume	0.10^{***}	0.12^{***}	0.14^{***}
	(0.02)	(0.01)	(0.00)
Age	-0.31^{***}	-0.34^{***}	-0.20^{***}
	(0.04)	(0.03)	(0.01)
Amount outstanding	0.93^{***}	1.37^{***}	1.12^{***}
	(0.07)	(0.07)	(0.02)
ILB	-0.11^{***}	-0.08^{***}	-0.10^{***}
	(0.01)	(0.00)	(0.00)
RAT	0.16^{***}	0.14^{***}	0.15^{***}
	(0.01)	(0.00)	(0.00)
Constant	-0.15	-0.30	-0.94
	(0.16)	(0.12)	(0.04)
R^2	0.19	0.16	0.15

basis coeffcient γ_1 in Equation 3.3 is not significant. This means that risks involved in the arbitrage trade does not predict bond returns during the post-crisis period. This indicates that arbitrage activity is not as important as it used to be in the pre-crisis period. Indeed, if it were the case, the arbitraging channel would transmit basis risks into bond prices and the coefficient would be significant. Kim, Li, Zhang (2017) adopt the same reasoning to explain the non-significant results for HY bonds that were not very popular among basis-arbitrageurs.

Empirical evidence supports our hypothesis of a decrease in arbitrage activity following the financial crisis of 2008, by showing that arbitrage forces are no longer affecting the transaction volumes and the pricing mechanism in the corporate bond market. Consequently, when investors are no more interested in the negative-basis trading, it is not surprising for the negative basis not to revert to its fundamental value. Indeed, the correction mechanism is mainly conducted by arbitraging forces.

3.7.3.3 Impact of the basis arbitrage activity on the bond market during the regulation era

As seen in the two preceding sections, empirical results show a defection in the arbitrage mechanism during the post-crisis period. We now investigate whether this defection can be attributed to changes in the regulatory environment, namely to the reforms advocated in the Dodd-Frank Act and in the Basel III accord. We do so by examining the impact of the residual basis and of the predicted basis on the bond purchased volumes and on bond returns in the post-crisis period, divided into three sub-periods: before the reforms, after the Dodd-Frank Act signature, and after the implementation of Basel III.

Tables 3.12 and 3.13 report on the regression results. Interestingly, the coefficients of the residual and of the predicted basis are both significant with the expected sign in the post-crisis, but pre-reforms period. This result indicates that the relation between arbitrage trades and the corporate bond market trading volume and returns

Table 3.11: Regression of bond returns on predicted basis

This table reports the results of the daily cross-sectional regressions of the future bond returns over a 20-day horizon, on the predicted basis and a set of control variables. The predicted basis is the portion of the basis explained by the arbitrage risk factors in Equation (3.1). Control variables are the bond's Moody's rating (RAT), age, annual coupon, issuance amount and illiquidity factor (ILB). Results are provided for three periods: pre-crisis (from 02/01/2006 to 30/06/2007), crisis (from 01/07/2007 to 31/03/2009) and post-crisis (from 01/04/2009 to 30/09/2014). *,**,*** denote significance at the 10%, 5% and 1% levels respectively.

Variable	Pre-crisis 02/01/2006-30/06/2007	Crisis 01/07/2007-31/03/2009	Post-crisis 01/04/2009-30/09/2014
Predicted basis	-0.96^{***}	0.34	-0.09
	(0.26)	(0.29)	(0.16)
RAT	0.08	-3.56	5.71^{***}
	(0.85)	(2.94)	(0.85)
Age	0.02	-0.09^{**}	-0.00
	(0.03)	(0.04)	(0.00)
Coupon	-0.33	1.2^{***}	-0.20^{***}
	(0.21)	(0.43)	(0.08)
Issuance_amount	-0.02	-0.08^{*}	0.06^{***}
	(0.02)	(0.04)	(0.01)
ILB	3.72^{***}	4.09^{***}	4.90^{***}
	(1.08)	(1.49)	(0.43)
Constant	0.78	0.35	0.23^{***}
	(0.11)	(0.27)	(0.07)
R^2	0.27	0.24	0.16

rallied after the end of the financial crisis, suggesting that arbitrage activity did resume and impact the cash market. However, this relation is no longer detectable in the post-Dodd Frank Act period nor in the post- Basel III period. One plausible conclusion is that, following a relative return to normal at the end of the financial crisis, the arbitrage mechanism became dysfunctional starting from the Dodd-Frank act reform date.

Table 3.12: Regression of purchased bond volumes on the residual basis during the post-crisis period.
This table reports on the results of the daily cross-sectional regressions of the bond purchase volume on the residual basis and a set of control variables. The residual basis RB is the portion that is unexplained by the arbitrage risk factors in Equation 3.1. Control variables are: the bond's lagged volume, age, amount outstanding, Moody's rating (RAT) and illiquidity factor (ILB). Results are provided for three periods: after the crisis but before the Dodd-Frank act signature (01/04/2009 to 20/07/2010), after the Dodd-Frank act signature (21/07/2010 to 30/06/2014), and after the Basel III reform (01/07/2013 to 09/30/2014). *,** and *** denote significance at the 10%, 5% and 1% levels respectively.

Variable	Before Dodd-Frank 01/04/2009-20/07/2010	After Dodd-Frank 21/07/2010-30/06/2013	After Basel III 01/07/2013-30/09/2014
Residual basis	0.10**	0.05	−0.02
	(0.03)	(0.03)	(0.05)
Lagged volume	0.15***	0.13***	0.13***
	(0.01)	(0.01)	(0.01)
Age	−0.19***	−0.21***	−0.21***
	(0.01)	(0.02)	(0.14)
Amount outstanding	1.53***	1.02***	0.94***
	(0.06)	(0.04)	(0.04)
ILB	−0.11***	−0.11***	−0.09***
	(0.01)	(0.00)	(0.00)
RAT	0.19***	0.14***	0.12***
	(0.09)	(0.00)	(0.00)
Constant	-1.24***	-0.89***	-0.71***
	(0.16)	(0.12)	(0.08)
R^2	0.17	0.14	0.12

Table 3.13: Regression of bond returns on predicted basis during the post-crisis period.

This table reports on the results of the daily cross-sectional regressions of the future bond returns over a 20-day horizon, on the predicted basis and a set of control variables. The predicted basis PB is the portion of the basis explained by the arbitrage risk factors in Equation (3.1). Control variables are the bond's Moody's rating (RAT), age, annual coupon, issuance amount and illiquidity factor (ILB). Results are provided for three periods: after the crisis but before the Dodd-Frank act signature (01/04/2009 to 20/07/2010), after the Dodd-Frank act signature (21/07/2010 to 30/06/2014), and after the Basel III reform (01/07/2013 to 09/30/2014). *,** and *** denote significance at the 10%, 5% and 1% levels respectively.

Variable	Before Dodd-Frank 01/04/2009-20/07/2010	After Dodd-Frank 21/07/2010-30/06/2013	After Basel III 01/07/2013-30/09/2014
Predicted basis	-0.71^{***}	0.20	-0.07
	(0.13)	(0.17)	(1.26)
RAT	5.53^{**}	-7.32^{***}	1.50
	(2.70)	(1.69)	(0.95)
Age	0.03	-0.02	-0.01
	(0.02)	(0.01)	(1.17)
Coupon	-0.51^{*}	0.09	-0.08
	(0.27)	(0.11)	(0.05)
Issuance_amount	-0.09	-0.06^{*}	0.02^{***}
	(0.03)	(0.04)	(0.01)
ILB	5.12^{***}	4.46^{***}	6.03^{***}
	(1.14)	(0.90)	(0.56)
Constant	0.44^{***}	0.06	0.39^{***}
	(0.21)	(0.15)	(0.07)
R^2	0.21	0.15	0.12

3.8 Conclusion

This chapter analyzes the behavior of the CDS-bond basis over a time period encompassing three distincts epochs: before, during, and after the last financial crisis, with the aim of explaining the basis cross-sectional variation and the persistent negativity of the post-crisis basis.

We first show that the evolution of the basis over time allows to identify three distinct regimes. We find that the post-crisis basis level and variability significantly differ from the corresponding values before the financial crisis, and that the regime of the post-crisis basis is the same as the regime prevailing during the first months of the financial crisis.

We then focus on exploring the cross-sectional variation of the CDS bond basis, with the aim of identifying the portion of the basis that represents pure arbitrage profit. In order to do so, we consider the different risk factors to which are exposed arbitrageurs involved in a negative-basis arbitrage trade as explanatory variables. The way we express risk sources allows our model to be remarkably performant compared to the existing literature and to explain a large part of the basis cross-sectional variation. We are able to show that, in all periods and not only during the financial crisis, a significant portion of the basis consists of a compensation for the exposure to arbitrage risks.

Finally, we argue that the puzzling persistence of a negative basis after the crisis is caused by a dysfunction in the correction mechanism of the market, namely the negative-basis arbitrage activity. We circumvent the problem of the arbitrage being unobservable and unmeasurable and use an indirect approach to empirically document the decrease in arbitrage activity by tracing its impact on the bond market. We find that the relation between arbitrage profitability and bond purchases, and between arbitrage risks and bond prices, is no longer significant in the post-crisis period. This empirical evidence points to a dysfunctional arbitrage activity, which should be the correcting force in the market, causing a constant disequilibrium situation between CDS and bond spreads.

3.9 Appendix 1

Illiquidity measures

1. Amihud measure (AMI): Defined as the ratio of the absolute average daily return over the daily trading volume, this variable characterizes the daily price impact of bond trades, that is, how much prices move following a given trade volume. The Amihud measure increases with the sensitivity of prices to transaction volumes, and is an indication of illiquidity. The Amihud measure for a reference entity i at date t is computed by

$$A_{it} = \frac{1}{N_{it}} \sum_{j=1}^{N_{it}} \frac{1}{Q_{jt}^{i}} \frac{\left|P_{jt}^{i} - P_{j-1,t}^{i}\right|}{P_{j-1,t}^{i}}$$

   where N_{it} is the number of transactions on date t and Q_{jt}^{i} and P_{jt}^{i} are, respectively, the volume and price of transaction $j = 1, ..., N_{it}$. Liquidity increases with transaction numbers and volumes, and decreases with price differentials.

2. Imputed Roudtrip Cost (IRC): This measure, proposed by Feldhütter (2012), is computed by

$$IRC = \frac{P_{Max} - P_{Min}}{P_{Max}}$$

   where P_{Max} and P_{Min} are the maximum and minimum prices of an *Imputed Roundtrip Trade*, observed when, on a given day, a bond trades two or three times with the same volume. This is likely to be a trade between a buyer, a seller and a dealer, so that the difference between the minimum and maximum prices reflects the bid-ask spread.

3. Amihud variability (σ_{AMI}): the standard deviation of daily Amihud illiquidity

measure over a 21-day moving window. The variability of a bond illiquidity measure gives an indication of the range of its possible future levels.

4. IRC variability (σ_{IRC}): the standard deviation of daily IRC over a 21-day moving window.

5. Roll measure (ROL): As shown by Roll (1984), under certain assumptions, it is possible to infer bond's bid-ask spread from consecutive transaction prices, according to the following formula:

$$R_{it} = 2\sqrt{-cov\left(\Delta P_{it}, \Delta P_{i,t-1}\right)}$$

   where ΔP_{it} is a series of differences between transaction prices. The Roll measure is computed on a daily basis using a 21-day moving window, with at least four transactions in each window. The rationale behind this measure is that transaction prices alternate between bid and ask levels, so that a higher bid-ask spread leads to a higher (negative) covariance between successive prices.

6. Bond holding time (BHT): The average holding time of a bond can be expressed as the inverse of turnover, that is, the ratio of amount outstanding over total trading volume. The higher is the bond holding time, the more illiquid is the bond.

7. Bond zero-trading days ($B0$): This variable measures the proportion of days where the bond is not trading during a given period; here, it is computed over a rolling window of 21 days. A higher ratio reflects a more illiquid bond.

8. Firm zero-trading days ($F0$): This variable measures the proportion of days where none of the bonds issued by the firm trade during a given period (here, 21 days).

3.10 Appendix 2

Basis regression with BHT

Table 3.14: Multivariate Fama-MacBeth regression for the whole sample using the bond holding time illiquidity variable.
This table provides the results of the multivariate cross-sectional Fama-Macbeth regression of the negative CDS-bond basis on bond and CDS illiquidity, counterparty, and funding risk factors. In this table, bond illiquidity is measured using both: the illiquidity factor ILB and the bond holding time variable BHT. We report the mean coefficients, standard errors and R-squared values. The cross sectional regressions run at daily frequency. *,** and *** denote significance at the 10%, 5% and 1% levels respectively.

Variable	Pre-crisis 02/01/2006-30/06/2007	Crisis 01/07/2007-31/03/2009	Post-crisis 01/04/2009-30/09/2014
ILB	-1.38^{1***}	-6.09^{***}	-2.17^{***}
	(0.13)	(0.95)	(0.69)
β_{ILB}	-0.55^{***}	-0.81	2.80^{***}
	(0.20)	(1.81)	(1.18)
ILC	-0.13^{***}	-0.05^{***}	-0.08^{***}
	(0.02)	(0.02)	(0.02)
β_{CNT}	-4.13^{***}	-68.45^{***}	-10.16^{***}
	(0.71)	(12.41)	(2.02)
β_{LIB}	0.25^{***}	0.08^{***}	-0.02^{***}
	(0.06)	(0.02)	(0.00)
β_{REP}	0.20^{***}	-0.10**	0.01^{***}
	(0.04)	(0.04)	(0.00)
RAT	-1.23^{***}	-14.69^{***}	-9.24^{***}
	(0.14)	(2.20)	(0.67)
BHT	-0.70	1.46	-2.24*
	(0.40)	(1.41)	(1.24)
Constant	4.21**	90.72***	36.42***
	(0.16)	(18.19)	(12.74)
R^2	0.55	0.48	0.38

Chapter 4

Impact of Rating Changes on the CDS-bond Basis

4.1 Introduction

Credit rating agencies play a central role in financial markets as they provide a reliable evaluation of the creditworthiness of corporate and sovereign debtors and help alleviate information asymmetries between market participants. Investors such as bank, insurance companies, pension funds, etc. use credit ratings to understand risks associated with their investments, which enables them to make better hedging and investment decisions. Given that credit rating agencies are major sources of financial information, one might think that changes in credit ratings have a significant impact on the financial market and, particularly, on markets that are closely related to credit risk. The bond and the CDS markets are of the most important credit-sensitive markets.

The aim of this chapter is to fill a research gap by providing insights on how credit rating announcements affect the parity relation between the spreads of a CDS and that of the corresponding corporate bond. Chapter 3 suggested significant differences between corporate bond and CDS spreads, reflected by a negative basis, and showed that this gap has widened during the post-crisis regulation period. We now address three specific questions, related to the way these spreads reflect credit events:

Are responses of CDS and bond markets to the same credit event also different?

Is the CDS-bond relation altered following a rating announcement?

Is the impact of credit stress events on the basis more pronounced during the after-crisis regulation period compared to the pre-crisis period?

To answer these questions, in a first step, we employ an event study approach, namely, a matching portfolio methodology, which allows us to compare the behavior of a treatment group, that is, the upgraded or downgraded reference entities, to a control group in order to detect any abnormal changes around credit events. The control group contains reference entities that have the same rating as the firms in the treatment group but did not experience any rating change during the period around the treatment group's credit event. This approach is applied to bond prices, CDS spreads, and the CDS-bond basis. Results show that both markets react to credit changes, but exhibit different reactions to the same rating announcement. Indeed, we observe statistically significant abnormal basis around credit changes. We refine our analysis by investigating different rating classes during different sub-periods.

In a second step, we run a cross-sectional analysis to identify the main determinants of this abnormal behavior following rating events.

Finally, in the spirit of what was done in Bao, O'Hara and Zhou (2018), we use regressions to compare the impact of difficult conditions on the basis between the pre-crisis and the post crisis periods. Stress events are proxied by downgrades that move the reference entities from the investment grade to the high yield category.

Our chapter contributes to the literature in multiple ways. Many prior studies explored the relation between borrower credit quality and financial markets. We differ from these works in that we do not solely investigate the impact of credit changes on the CDS and bond markets separately, but also examine the difference between the two markets' reactions to rating announcements. To the best of our knowledge, we are the first to make such an investigation. In Norden and Weber (2004), one of the rare papers comparing the reaction of different markets around downgrades and upgrades (more precisely the CDS and stock markets), the authors mention the problem that "levels of bond and stock abnormal returns were not directly comparable." In our case, we are able to avoid this problem by using the CDS-bond basis, which allows us to compare the CDS and bond market behavior around credit events in an elegant, accurate and direct way. The CDS-bond basis is indeed the most reliable measure quantifying the relation between the two instruments and making incomparable quantities comparable.

In that sense, our contribution to the existing literature also contains a methodological aspect. We propose a different approach to explore the relative reactions to credit events of the bond market vis-à-vis the CDS market, which links our work to the research on market efficiency. Our work is also related to the literature aimed at improving our understanding of the corporate bond and CDS markets, and of the linkage between them. It also contributes to the literature exploring the informational content of rating change events and their impact on related financial markets.

Our research results are also useful to practitioners. Indeed, the fact that CDS and bond markets react differently to credit rating changes indicates an opportunity for arbitrageurs to exploit these price differentials. This is particularly interesting given our finding that negative-basis arbitrage is no longer an easy risk-free trade. Moreover, risk managers, who are always seeking to improve their early warning systems, could consider the basis' abnormal behavior as a signal and act earlier against negative rating announcements. In addition, our analysis can be useful for market participants managing portfolios sensitive to credit risk by enhancing their understanding of the way in which the bond spreads and CDS premia behave around credit rating changes and be able to mitigate the related risks.

The rest of this chapter is organized as follows. We start by an overview of the litterature pertaining to the impact of credit rating changes on financial markets. Section 4.3 describes the rating process and highlights the importance of credit rating agencies in the financial system. In section 4.4, we describe our data. Section 4.5 provides details on the empirical methodology used to explore the CDS, bond and basis reactions to rating announcements. Our results are discussed in Section 4.6. Section 4.7 is a conclusion.

4.2 Litterature review

There is an extensive literature exploring the impact of changes in borrower quality on financial markets. This literature is mainly focused on investigating reactions to rating announcements on the bond and stock markets.

Early studies report mixed evidence about market reactions to downgrades and/or upgrades. Wansley and Clauretie (1985) and Weinstein (1977), using monthly corporate bond data, are unable to detect significant reactions to positive and negative credit events. In contrast, Hite and Warga (1997) and Hand, Holthausen and Leftwich (1992) find evidence of significant price changes following downgrades, but not so for upgrades. According to Grier and Kartz (1976), significant changes are observed in the period following the event. Inconclusive results between first studies are mainly due to the unavailability, or poor quality, of bond data. Indeed, many of these initial credit-rating event studies used monthly, infrequent and sparse trading data.

The advent of TRACE (Trade Reporting and Compliance Engine) represented a revolution in the credit-rating events literature. TRACE provides daily and detailed transaction data covering a large part of the market activity. The availability of transaction data greatly improved the quality and reliability of the research on credit events (Bessembinder, Kahle and Xu 2009, Cho, Kim and Shin 2011, Chen, Lookman and Schürhoff 2014, May 2010, Marble 2011).

Several studies document significant negative reactions to downgrades in both the bond and stock markets (Griffin and Sanvicente 1982, Steiner and Heinke 2001, Gande and Parsley 2005, Bannier and Hirsch 2010, Gropp and Richards 2001, Cantor 2004). However, results pertaining to market reactions to positive credit events are mixed. Jorion, Liu, and Shi (2005) empirically show that upgrades have a significant impact on stock prices. On the other hand, other studies find that upgrades have either insignificant or weak impact (Dichev and Piotroski 2001, Goh and Ederington 1999, Kiesel and Schiereck 2015, Jorion and Zhang 2007).

Reactions to credit-rating events are not restricted to the event day, but can appear during the days prior to or following the downgrade or upgrade date. Again, mixed results are reported in the literature. Katz (1974) and Weinstein (1977) do not find anticipation of future rating events by the market. On the other hand, Holthausen and Leftwich (1986), Pinches and Singelton (1978), Hettenhouse and Sartoris (1976) and Crosta (2014) find that equity and bond markets do have early reactions to upgrades and downgrades. Steiner and Heinke (2001) provide evidence of overreaction directly after the event.

The literature investigating reactions to rating announcements in the bond and stock markets also proposes finer analyses, by distinguishing samples according to industries or to rating classes. For instance, Goh and Ederington (1999) and Hite and Warge (1997) find that downgrades to the high-yield category induce a larger reaction than other downgrades.

With the introduction of credit default swaps, the scope of the credit-rating literature widened to incorporate the reaction of the CDS market to rating announcements. Norden and Weber (2004) and Hull, Predescu and White (2004) were the first to investigate the relation between rating events and CDS spreads. They find that changes in the CDS premia occur in the days prior to the credit event, that is, the CDS market anticipates negative credit events. They do not find significant reactions on the announcement date, or during the following days. However, Daniels and Jensen (2005) and Micu, Remolona and Wooldridge (2006) find evidence of a lagged CDS market reaction, reporting that CDS abnormal values continue to be significant up to one month after the event date, indicating a lack of efficiency in the CDS market.

Another issue addressed in the literature is the asymmetric reaction to negative and positive news. Norden and Weber (2004) and Hull, Predescu and White (2004) find that the CDS market reacts significantly to downgrades, but do not find any significant reaction around upgrades. This finding was however revoked by later studies. Micu, Remolona and Wooldridge (2006) show that positive rating events result in abnormal CDS values. This result is confirmed by Galil and Soffer (2011) and Finnerty, Miller and Chen (2013), who showed that all credit events affect the CDS market, but that downgrades have a greater impact than upgrades. Wengner, Burghof and Schneider (2014) note that the reaction in the CDS market differs according to the industry.

Finally, another branch of the literature studies the divergence in reactions of different markets to the same event. Norden and Weber (2004) find that the CDS market reacts earlier than the stock market. Forte and Pena (2009) used a vector error correcting model to compare changes in bond, stock and CDS markets following rating announcements. They show that it is more frequent that the equity leads the CDS and bond markets and that the CDS market leads the bond market.

4.3 Credit ratings

A rating agency provides independent evaluations of the financial risk profile of borrowers, whether governments or corporations, and of the creditworthiness of specific debt issues. A corporate credit rating measures the ability of the issuer firm to honor the contractual principal and interest payments on its debt.

A company wishing to issue a debt security presents a formal request to the rating agency. A team of analysts is then assigned to the examination of the financial health of the issuer. In their evaluation, the analysts consider publicly available information as well as private and confidential information provided by the company's management. If the issuer is seeking for public financing, then the credit-rating agency publishes the assigned rating, whether the issuing firm agrees or not. For the rating to stay in line with the firm's situation, the credit-rating agency keeps monitoring the risk profile of the company; if an important change in the firm's credit risk is detected, the agency updates the rating of the debt security, to a higher or a lower level.

There are approximately two hundred credit-rating agencies, but the industry is mainly dominated by three large competitors (Moody's, Standard & Poor's and Fitch) that control roughly 95% of the rating business.[1]

For several decades, credit-rating agencies have been considered significant actors in the financial markets, where they play a central role. By providing an objective opinion about the creditworthiness of corporate debtors, rating agencies help reduce information asymmetry between investors and issuers. With the growth of financial markets, and given the large number of debt instruments, resorting to an independent entity to evaluate their credit-risk level has become essential. Moreover, the evaluation of these instruments being time consuming and requiring specific skills encourages investors to rely on credit rating agencies. Assigned ratings and their subsequent updates are commonly used in asset pricing and risk management. Credit ratings help investors to understand the inherent risks in their debt investments and provide them with an internationally accepted mean of comparison between issues (Finnerty, Miller, and Chen 2013, Boot, Milbourn, and Schmeits 2006, Bannier and Hirsch 2010). Credit ratings also affect the governments and corporates cost of borrowing money (Afonso, Gomes and Rother 2007); for instance, a downgrade pushes up the loans' interest rates, making the debt capital more expensive. Credit-rating agencies also help in maintaining financial stability, as financial institutions are compelled to hold provisions against positions that are considered risky by credit-rating

[1] U.S. CFR 2015 report.

agencies. These provisions act as a buffer against economic downturn. Institutional investors are also not allowed to hold instruments rated below the investment-grade threshold.

The importance of credit-rating agencies in the financial system made them heavily criticized during the 2008 financial crisis. Rating agencies were blamed for underestimating the risk associated with mortgage-backed securities that led to the meltdown of the real-estate market in the United States (Pagano and Volpin 2010), and for their overoptimistic rating of some financial institutions (for instance, Lehman Brothers, which was rated IG one day before its collapse). There were also concerns about potential conflict of interest between credit-rating agencies and debt issuers, as the major part of rating agencies' revenue comes from securities' issuers (Rafailov 2011), which could tempt rating agencies to overrate their clients.

The financial crisis has revealed clear shortcomings in the rating system and the calls for a regulation of the rating business were too loud to ignore. The response was the Dodd-Frank Act, which increases the legal liabilities of credit-rating agencies and gives more power to the Stock Exchange Commission (SEC) over them. Despite these shortcomings, empirical evidence shows that investors still rely on rating agencies, and that rating changes still affect market prices (Kiesel 2016).

4.4 Data and summary statistics

Rating change information, such as rating change dates and previous and new ratings, of the three most important credit rating agencies (Moody's, Standard & Poor's and Fitch) are provided by the FISD data set. Our database spans the time period from 1 January 2006 to 30 September 2014, divided into three sub-periods relatively to the 2008 financial crisis, pre-crisis (02/01/2006 to 30/06/2007), crisis (01/07/2007 to 31/03/2009) and post-crisis (01/04/2009 to 30/09/2014). It consists of 4565 downgrades (1785 by Moody's, 1659 by S&P and 1121 by Fitch) and 3234 upgrades (1182 by Moody's, 1281 by S&P and 771 by Fitch).

Figure 4-1 plots the annual evolution of rating announcements, distinguishing negative and positive changes. We observe that upgrades are usually less frequent that downgrades, more so during the financial crisis. This is one of the reasons why downgrading events have attracted more attention in the literature. Figure 4-2 and 4-3 shows the distribution of downgrading and upgrading events across rating classes. We observe that most of the rating change events are concentrated within the IG category, which accounts for 73% of all the downgrades and 55% of all the upgrades.

Tables 4.1 and 4.2 report on the distribution of our sample of downgrade and upgrade events respectively, according to credit-rating agency, calendar years, ratings, Fallen Angels, Rising Stars and to the "size" of the change. As expected, the financial crisis sub-period saw a greater number of downgrades, accounting for 45% of the whole sample downgrades. Most of the rating change events, whether they are upgrades or downgrades, consists of a single-grade move. Tables 4.1 and 4.2 also show that rating events that involve downgrades from investment to high-yield grade (Fallen Angels) are more frequent than upgrades to the investment-grade category (Rising Stars), which reflects the difficulty of achieving a positive cross over.

Figure 4-1: Annual evolution of rating events.

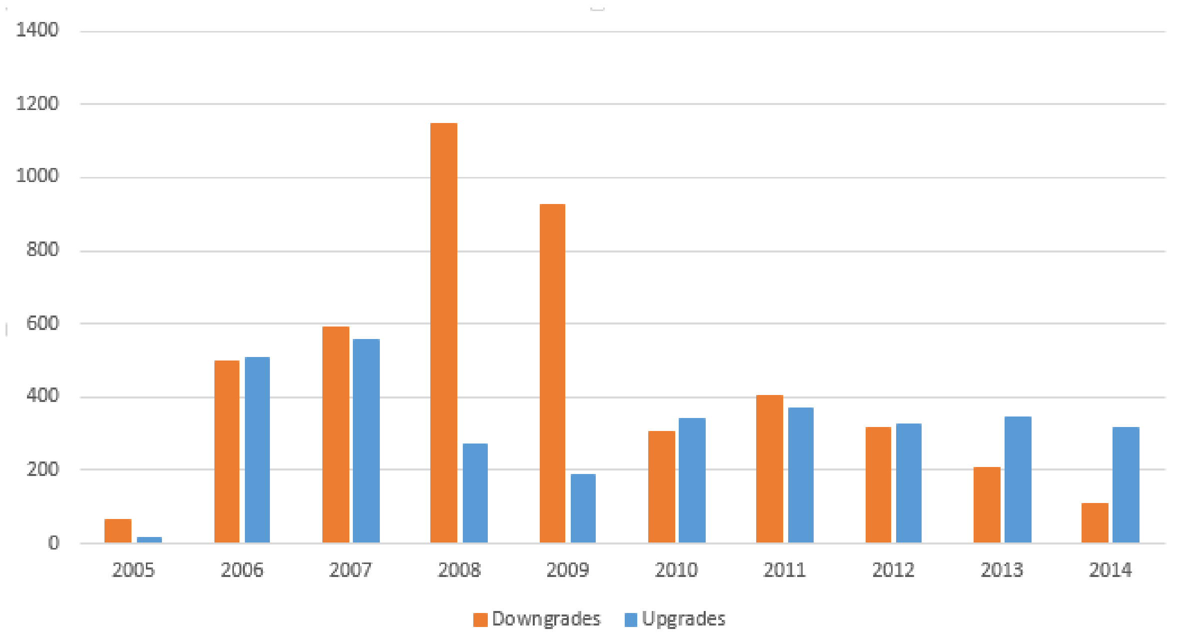


Figure 4-2: Number of downgrades by pre-downgrade rating class

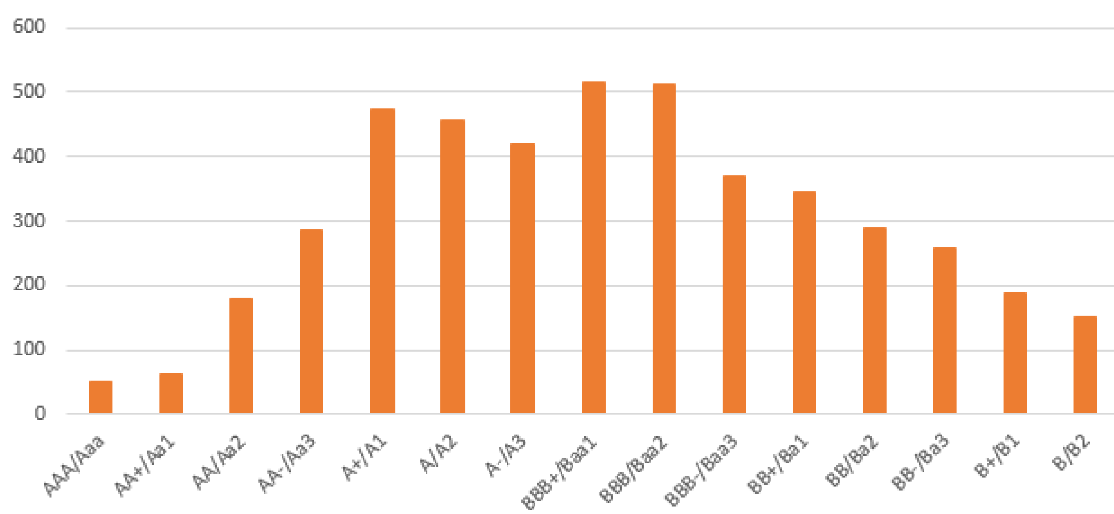


Table 4.1: Sample distribution of downgrades

This table shows the composition of our sample of 4565 downgrades by credit rating agency. Panel A reports the sample distribution by calendar year. Panel B reports the sample distribution by pre-downgrade rating class. Panel C reports the sample distibution by the size of the downgrade. Panel D reports the number of downgrades that keep the reference entity within the same rating category and the number of downgrades that move the reference entity from IG to HY category.

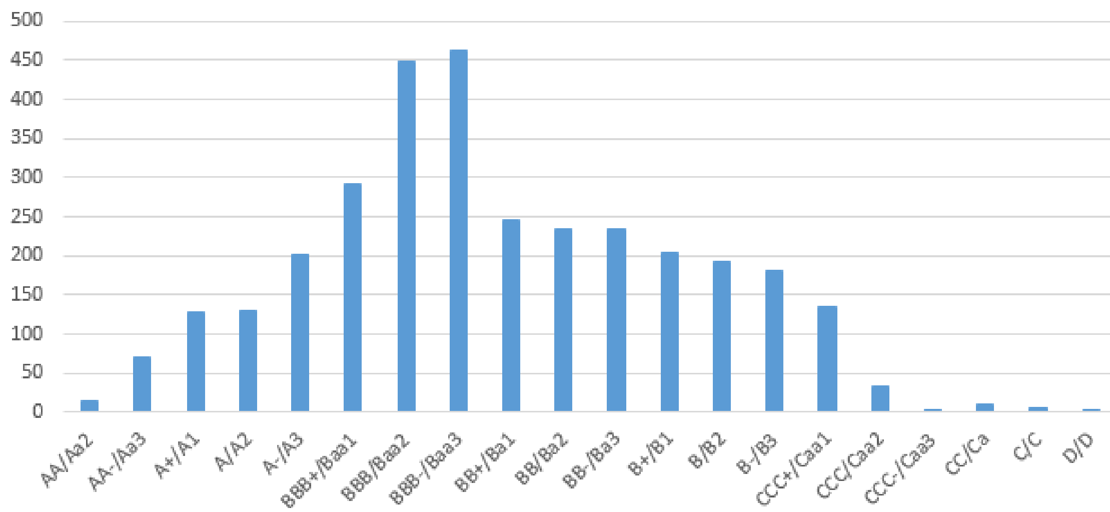
	All	Moody's	S&P	Fitch
Panel A: Sample distribution by calendar year				
2005	64	11	32	21
2006	498	219	188	91
2007	590	233	215	142
2008	1149	422	426	301
2009	925	420	275	230
2010	306	79	164	63
2011	406	100	164	142
2012	315	163	86	66
2013	205	116	58	31
2014	107	22	51	34
Total	4565	1785	1659	1121
Panel B: Sample distribution by pre-downgrade rating class				
AAA,Aaa	52	27	19	6
AA,Aa	531	221	185	125
A	1351	527	465	359
BBB,Baa	1398	485	515	398
BB,Ba	892	375	330	187
B	341	150	145	46
Panel C:Sample distribution by size of the downgrade				
1 grade	3497	1345	1291	861
2 grades	801	353	263	185
3 grades	150	42	55	53
4 grades	57	21	27	9
5 grades	42	13	30	9
$\geq$6grades	18	11	3	4
Panel D: Number of downgrades by credit rating grade				
Within the same rating category	4065	1605	1491	969
Fallen Angel	500	180	168	152

Table 4.2: Sample distribution of upgrades

This table shows the composition of our sample of 3234 upgrades by credit rating agency. Panel A reports the sample distribution by calendar year. Panel B reports the sample distribution by pre-upgrade rating class. Panel C reports the sample distibution by the size of the upgrade. Panel D reports the number of upgrades that keep the reference entity within the same rating category and the number of upgrades that move the reference entity from HY to IG category.

	All	Moody's	S&P	Fitch
Panel A: Sample distribution by calendar year				
2005	17	3	6	8
2006	506	204	203	99
2007	559	174	221	164
2008	272	63	14	64
2009	188	91	68	29
2010	339	141	112	86
2011	369	129	144	96
2012	324	133	104	87
2013	347	120	187	40
2014	313	124	91	98
Total	3234	1182	1281	771
Panel B: Sample distribution by pre-upgrade rating class				
AA,Aa	87	32	45	10
A	460	163	213	84
BBB,Baa	1203	422	467	314
BB,Ba	716	257	261	198
B	579	236	225	118
CCC,Caa	174	71	68	35
CC,Ca	11	1	1	9
C	6	0	0	6
D	1	0	1	0
Panel C:Sample distribution by size of the upgrade				
1 grade	2685	1007	1062	616
2 grades	402	134	170	98
3 grades	55	13	19	23
4 grades	26	10	3	13
5 grades	35	7	13	15
$\geq$6grades	31	11	14	6
Panel D: Number of upgrades by credit rating grade				
Within the same rating category	2909	1056	1176	677
Rising Star	325	126	105	94

Figure 4-3: Number of upgrades by pre-upgrade rating class



4.5 Methodology

4.5.1 Univariate analysis

We use an event study methodology in order to explore the impact of credit quality changes and more precisely upgrades and downgrades on our three variables of interest: Bond price, CDS spread and the CDS-bond basis. This is the most common approach to investigate the informational content of credit events and their effects on financial markets.

Many event study methodologies are available. We opt for the matching portfolio model, as in May (2010), Bessembinder, Kahle and Maxwell (2009), Ellul, Jotikasthira and Lundblad (2011) and others. This model has many advantages, as shown by Bessembinder et al. (2009), who compare various event-study models and conclude that this approach, combined with non-parametric statistics tests, dominates all other approaches.

In the subsequent description of our methodological approach, V_{it} designates the variable of interest (here, the bond price, the CDS spread or the CDS-bond basis) of an entity i on date t and $\overline{V}_t$ is the average value of the relevant variable in a control group, called the *reference portfolio*, at date t. The abnormal variable AV_{it} is defined as the difference between V_{it} and $\overline{V}_t$,

$$AV_{it} = V_{it} - \overline{V}_t.$$

For the analysis of the CDS-bond relation, we have

$$AB_{it} = B_{it} - \overline{B}_t,$$

where AB_{it}, B_{it} and $\overline{B}_t$ represent respectively the abnormal basis, the basis and the portfolio basis.

For the bond market analysis we have

$$AP_{it} = P_{it} - \overline{P}_t,$$

where AP_{it}, P_{it} and $\overline{P}_t$ represent respectively the abnormal bond price, the bond price and the the portfolio bond price.

For the CDS market analysis, the equation becomes

$$AS_{it} = S_{it} - \overline{S}_t,$$

where AS_{it}, S_{it} and $\overline{S}_t$ represent respectively the abnormal CDS spread, the CDS spread and the portfolio CDS spread.

Our matching criterion to determine the composition of the control group is based on seven rating classes designated by *AAA/Aaa, AA/Aa, A, BBB/Baa, BB/Ba, B* and *CCC/Caa* according to the rating agency. At a given date t, the reference portfolio is composed of firms belonging to the same rating class as the event firm but that did not experience any rating change during the period $t-30$ and $t+30$. As CDS spreads, bond prices and the CDS-bond basis all depend on default probabilities, this matching criterion allows us to control for default risk, proxied by rating classes. This is crucial, especially when studying the impact of rating changes on credit risk sensitive markets. Since our sample consists of reference entities with a 5 year time-to-maturity, the reference portfolio also matches the maturity of event entities.

If an entity experiences more than one rating change within a five-day interval, we consider only the first rating event. We exclude changes to the rating class CCC, because, as mentioned in May (2010), these downgrades are concurrent with a likely default and are then associated with other simultaneous events.

We define the event date as the day where the reference entity is downgraded or upgraded. The time period over which we assess the impact of the rating change on the variable of interest is the *event window*. In our study, we analyze eight event windows, before, after and around the event date: $[-20,-11]$, $[-10,-6]$, $[-5,-1]$, $[-5,15]$, $[0,20]$, $[1,5]$, $[6,10]$ and $[11,20]$. Windows prior to the event allow us to analyze whether the market has anticipated the subsequent rating change. Post-event windows allow us to examine for a lagged reaction. For each event window $[t_1,t_2]$, we compute the cumulative abnormal variable $CAV_{[t_1,t_2],i}$ of a reference entity i defined as:

$$CAV_{[t_1,t_2],i} = \sum_{t=t_1}^{t_2} AV_{it},$$

that is, $CAB_{[t_1,t_2],i}$, $CAP_{[t_1,t_2],i}$ and $CAS_{[t_1,t_2],i}$ respectively for the analysis of the CDS-bond relation, the bond market and the CDS market respectively.

Finally, we compute the average of the CAV of all reference entities. Under the null hypothesis, which states that the rating change event has no significant impact on the variable of interest, the mean CAV should be equal to zero. To test this hypothesis, we apply both the parametric cross-sectional T-test and the non-parametric Wilcoxon signed rank test, which has the advantage of considering both the sign and the magnitude of the CAV.

4.5.2 Multivariate analysis

In a second step, we investigate the factors that influence the magnitude of the variable's abnormal levels induced by the credit rating event. In order to do so, we run cross-sectional regressions where the dependent variable is the CAV over the $[0, 20]$ event window. We estimate separate regressions for upgrades and downgrades.

The main variables used in the regressions for CDS, bond and basis analysis are:

$Fallen\_Angel$: an indicator variable equal to 1 if the entity is downgraded from IG to HY category, 0 otherwise.

$Rising\_Star$: an indicator variable equal to 1 if the entity is upgraded from HY to IG category, 0 otherwise.

$Crisis$ and $Post\_Crisis$: indicator variables for the corresponding periods in our data sample. Our benchmark is the pre-crisis period.

Old_Rating: a numerical variable indicating the initial rating before the credit event, where AAA is equal to 1, AA is equal to 2 and so on. Hamilton and Cantor (2004) find that the distance between default probabilities of two adjacent rating categories increases as credit quality deteriorates. We expect reactions to rating changes to be more pronounced for securities with lower credit quality (Jorion and Zhang 2010), so that we expect the coefficient to be negative (resp. positive) for bond downgrades (resp. upgrades), and the opposed signs for the CDS spread.

$Number\_of\_Grades$: a variable representing the "size" of the jump in credit quality. This variable is computed as the absolute value of the difference between the numerical translation of the old and the new ratings. A larger value for this variable indicates a stronger change in the creditworthiness judgment about the security. We expect this variable to have a negative (resp. positive) impact on the bond price reaction to downgrades (resp. upgrades), and the opposed signs for the CDS spread.

All regressions are estimated by OLS with the White heteroscedasticity-consistent covariance matrix, according to the following equation:

$$CAV_{[0,20],i} = \alpha + \sum_{j=1}^{n} \gamma_j \ indep\_variable_{i,j} + \varepsilon_i,$$

where $CAV_{[0,20],i}$ is the cumulative abnormal variable level of reference entity i over the twenty days following the event, including the event date and n is the number of independant variables.

4.6 Results

4.6.1 Corporate bond and CDS markets reactions to credit rating changes

Univariate analysis for downgrades

Tables 4.3 and 4.4 show respectively the average CAP and the average CAS, computed for different time windows around downgrade announcements.

These results provide evidence that downgrades have a significant impact on bond prices and on CDS spreads. Adverse credit rating changes, making the debt less worthy on the market, result in bond price decreases and CDS spread increases.

Results show that abnormal levels are observed, in both markets, during the days following the downgrade. This suggests that, in both the corporate bond and the CDS markets, the informational content of such credit events is incorporated gradually. This finding is in line with Daniels and Jensen (2005).

Reactions to downgrades are also detected prior to the announcement date. This is also reported in May (2010), Hull, Predescu and White (2004) and Micu, Remolona and Wooldridge (2006), who explain that the reaction of credit rating agencies to public information is not immediate, so that their rating change decisions are delayed. As a consequence, the market would already have adjusted to the event before it actually happened, meaning that rating changes are partially anticipated by the CDS and corporate bond markets.

An interesting way to refine our analysis is to split our sample into crossover and non-crossover groups. In the case of a downgrade, the crossover group consists of bonds moved from IG to HY, known as Fallen Angels, while the non cross-over group is formed by securities downgraded within the same rating category.

This is motivated by the fact that many financial institutions, for instance insurance companies and pension funds, are not allowed to keep speculative grade securities in their portfolio. In that sense, cross-over downgrades could cause a considerable selling activity of the Fallen Angel bonds and, consequently, an important decrease of their prices. Cross-over downgrades are therefore expected to produce a stronger impact on bond prices than other downgrades. We find that the average CAP is significantly negative for the two groups, suggesting that the two types of downgrades do affect the bond price. However, as expected, the average CAP is significantly larger in the cross-over group, that is, Fallen Angel downgrades are more consequential than others in the corporate bond market.

In the CDS market, we find that Fallen Angels do not have a significantly higher mean CAS than the remaining downgraded securities. As important financial instituitions are compelled to get rid of Fallen Angel bonds but not CDSs, the reaction of downgraded Fallen Angels is more pronounced in the bond than the CDS market.

We then perform the same analysis using three sub-samples, corresponding to the three sub-periods (before, during and after the crisis). Our results show that negative credit changes have a significant adverse impact on both bond prices and CDS spreads, in all sub-periods. It is worth noting that the largest reaction is obtained during the crisis period (Finnerty,Miller and Chen 2013), indicating that during this period characterized by a nervous, jumpy and uncertain environment, reactions to bad news were amplified. We also notice that the average CAP and CAS are significantly larger in the post-crisis period than in the pre-crisis one.

Univariate analysis for upgrades

Tables 4.5 and 4.6 report on average CAP and the average CAS, computed for different time windows around upgrade announcements. These results show a significant increase in bond prices and decrease in CDS premiums around an upgrade event, reflecting an improvement of the credit quality of the upgraded security. Interestingly, and in line with the results of Finnerty, Miller and Chen (2013), average CAP and CAS for downgrades are about three to four times larger than for upgrades, indicating that negative news have more impact than positive news for market investors. This observation is consistent with previous studies (Goh and Ederington 1993, Wansley, Glascock and Clauretie 1992, Hite and Warga 1997, Steiner and Heinke 2001, Galil and Soffer 2011). One possible explanation of this asymmetric reaction is that firms are usually more eager to announce good news (Goh and Ederington 1999), so that the informational content of upgrades may be partially reflected in bond prices and CDS spreads before the event. In contrary, a downgrade is more surprising for market investors and bring more information. Consequently, its impact on markets is more pronounced than an upgrade.

Results also show that, similarly to downgrades, bond and CDS markets response to upgrades is stronger during the crisis than during the other sub-periods. A plausible explanation is that, in a weak economy, improvements in credit quality are difficult to achieve and thus less expected, generating larger reactions among investors.

Multivariate analysis

We now run cross-sectional regressions of the variables CAP and CAS over the [0,20] window for rating downgrades and upgrades, in order to identify the determinants of the corporate bond and CDS markets' reactions to rating changes.

Regressions for both variables following a downgrade are reported in panels A of Tables 4.7 and 4.8. We observe that both the decrease in bond prices and the

Table 4.3: The impact of downgrades on bond price

This table reports the impact of rating downgrades on bond prices. CAP is the sum of the reference entity's abnormal bond price over the event window. Panel A shows the impact of downgrades using the whole sample. Panel B shows the impact of downgrades within the same category. Panel C shows the impact of downgrades that move the reference entity from IG to HY category. Panel D shows the impact of downgrades during the pre-crisis period (02/01/2006 to 30/06/2007). Panel E shows the impact of downgrades during the crisis period (01/07/2007 to 31/03/2009). Panel F shows the impact of downgrades during the post-crisis period (01/04/2009 to 30/09/2014). *,**and*** indicate respectively significance at level 10%, 5% and 1%. t is for the t-test and s is for the signed-rank test.

Panel A: Downgrades in whole sample			Panel D: Downgrades during pre-crisis		
	CAP			CAP	
	N	Mean		N	Mean
[-20,-11]	4274	$-6.50^{t(***)}_{s(***)}$	[-20,-11]	612	$-1.65^{t(***)}_{s(***)}$
[-10,-6]	3995	$-6.81^{t(***)}_{s(***)}$	[-10,-6]	610	$-1.97^{t(***)}_{s(***)}$
[-5,-1]	3994	$-6.96^{t(***)}_{s(***)}$	[-5,-1]	607	$-2.24^{t(***)}_{s(***)}$
[0,20]	4565	$-7.36^{t(***)}_{s(***)}$	[0,20]	707	$-2.24^{t(***)}_{s(***)}$
[1,5]	4026	$-7.38^{t(***)}_{s(***)}$	[1,5]	630	$-2.41^{t(***)}_{s(***)}$
[6,10]	4003	$-7.52^{t(***)}_{s(***)}$	[6,10]	611	$-2.44^{t(***)}_{s(***)}$
[11,20]	4291	$-7.44^{t(***)}_{s(***)}$	[11,20]	662	$-2.28^{t(***)}_{s(***)}$
Panel B: Downgrades within the same category			Panel E: Downgrades during crisis		
	CAP			CAP	
	N	Mean		N	Mean
[-20,-11]	3802	$-5.76^{t(***)}_{s(***)}$	[-20,-11]	1947	$-9.05^{t(***)}_{s(***)}$
[-10,-6]	3558	$-6.07^{t(***)}_{s(***)}$	[-10,-6]	1781	$-9.79^{t(***)}_{s(***)}$
[-5,-1]	3551	$-6.25^{t(***)}_{s(***)}$	[-5,-1]	1770	$-10.10^{t(***)}_{s(***)}$
[0,20]	4065	$-6.92^{t(***)}_{s(***)}$	[0,20]	2042	$-11.01^{t(***)}_{s(***)}$
[1,5]	3591	$-7.01^{t(***)}_{s(***)}$	[1,5]	1784	$-10.87^{t(***)}_{s(***)}$
[6,10]	3573	$-7.17^{t(***)}_{s(***)}$	[6,10]	1776	$-11.13^{t(***)}_{s(***)}$
[11,20]	3823	$-7.10^{t(***)}_{s(***)}$	[11,20]	1916	$-11.17^{t(***)}_{s(***)}$
Panel C: Downgrades from IG to HY			Panel F:Downgrades during post-crisis		
	CAP			CAP	
	N	Mean		N	Mean
[-20,-11]	472	$-12.50^{t(***)}_{s(***)}$	[-20,-11]	1715	$-5.35^{t(***)}_{s(***)}$
[-10,-6]	437	$-12.80^{t(***)}_{s(***)}$	[-10,-6]	1604	$-5.34^{t(***)}_{s(***)}$
[-5,-1]	443	$-12.65^{t(***)}_{s(***)}$	[-5,-1]	1617	$-5.29^{t(***)}_{s(***)}$
[0,20]	500	$-10.95^{t(***)}_{s(***)}$	[0,20]	1752	$-5.28^{t(***)}_{s(***)}$
[1,5]	435	$-10.49^{t(***)}_{s(***)}$	[1,5]	1612	$-5.42^{t(***)}_{s(***)}$
[6,10]	430	$-10.40^{t(***)}_{s(***)}$	[6,10]	1593	$-5.52^{t(***)}_{s(***)}$
[11,20]	468	$-10.25^{t(***)}_{s(***)}$	[11,20]	1649	$-5.31^{t(***)}_{s(***)}$

Table 4.4: The impact of downgrades on CDS spread

This table reports on the impact of rating downgrades on CDS spreads. CAS is the sum of the reference entity's abnormal CDS spreads over the event window. Panel A shows the impact of downgrades using the whole sample. Panel B shows the impact of downgrades within the same category. Panel C shows the impact of downgrades that move the reference entity from IG to HY category. Panel D shows the impact of downgrades during the pre-crisis period (02/01/2006 to 30/06/2007). Panel E shows the impact of downgrades during the crisis period (01/07/2007 to 31/03/2009). Panel F shows the impact of downgrades during the post-crisis period (01/04/2009 to 30/09/2014). *,**and*** indicate respectively significance at level 10%, 5% and 1%. t is for the t-test and s is for the signed-rank test.

Panel A: Downgrades in whole sample			Panel D: Downgrades during pre-crisis		
	CAS			CAS	
	N	Mean		N	Mean
[-20,-11]	1.994	$1.99^{t(***)}_{s(***)}$	[-20,-11]	397	$0.57^{t(***)}_{s(***)}$
[-10,-6]	1758	$2.13^{t(***)}_{s(***)}$	[-10,-6]	348	$0.78^{t(***)}_{s(***)}$
[-5,-1]	1557	$2.30^{t(***)}_{s(***)}$	[-5,-1]	302	$0.83^{t(***)}_{s(***)}$
[0,20]	2319	$2.06^{t(***)}_{s(***)}$	[0,20]	470	$0.31^{t(***)}_{s(*)}$
[1,5]	1819	$1.90^{t(***)}_{s(***)}$	[1,5]	375	$0.39^{t(***)}_{s(***)}$
[6,10]	1843	$2.12^{t(***)}_{s(***)}$	[6,10]	361	$0.41^{t(***)}_{s(***)}$
[11,20]	2091	$2.21^{t(***)}_{s(***)}$	[11,20]	428	$0.34^{t(***)}_{s()}$
Panel B: Downgrades within the same category			Panel E: Downgrades during crisis		
	CAS			CAS	
	N	Mean		N	Mean
[-20,-11]	1739	$1.70^{t(***)}_{s(***)}$	[-20,-11]	853	$3.12^{t(***)}_{s(***)}$
[-10,-6]	1530	$1.90^{t(***)}_{s(***)}$	[-10,-6]	783	$3.31^{t(***)}_{s(***)}$
[-5,-1]	1348	$2.01^{t(***)}_{s(***)}$	[-5,-1]	657	$3.72^{t(***)}_{s(***)}$
[0,20]	2030	$1.97^{t(***)}_{s(***)}$	[0,20]	1038	$3.93^{t(***)}_{s(***)}$
[1,5]	1586	$1.89^{t(***)}_{s(***)}$	[1,5]	778	$3.57^{t(***)}_{s(***)}$
[6,10]	1603	$2.10^{t(***)}_{s(***)}$	[6,10]	801	$3.95^{t(***)}_{s(***)}$
[11,20]	1825	$2.11^{t(***)}_{s(***)}$	[11,20]	925	$4.28^{t(***)}_{s(***)}$
Panel C: Downgrades from IG to HY			Panel F: Downgrades during post-crisis		
	CAS			CAS	
	N	Mean		N	Mean
[-20,-11]	255	$4.00^{t(***)}_{s(***)}$	[-20,-11]	744	$1.46^{t(***)}_{s(***)}$
[-10,-6]	288	$3.69^{t(***)}_{s(***)}$	[-10,-6]	672	$1.55^{t(***)}_{s(***)}$
[-5,-1]	209	$4.17^{t(***)}_{s(***)}$	[-5,-1]	598	$1.48^{t(***)}_{s(***)}$
[0,20]	289	$2.71^{t(***)}_{s(}$	[0,20]	783	$0.64^{t(***)}_{s(***)}$
[1,5]	233	$2.01^{t(***)}_{s()}$	[1,5]	665	$0.81^{t(***)}_{s(***)}$
[6,10]	240	$2.30^{t(***)}_{s()}$	[6,10]	670	$0.88^{t(***)}_{s(***)}$
[11,20]	266	$2.93^{t(***)}_{s()}$	[11,20]	710	$0.67^{t(***)}_{s(***)}$

Table 4.5: The impact of upgrades on bond price

This table reports on the impact of rating upgrades on bond prices. CAP is the sum of the reference entity's abnormal bond prices over the event window. Panel A shows the impact of upgrades using the whole sample. Panel B shows the impact of upgrades within the same category. Panel C shows the impact of upgrades that move the reference entity from HY to IG category. Panel D shows the impact of upgrades during the pre-crisis period (02/01/2006 to 30/06/2007). Panel E shows the impact of upgrades during the crisis period (01/07/2007 to 31/03/2009). Panel F shows the impact of upgrades during the post-crisis period (01/04/2009 to 30/09/2014). *,**and*** indicate respectively significance at level 10%, 5% and 1%. t is for the t-test and s is for the signed-rank test.

Panel A: Upgrades in whole sample			Panel D: Upgrades during pre-crisis		
	CAP			CAP	
	N	Mean		N	Mean
[-20,-11]	3010	$3.30^{t(***)}_{s(***)}$	[-20,-11]	828	$1.96^{t(***)}_{s(***)}$
[-10,-6]	2823	$3.36^{t(***)}_{s(***)}$	[-10,-6]	733	$1.93^{t(***)}_{s(***)}$
[-5,-1]	2860	$3.49^{t(***)}_{s(***)}$	[-5,-1]	791	$1.91^{t(***)}_{s(***)}$
[0,20]	3234	$2.34^{t(***)}_{s(***)}$	[0,20]	900	$1.92^{t(***)}_{s(***)}$
[1,5]	2893	$2.29^{t(***)}_{s(***)}$	[1,5]	805	$1.96^{t(***)}_{s(***)}$
[6,10]	2869	$2.33^{t(***)}_{s(***)}$	[6,10]	808	$1.91^{t(***)}_{s(***)}$
[11,20]	3021	$2.36^{t(***)}_{s(***)}$	[11,20]	849	$1.90^{t(***)}_{s(***)}$
Panel B: Upgrades within the same category			**Panel E: Upgrades during crisis**		
	CAP			CAP	
	N	Mean		N	Mean
[-20,-11]	2771	$2.98^{t(***)}_{s(***)}$	[-20,-11]	464	$5.94^{t(***)}_{s(***)}$
[-10,-6]	2540	$2.54^{t(***)}_{s(***)}$	[-10,-6]	405	$623^{t(***)}_{s(***)}$
[-5,-1]	2574	$3.16^{t(***)}_{s(***)}$	[-5,-1]	415	$6.50^{t(***)}_{s(***)}$
[0,20]	2909	$2.32^{t(***)}_{s(***)}$	[0,20]	494	$4.01^{t(***)}_{s(***)}$
[1,5]	2592	$2.27^{t(***)}_{s(***)}$	[1,5]	429	$3.84^{t(***)}_{s(***)}$
[6,10]	2589	$2.32^{t(***)}_{s(***)}$	[6,10]	394	$4.42^{t(***)}_{s(***)}$
[11,20]	2727	$2.34^{t(***)}_{s(***)}$	[11,20]	451	$3.95^{t(***)}_{s(***)}$
Panel C: Upgrades from HY to IG			**Panel F: Upgrades during post-crisis**		
	CAP			CAP	
	N	Mean		N	Mean
[-20,-11]	299	$6.34^{t(***)}_{s(***)}$	[-20,-11]	1778	$3.25^{t(***)}_{s(***)}$
[-10,-6]	283	$5.98^{t(***)}_{s(***)}$	[-10,-6]	1645	$3.33^{t(***)}_{s(***)}$
[-5,-1]	286	$6.47^{t(***)}_{s(***)}$	[-5,-1]	1654	$3.50^{t(***)}_{s(***)}$
[0,20]	325	$2.47^{t(***)}_{s(***)}$	[0,20]	1823	$2.10^{t(***)}_{s(***)}$
[1,5]	301	$2.47^{t(***)}_{s(***)}$	[1,5]	1659	$2.05^{t(***)}_{s(***)}$
[6,10]	280	$2.46^{t(***)}_{s(***)}$	[6,10]	1660	$2.06^{t(***)}_{s(***)}$
[11,20]	294	$2.58^{t(***)}_{s(***)}$	[11,20]	1704	$2.18^{t(***)}_{s(***)}$

Table 4.6: The impact of upgrades on CDS spread

This table reports the impact of rating upgrades on CDS spread. CAS is the sum of the reference entity's abnormal CDS spreads over the event window. Panel A shows the impact of upgrades using the whole sample. Panel B shows the impact of upgrades within the same category. Panel C shows the impact of upgrades that move the reference entity from HY to IG category. Panel D shows the impact of upgrades during the pre-crisis period (02/01/2006 to 30/06/2007). Panel E shows the impact of upgrades during the crisis period (01/07/2007 to 31/03/2009). Panel F shows the impact of upgrades during the post-crisis period (01/04/2009 to 30/09/2014). *,**and*** indicate respectively significance at level 10%, 5% and 1%. t is for the t-test and s is for the signed-rank test.

Panel A: Upgrades in whole sample			Panel D: Upgrades during pre-crisis		
	CAS			CAS	
	N	Mean		N	Mean
[-20,-11]	1784	$-1.23^{t(***)}_{s(***)}$	[-20,-11]	475	$-0.72^{t(***)}_{s(***)}$
[-10,-6]	1518	$-1.28^{t(***)}_{s(***)}$	[-10,-6]	427	$-0.68^{t(***)}_{s(***)}$
[-5,-1]	1379	$-1.26^{t(***)}_{s(***)}$	[-5,-1]	375	$-0.62^{t(***)}_{s(***)}$
[0,20]	2017	$-0.41^{t(***)}_{s(***)}$	[0,20]	582	$-0.17^{t(***)}_{s(***)}$
[1,5]	1648	$-0.38^{t(***)}_{s(***)}$	[1,5]	478	$-0.15^{t(***)}_{s(***)}$
[6,10]	1658	$-0.37^{t(***)}_{s(***)}$	[6,10]	469	$-0.17^{t(***)}_{s(***)}$
[11,20]	1822	$-0.42^{t(***)}_{s(***)}$	[11,20]	534	$-0.17^{t(***)}_{s(***)}$
Panel B: Upgrades within the same category			Panel E: Upgrades during crisis		
	CAS			CAS	
	N	Mean		N	Mean
[-20,-11]	1592	$-1.09^{t(***)}_{s(***)}$	[-20,-11]	318	$-2.59^{t(***)}_{s(***)}$
[-10,-6]	1339	$-1.09^{t(***)}_{s(***)}$	[-10,-6]	261	$-2.85^{t(***)}_{s(***)}$
[-5,-1]	1220	$-1.08^{t(***)}_{s(***)}$	[-5,-1]	241	$-2.83^{t(***)}_{s(***)}$
[0,20]	1782	$-0.46^{t(***)}_{s(***)}$	[0,20]	382	$-1.25^{t(***)}_{s(***)}$
[1,5]	1456	$-0.43^{t(***)}_{s(***)}$	[1,5]	281	$-1.07^{t(***)}_{s(***)}$
[6,10]	1475	$-0.41^{t(***)}_{s(***)}$	[6,10]	285	$-1.12^{t(***)}_{s(***)}$
[11,20]	1618	$-0.46^{t(***)}_{s(***)}$	[11,20]	340	$-1.30^{t(***)}_{s(***)}$
Panel C: Upgrades from IG to HY			Panel F: Upgrades during post-crisis		
	CAS			CAS	
	N	Mean		N	Mean
[-20,-11]	192	$-2.47^{t(***)}_{s(***)}$	[-20,-11]	991	$-1.04^{t(***)}_{s(***)}$
[-10,-6]	179	$-2.80^{t(***)}_{s(***)}$	[-10,-6]	830	$-1.10^{t(***)}_{s(***)}$
[-5,-1]	159	$-2.70^{t(***)}_{s(***)}$	[-5,-1]	763	$-1.09^{t(***)}_{s(***)}$
[0,20]	235	$-0.07^{t()}_{s()}$	[0,20]	1044	$-0.24^{t(***)}_{s(***)}$
[1,5]	192	$-0.06^{t()}_{s()}$	[1,5]	889	$-0.29^{t(***)}_{s(***)}$
[6,10]	183	$-0.05^{t()}_{s()}$	[6,10]	901	$-0.24^{t(***)}_{s(***)}$
[11,20]	204	$-0.09^{t()}_{s()}$	[11,20]	939	$-0.25^{t(***)}_{s(***)}$

increase in CDS spreads following a downgrade are larger during the crisis and post-crisis periods compared to our benchmark pre-crisis period, and that reactions to downgrades are significantly more pronounced during the crisis period. We notice that the coefficient of $Number\_of\_Grades$ is significant and has the expected sign, meaning that the larger the rating jump is the more the downgrade is consequential for the bond price and the CDS spread. The hypothesis that reactions to rating changes are more pronounced for securities with lower credit quality is supported by the regression result, the coefficient of the Old_Rating variable having the expected negative (resp. positive) sign for bond (resp. CDS) market. Interestingly, unlike the univariate analysis result, the $Fallen\_Angel$ coefficient is not significant for the corporate bond market (table 4.7) .

4.6.2 The impact of credit rating changes on CDS-bond relation

The previous univariate and multivariate analyses showed that the CDS and bond markets have many similarities in their reactions to changes in credit ratings. We found that both markets are able to predict, and react significantly to positive and negative news, and that downgrades have a more pronounced impact than upgrades. However, separately studying the CDS and bond markets reactions does not allow to answer questions like:

Given that CDS and bonds are considered reliable gauges of credit risk, do they react similarly to the same event concerning the credit worthiness of the same reference entity?

Is the CDS-bond equilibrium altered and, consequently are arbitrage opportunities created following a rating announcement?

Do stress events have now a more pronounced impact on basis levels and on the markets' equilibrium, more than they did in the past?

Table 4.7: Determinants of the bond market response to rating changes
This table reports on the results of a cross-sectional regression for the analysis of the main determinants of the cumulative abnormal bond prices around downgrades and upgrades. The dependant variable is the CAP measured over the window [0,20]. $Crisis$ is an incicator variable of the period from 01/07/2007 to 31/03/2009. $Post\_Crisis$ is an indicator variable of the period from 01/04/2009 to 30/09/2014. $Fallen\_angel$ is an indicator variable of a downgrade from IG to HY category. $Rising\_star$ is an indicator variable of an upgrade from HY to IG category. Old_Rating represents the pre-event credit rating in numeric notches (AAA=1,AA=2, etc). $Number\_of\_grades$ is the absolute value of the number of grades that the rating is decreased by in a downgrade, or increased by in an upgrade. All regressions are etimated by OLS. t-stats are based on robust standard errors adjusted for heteroskedasticity. *, ** and *** indicate respectively significance at level 10%, 5% and 1%.

Panel A: Determinants of the bond market response to downrades	
$Crisis$	-10.55***
	(0.40)
$Post-crisis$	-4.87***
	(0.35)
$Fallen\_Angel$	-0.17
	(0.65)
Old_Rating	-0.78***
	(0.04)
$Number\_of\_Grades$	-3.87***
	(0.27)
Constant	10.94***
	(0.60)
Obs	4565
Adjusted R^2	0.18

Panel B: Determinants of the bond market response to upgrades	
$Crisis$	1.99***
	(0.35)
$Post-crisis$	0.02
	(0.23)
$Rising\_star$	0.07
	(0.33)
Old_Rating	0.15***
	(0.03)
$Number\_of\_Grades$	-0.38***
	(0.13)
Constant	0.82
	(0.39)
Obs	3234
Adjusted R^2	0.02

Table 4.8: Determinants of the CDS market response to rating changes. This table reports on the results of a cross-sectional regression for the analysis of the main determinants of the cumulative abnormal CDS spread around downgrades and upgrades. The dependant variable is the CAS measured over the window [0,20]. $Crisis$ is an incicator variable of the period from 01/07/2007 to 31/03/2009. $Post\_Crisis$ is an indicator variable of the period from 01/04/2009 to 30/09/2014. $Fallen\_angel$ is an indicator variable of a downgrade from IG to HY category. $Rising\_star$ is an indicator variable of an upgrade from HY to IG category. Old_Rating represents the pre-event credit rating in numeric notches (AAA=1,AA=2, etc). $Number\_of\_grades$ is the absolute value of the number of grades that the rating is decreased by in a downgrade, or increased by in an upgrade. All regressions are etimated by OLS. t-stats are based on robust standard errors adjusted for heteroskedasticity. *, ** and *** indicate respectively significance at level 10%, 5% and 1%.

Panel A: Determinants of the CDS market response to downrades	
$Crisis$	3.89***
	(0.34)
$Post-crisis$	0.72***
	(0.18)
$Fallen\_Angel$	-0.40
	(0.63)
Old_Rating	0.28***
	(0.04)
$Number\_of\_Grades$	1.18***
	(0.32)
Constant	-4.04***
	(0.67)
Obs	2319
Adjusted R^2	0.08

Panel B: Determinants of the CDS market response to upgrades	
$Crisis$	-1.09***
	(0.11)
$Post-crisis$	-0.06
	(0.04)
$Rising\_star$	0.44***
	(0.06)
Old_Rating	-0.04***
	(0.01)
$Number\_of\_Grades$	0.06*
	(0.03)
Constant	0.21
	(0.12)
Obs	2017
Adjusted R^2	0.10

In this section, we answer these questions by focusing on the difference between the reactions of the CDS and bond markets to the same rating event. We are able to do so thanks to the basis variable, which allows us to directly compare reactions in both markets.

Our previous results indicated that downgrades are by far more consequential than upgrades for both markets, and that downgrades are also much more frequent than upgrades. For that reason, we focus on negative credit events.

Recall that the abnormal basis level following a downgrade of reference entity i is defined as:

$$AB_{it} = B_{it} - \overline{B}_t.$$

Using the definition of the basis

$$B_{it} = CDS\_Spread_{it} - Bond\_Spread_{it}{}^{2}$$

the previous equation can be written

$$\begin{aligned} AB_{it} &= (CDS\_Spread_{it} - Bondspread_{it}) - (\overline{CDS\_Spread}_t - \overline{Bondspread}_t) \\ &= \left(CDS\_Spread_{it} - \overline{CDS\_Spread}_t\right) - (Bondspread_{it} - \overline{Bondspread}_t) \end{aligned} \quad (4.1)$$

In the previous section, we showed that a worsening in credit quality results in an increase of CDS spread and bond spread (or equivalently a decrease in the bond price) compared to their control portfolios spreads.

Then, according to the equation 4.1, if we obtain that $AB_{it} < 0$, we can conclude that the CDS spread increase caused by the rating event is smaller than the bond spread increase caused by the same rating event.

[2] The bond spread is calculated as the PECDS spread

4.6.2.1 Univariate analysis of the whole sample

Panel A of Table 4.9 reports the average CAB for all CDS-bond pairs in our sample, and for different windows, along with the significance level of the parametric and non-parametric tests of whether this difference is statistically different from zero.

Results show that the mean CAB is significantly negative, meaning that a worsening in the credit quality results in a deterioration of the CDS-Bond basis, for all the windows considered. This is not surprising as a downgraded debt is worth less as a collateral on repo markets, which may increase the haircut applied and adversely affect the funding cost, and even its availability. Hence, a lower credit quality of the collateral makes the arbitrage activity less profitable and consequently less attractive, resulting in a more persistent and higher gap between the CDS and bond markets. This interpretation is obtained from the arbitrage activity point of view.

However, another way of looking at the negativity of the mean CAB is to link it to fundamental and structural differences between the CDS and bond markets that make them react differently to the same event. A negative mean CAB indicates that a downgrade has a different impact on the CDS and bond markets. More precisely, according to equation (4.1), a negative mean CAB indicates that the increase in the bond spread following a downgrade is higher than the increase in the CDS spread. This result is expected, as it finds its roots in the fact that the CDS and bond markets differ in several ways.

Firstly, they differ in terms of liquidity, which creates a difference in their reaction to the same credit event. Early studies ignore the liquidity premium in the CDS market and consider that CDS spreads are a pure measure of default risk (Longstaff and Mithal 2005, Blanco, Brennan and Marsh 2005). On the contrary, subsequent studies show that CDS spreads also have a liquidity component (Tang and Yan 2007, Bongaerts, Jong and Driessen 2011, Qiu and Yu 2012). However, compared to its related corporate bond, the CDS contract is often a more liquid instrument (Kim 2017). Indeed, the CDS being an unfunded instrument is less affected by funding difficulties. Thus, the CDS market is a more straightforward and cheaper avenue through which investors can trade credit risk. Moreover, the corporate bond market is mainly dominated by insurance companies and pension funds with long-term investment strategies (Bessembinder and Maxwell (2008)). Consequently, most of the issued bonds are absorbed in their stable buy-and hold portfolios. On the other hand, major players in the CDS market are active institutional investors, mainly banks (Augustin, Subrahmanyam, Tang, and Wang 2014). These distinctions favor a more liquid CDS market. Indeed, Kim (2017) compares the liquidity of CDS and cash instruments and shows the existence of a liquidity basis that tends to exhibit negative levels, implying a more illiquid corporate bond market.

Since liquidity is generally defined as the ability of an asset to be traded in any quantity without affecting its price, price adjustments resulting from a credit event should be more pronounced in the less liquid market. Accordingly, the bond spread variation following a downgrade is larger than the CDS spread variation, which results into an amplification of the already existing gap between bond and CDS spreads, or, equivalently, into a negative variation of the basis around downgrades.

Secondly, another divergence between the CDS and bond instruments is the fact that participants in these markets are different and, consequently, may not have the same access to information. While in the cash market there are both informed and uninformed investors, the CDS market is dominated by informed, large and sophisticated investors such as banks and hedge funds (Da and Gao 2010, Acharya and Johnson 2007), who would pay less attention to the public information of a downgrade, making the credit event less consequential in the CDS market. For example, banks, who have access to documents in relation with the firm's financial health well before their public release, play the role of financial intermediaries and quotes providers in the CDS market. These financial institutions have often a credit department, which based on both privileged and public information, assign internal rating to companies which moves more often and rapidly than rating agencies' changes. Thus, the informed CDS players care less about credit changes events than bond traders and consequently, have lower reactions to downgrades.

These arguments justify the result that a decline in the credit worthiness of a reference entity has a more pronounced impact on bond than CDS spreads.

4.6.2.2 Univariate analysis of downgrades from IG to HY vs. within the same rating class downgrades

Results are reported in panels B, C, D and E of Table 4.9. Panel B and E report respectively the average CAB for downgrades within the same grade and for downgrades from IG to HY category. We find that the mean CAB is significantly negative in both cases, and for all time windows, indicating that the reaction to a negative credit event is larger in the cash market than in the CDS market, for all types of downgrades.

More interestingly, and as expected, the magnitude of the difference in reactions between CDS and bond markets measured by the mean CAB is significantly much more important for downgrades from IG to HY than for downgrades that keep the reference entity in the same rating category.

Financial institutions, constrained by regulations to limit their risk-taking capacity, are prohibited from keeping Fallen Angel bonds. A downgrade to the HY category therefore results in a forced selling of these securities, at a time when other financial institutions cannot buy them. Such bonds are then traded at prices significantly below their fundamental values. One of the most constrained institutions are insurance companies, which hold over a third of IG bonds (Schultz 2001, Bessembinder and Maxwell 2008, Becker 2016). Thus, a downgrade forcing these institutions to sell can result in a "fire sale," and in an artificially sharp decline in the bond's price (Ellul, Jotikasthira and Lundblad 2011). This mechanism is not observable in the CDS market. A cross-over downgrade therefore deepens the difference in reactions between the two markets.

To dig deeper, we can also investigate whether the impact of downgrades differs according to being within IG or within HY category. Results are in panels C and

Table 4.9: The impact of downgrades on the CDS-bond basis

This table reports on the impact of rating downgrades on the CDS-bond basis. CAB is the sum of the reference entity's abnormal basis over the event window. Panel A shows the impact of downgrades using the whole sample. Panel B shows the impact of downgrades within the same category. Panel C shows the impact of downgrades within the IG category. Panel D shows the impact of downgrades within the HY category. Panel E shows the impact of downgrades that move the reference entity from IG to HY category. Panel F shows the impact of downgrades during the pre-crisis period (02/01/2006 to 30/06/2007). Panel G shows the impact of downgrades during the crisis period (01/07/2007 to 31/03/2009). Panel H shows the impact of downgrades during the post-crisis period (01/04/2009 to 30/09/2014). *, ** and *** indicate respectively significance at level 10%, 5% and 1%. t is for the t-test and s is for the signed-rank test.

Panel A: Downgrades in whole sample			Panel B: Downgrades within the same category		
	CAB			CAB	
	N	Mean		N	Mean
[-20,-11]	4113	-51.20$^{t(***)}_{s(***)}$	[-20,-11]	3664	-38.75$^{t(***)}_{s()}$
[-10,-6]	3877	-48.22$^{t(***)}_{s(***)}$	[-10,-6]	3455	-35.11$^{t(***)}_{s()}$
[-5,-1]	3695	-52.24$^{t(***)}_{s(***)}$	[-5,-1]	3282	-39.98$^{t(***)}_{s(*)}$
[-5,15]	4551	-59.25$^{t(***)}_{s(***)}$	[-5,15]	4048	-46.73$^{t(***)}_{s(***)}$
[0,20]	4565	-69.86$^{t(***)}_{s(***)}$	[0,20]	4065	-55.60$^{t(***)}_{s(***)}$
[1,5]	4081	-59.11$^{t(***)}_{s(***)}$	[1,5]	3645	-48.30$^{t(***)}_{s(***)}$
[6,10]	4003	-53.15$^{t(***)}_{s(***)}$	[6,10]	3573	-45.09$^{t(***)}_{s(**)}$
[11,20]	4291	-63.18$^{t(***)}_{s(***)}$	[11,20]	3823	-51.13$^{t(***)}_{s(***)}$
Panel C: Downgrades within IG			Panel D: Downgrades within HY		
	CAB			CAB	
	N	Mean		N	Mean
[-20,-11]	2561	-46.93$^{t(***)}_{s(***)}$	[-20,-11]	1103	-19.76$^{t(***)}_{s(***)}$
[-10,-6]	2412	-47.99$^{t(***)}_{s(***)}$	[-10,-6]	1043	-5.31$^{t(***)}_{s(***)}$
[-5,-1]	2281	-54.25$^{t(***)}_{s(***)}$	[-5,-1]	1001	-7.47$^{t()}_{s(***)}$
[-5,15]	2818	-50.29$^{t(***)}_{s(***)}$	[-5,15]	1230	-38.60$^{t(***)}_{s()}$
[0,20]	2832	-61.02$^{t(***)}_{s(***)}$	[0,20]	1233	-43.15$^{t(***)}_{s()}$
[1,5]	2556	-59.95$^{t(***)}_{s(***)}$	[1,5]	1089	-20.94$^{t(*)}_{s(**)}$
[6,10]	2505	-60.36$^{t(***)}_{s(***)}$	[6,10]	1068	-9.27$^{t()}_{s(***)}$
[11,20]	2671	-62.34$^{t(***)}_{s(***)}$	[11,20]	1152	-25.14$^{t(**)}_{s()}$

Panel E: Downgrades from IG to HY			Panel F: Downgrades during pre-crisis		
	CAB			CAB	
	N	Mean		N	Mean
[-20,-11]	449	$-152.76^{t(***)}_{s(***)}$	[-20,-11]	609	$10.59^{t(*)}_{s()}$
[-10,-6]	422	$-155.60^{t(***)}_{s(***)}$	[-10,-6]	583	$13.57^{t()}_{s()}$
[-5,-1]	413	$-149.60^{t(***)}_{s(***)}$	[-5,-1]	541	$16.19^{t(*)}_{s()}$
[-5,15]	503	$-159.98^{t(***)}_{s(***)}$	[-5,15]	714	$9.23^{t()}_{s()}$
[0,20]	500	$-185.79^{t(***)}_{s(***)}$	[0,20]	707	$8.91^{t()}_{s()}$
[1,5]	436	$-149.54^{t(***)}_{s(***)}$	[1,5]	630	$11.79^{t()}_{s()}$
[6,10]	430	$-120.14^{t(***)}_{s(***)}$	[6,10]	611	$11.60^{t(*)}_{s()}$
[11,20]	468	$-161.61^{t(***)}_{s(***)}$	[11,20]	622	$10.52^{t()}_{s()}$

Panel G: Downgrades during crisis			Panel H: Downgrades during post-crisis		
	CAB			CAB	
	N	Mean		N	Mean
[-20,-11]	1860	$-83.09^{t(***)}_{s(***)}$	[-20,-11]	1644	$-37.99^{t(***)}_{s(**)}$
[-10,-6]	1719	$-83.98^{t(***)}_{s(***)}$	[-10,-6]	1575	$-32.07^{t(***)}_{s(**)}$
[-5,-1]	1635	$-93.96^{t(***)}_{s(***)}$	[-5,-1]	1519	$-31.70^{t(***)}_{s(***)}$
[-5,15]	2055	$-97.76^{t(***)}_{s(***)}$	[-5,15]	1782	$-42.29^{t(***)}_{s(***)}$
[0,20]	2042	$-131.48^{t(***)}_{s(***)}$	[0,20]	1752	$-32.39^{t(***)}_{s(***)}$
[1,5]	1831	$-103.90^{t(***)}_{s(***)}$	[1,5]	1620	$-36.07^{t(***)}_{s(***)}$
[6,10]	1776	$-98.27^{t(***)}_{s(***)}$	[6,10]	1593	$-28.35^{t(***)}_{s(*)}$
[11,20]	1916	$-128.43^{t(***)}_{s(***)}$	[11,20]	1649	$-19.36^{t(***)}_{s(**)}$

D of Table 4.9. We find that the mean CAB is significantly more negative within the IG category than within the HY category, indicating that the increase of the bond spread relatively to CDS spread is more pronounced when a downgrade is experienced by an IG bond. A possible explanation is that liquidity differences between CDS and cash markets are already high (Kim (2017)) for the HY category. Thus, a downgrade would not be of a great change for this category, in contrary to IG firms.

4.6.2.3 Univariate analysis of crisis vs. non-crisis periods

We now compare the impact of downgrades according to the sub-periods around the financial crisis. Results are reported in panels F, G and H of Table 4.9.

We observe that results differ significantly between the three sub-periods, the mean CAB being larger for the crisis period for all time windows, indicating that negative credit events had the most adverse impact on the CDS and bond markets' equilibrium during this period. This could be explained by the fact that, as during the crisis funding conditions are poor, downgrades would result in further widening the already existing gap between funded and unfunded instruments.

More interestingly, results are also different for the pre-crisis and the post-crisis periods. In fact, in the pre-crisis period, the mean CAB is not significantly different from 0, for all time windows, indicating that credit events did not have a significant impact on the CDS-bond equilibrium. This is not the case in the post-crisis period, where the mean CAB is negative. A possible explanation is the controversial deterioration of bond-market liquidity in the post-crisis period due to regulatory changes (Bao, O'Hara and Zhou 2018), making the bond spread more sensitive to downgrades than the CDS spread.

4.6.2.4 Multivariate analysis

To investigate the main determinants of the CDS-bond basis abnormal levels following downgrades, while controlling for other factors that are likely to affect the basis, we conduct a regression analysis of the [0,20] CAB on a set of independent variables.

In addition to the indicator variables defined earlier, we use the variable $Repo\_spread$ to control for the funding environment. As mentioned in the previous chapter, funding conditions are one of the determinants of the basis. We also use bond and CDS illiquidity variables ILB and ILC defined in Section 3.5 as we expect the difference in reaction to downgrades between the CDS and bond markets to be linked to a difference in liquidity.

The regression results are reported in Table 4.10. These results confirm that a downgrade that makes the reference entity move to the HY category has a more dramatic impact on the basis than a downgrade that keeps the bond in the same rating category.

More importantly, the regression analysis shows that liquidity plays an important role in explaining the cross-sectional variation in the abnormal basis levels around downgrades. However, only bond illiquidity plays a role in determining the magnitude of the downgrade impact. The coefficient of bond illiquidity is negative, indicating that bond illiquidity deteriorates the basis following a downgrade, while the coefficient of the CDS illiquidity variable is not significant.

Finally, when control variables are included, we find that the mean CAB in the crisis and the post-crisis periods are comparable. Both are negative, have similar amplitudes and are significantly different from the CAB level before the crisis. This suggests that during the post crisis period the downgrade impact on the basis is similar to its effect during the tumultuous period of the 2008 financial crisis.

As a robustness check, we conduct a regression with the same independent variables for the CAB in the window [-5,15]. Table 4.11 reports on the results, which

Table 4.10: Determinants of the CDS-bond basis response to downgrades during the [0,20] window

This table reports the results of the cross-sectional regression for the analysis of the main determinants of the cumulative abnormal CDS-bond basis around downgrades. The dependant variable is the CAB measured over the [0,20] window. $Crisis$ is an indicator of the period from 01/07/2007 to 31/03/2009, while $Post-Crisis$ is an indicator variable of the period from 01/04/2009 to 30/09/2014. $Fallen\_angel$ is an indicator variable of a downgrade moving the reference entity from IG to HY category. Old_Rating represents the pre-event credit rating in numeric notches (AAA=1, AA2, etc,). $Number\_of\_grades$ is the absolute value of the number of grades that the rating is decreased by. $Repo\_spread$ is the difference between the General Collateral repo rate and the Treasury Bills rate. ILB is the bond illiquidity factor defined in Section 3.5 while ILC is the CDS bid-ask spread. All regressions are estimated by OLS. t-stats are based on robust standard errors adjusted for heteroskedasticity. *, ** and *** indicate respectively significance at level 10%, 5% and 1%.

Panel A: Determinants of the CDS-bond basis response to downrades	
	[0,20] CAB
$Crisis$	-48.81***
	(14.73)
$Post-crisis$	-53.75***
	(11.63)
$Fallen\_Angel$	-74.46***
	(22.93)
Old_Rating	2.15
	(1.66)
$Number\_of\_Grades$	-18.70
	(12.39)
$Repo\_spread$	-22.34
	(29.53)
ILB	-21.56***
	(2.05)
ILC	4.23
	(13.14)
Constant	54.55**
	(26.56)
Obs	2743
Adjusted R^2	0.13

are qualitatively the same as for the [0,20] window.

4.6.2.5 The CDS-bond basis reaction to stress events during the regulation era

Bessembinder, Jacobsen, Maxwell and Venkataraman (2016), Dick-Nielsen and Rossi (2017), Trebbi and Xiao's (2015) and Bao, O'Hara and Zhou (2018) explored the post-crisis regulations' impact on market conditions, and more precisely on the liquidity dimension. According to these authors, the new regulatory environment after the 2008 financial crisis could have unintended adverse consequences on the bond market liquidity. As we found that the bond illiquidity affects the basis abnormal behavior around downgrades, we expect the regulatory reforms to alter the basis levels around these events. Particularly, we focus on investigating whether the basis is relatively worse around stress events, during the regulation implementation period compared to the pre-crisis period. In fact, fully understanding the CDS-bond parity relationship requires understanding how this relation described by the basis behaves during unfavorable conditions, when a deterioration of the basis has the most devastating consequences. Stress events are proxied by downgrades that have the highest impact on the equilibrium between the CDS and bond markets, that is, downgrades that move corporate bonds from the IG to the HY category. In the spirit of what was done in Bao, O'Hara and Zhou (2018), we compare the impact of such stress events during the pre-crisis and the post-crisis periods, further split into three sub-periods: Pre-reform (01 April 2009 to 21 July 2010), post-Dodd Frank Act (22 July 2010 to 30 June 2013) and post Basel III (01 July 2013 to 30 september 2014).

Results are reported in Table 4.12. We find that the corporate bond illiquidity plays a role in the CDS-bond basis reaction following a stress event. The coefficient of the variable $Number\_of\_Grades$ is significantly negative, indicating that an important change in the debt credit worthiness leads to a greater impact on the CDS-bond parity relation. More importantly, when we benchmark to the pre-crisis

Table 4.11: Determinants of the CDS-bond basis response to downgrades during the [-5,15] window

This table reports the results of the cross-sectional regression for the analysis of the main determinants of the cumulative abnormal CDS-bond basis around downgrades. The dependant variable is the CAB measured over the [-5,15] window. $Crisis$ is an indicator of the period 01/07/2007 to 31/03/2009, while $Post-Crisis$ is an indicator variable of the period 01/04/2009 to 30/09/2014. $Fallen\_angel$ is an indicator variable of a downgrade moving the reference entity from IG to HY category. Old_Rating represents the pre-event credit rating in numeric notches (AAA=1, AA2, etc,). $Number\_of\_grades$ is the absolute value of the number of grades that the rating is decreased by. $Repo\_spread$ is the difference between the General Collateral repo rate and the Treasury Bills rate. ILB is the bond illiquidity factor defined in Section 3.5 while ILC is the CDS bid-ask spread. All regressions are estimated by OLS. t-stats are based on robust standard errors adjusted for heteroskedasticity. *, ** and *** indicate respectively significance at level 10%, 5% and 1%.

Panel A: Determinants of the CDS-bond basis response to downrades	
	[-5,15] CAB
$Crisis$	-34.75**
	(13.57)
$Post-crisis$	-51.93***
	(10.64)
$Fallen\_Angel$	-55.59***
	(20.97)
Old_Rating	1.34
	(1.62)
$Number\_of\_Grades$	-22.19***
	(7.88)
$Repo\_spread$	-5.42
	(26.87)
ILB	-23.49***
	(2.01)
ILC	-5.09
	(14.77)
Constant	62.03***
	(20.74)
Obs	2770
Adjusted R^2	0.18

period, regression results indicate that the mean CAB is significantly lower during the post-Dodd Frank Act and the post Basel III periods than during the pre-crisis period. This suggests that basis deterioration around stress events has worsened in the post-regulation periods. This result could be first related to the adverse impact of the Dodd Frank's Volker Rule on the corporate bond market liquidity (Bao, O'hara and Zhou (2018)), leading to an increase of the bond illiquidity premium and consequently to a higher difference between the bond and the CDS spread. Moreover, Basel III puts additional limits on the institutional risk exposure which may lead to an amplified Fallen Angel impact.

Based on the result that stress events are more consequential to the basis after new regulations, one might expect that during the next stress event, for instance, the next financial crisis, to observe a more acute basis departure from parity compared to the last crisis.

Finally, it is worth noting that the Basel III reform comes after the Dodd Frank's Volcker Rule initiation. Thus, we can interpret the $Post - Basel\_III$ coefficient as the combined effect of the two reforms. We found that the coefficient of the $Post - Basel\_III$ indicator variable is not significantly lower than that of the $Post - Dodd\_Frank\_Act$ variable, indicating that there is no further deterioration of the CDS-bond equilibrium around stress events following the Basel III reform. This could be explained by an anticipatory response of the market to Basel III.

As a robustness check, we explore the basis reaction to stress events using a different time window. Table 4.13 reports on the results of the regression for a [-5,15] time window, and shows results that are qualitatively similar to the [0,20] window.

4.7 Conclusion

This chapter constitutes a contribution to the scarce literature addressing differences in reactions to credit events between related markets. We investigate the behavior of

Table 4.12: Determinants of the CDS-bond basis response to stress events during the [0,20] window

This table reports on the results of the cross-sectional regression for the analysis of the main determinants of the cumulative abnormal CDS-bond basis following a downgrade that moves the reference entity from IG to HY category, used as proxy for stress events. The dependant variable is the CAB measured over the [0,20] window. $Crisis$ is an indicator variable of the period from 01/07/2007 to 31/03/2009. $Pre-Reforms$ is an indicator of the period from 01/04/2009 to 20/07/2010. $Post-Dodd\_Frank\_Act$ is an indicator of the period from 21/07/2010 to 30/06/2013. $Post-Basel\_III$ is an indicator of the period from 01/07/2013 to 30/09/2014. $Number\_of\_Grades$ is the absolute value of the number of grades that the rating is decreased by. $Repo\_spread$ is the difference between the General Collateral repo rate and the Treasury Bills rate. ILB is the bond illiquidity factor defined in Section 3.5. ILC is the CDS bid-ask spread. All regressions are etimated by OLS. t-stats are based on robust standard errors adjusted for heteroskedasticity. *, ** and *** indicate respectively significance at level 10%, 5% and 1%.

Panel A: Determinants of the CDS-bond basis response to downrades	
	[0,20] CAB
$Crisis$	-332.86***
	(69.29)
$Pre-Reforms$	-281.80***
	(57.70)
$Post-Dodd\_Frank\_Act$	-151.49***
	(55.00)
$Post-Basel\_III$	-178.30***
	(60.83)
$Number\_of\_Grades$	-58.57***
	(20.11)
$Repo\_spread$	-20.85
	(177.94)
ILB	-16.38**
	(7.07)
ILC	12.44
	(16.88)
Constant	234.82
	(83.83)
Obs	268
Adjusted R^2	0.17

Table 4.13: Determinants of the CDS-bond basis response to stress events during the [-5,15] window

This table reports on the results of the cross-sectional regression for the analysis of the main determinants of the cumulative abnormal CDS-bond basis following a downgrade that moves the reference entity from IG to HY category, used as proxy for stress events. The dependant variable is the CAB measured over the [-5,15] window. $Crisis$ is an indicator variable of the period from 01/07/2007 to 31/03/2009. $Pre-Reforms$ is an indicator of the period from 01/04/2009 to 20/07/2010. $Post-Dodd\_Frank\_Act$ is an indicator of the period from 21/07/2010 to 30/06/2013. $Post-Basel\_III$ is an indicator of the period from 01/07/2013 to 30/09/2014. $Number\_of\_Grades$ is the absolute value of the number of grades that the rating is decreased by. $Repo\_spread$ is the difference between the General Collateral repo rate and the Treasury Bills rate. ILB is the bond illiquidity factor defined in Section 3.5. ILC is the CDS bid-ask spread. All regressions are etimated by OLS. t-stats are based on robust standard errors adjusted for heteroskedasticity. *, ** and *** indicate respectively significance at level 10%, 5% and 1%.

Panel A: Determinants of the CDS-bond basis response to downrades	
	[-5,15] CAB
$Crisis$	-266.64***
	(51.80)
$Pre-Reforms$	-157.34***
	(59.96)
$Post-Dodd\_Frank\_Act$	-88.05**
	(39.22)
$Post-Basel\_III$	-95.92**
	(38.50)
$Number\_of\_Grades$	-38.10***
	(12.75)
$Repo\_spread$	-185.03
	(165.87)
ILB	-20.75***
	(6.77)
ILC	-8.54
	(23.02)
Constant	116.54**
	(54.70)
Obs	283
Adjusted R^2	0.25

the credit sensitive CDS and bond markets and the relation between them, around credit rating announcements.

First, we show that the CDS and bond markets react to both negative and positive events, but that reaction to downgrades are larger than reactions to upgrades. When a debtor creditworthiness deteriorates, bond prices (resp. CDS spreads) decrease (resp. increase), and the opposite happens for a credit upgrade. We also show that CDS and bonds exhibit significant changes before the event date, indicating that the credit event is partially anticipated by the market. Abnormal behavior is also observed after the event. These results reveal efficiency problems in both markets. We also show that credit events have a larger impact on CDS and bond markets after the crisis, compared to the pre-crisis period.

We then examine how spreads of corporate bonds and CDS contracts issued by the same reference entity respond to the same credit event. Our results suggest that there are significant differences in the way bonds and their protections react to the same rating changes. We find that the CDS-bond basis decreases during the days around a downgrade announcement. The magnitude of this decline is related to the type of the downgrade, to the period in which the event occurs, and to the corporate bond illiquidity, but not to the CDS illiquidity. Furthermore, we show that downgrades that cross the border of the high yield category have by far a more dramatic impact on the CDS-bond relationship. Finally, we provide evidence that the impact of a stress event on the basis is higher during the post-crisis regulation period than during the pre-crisis period. This indicates that new regulatory reforms have an adverse impact on the CDS-bond equilibrium.

Chapter 5

General conclusion

This thesis deals with various issues related to the CDS-bond basis, used as an evaluation of the link between the bond and CDS markets.

The first essay is an introductory chapter that presents an overview of the CDS and bond instruments and describes the tight relation between their markets and the approach we use to compute the CDS-bond basis.

The second essay is an exploration of the basis unexpected negativity persistence after the 2008 financial crisis, that has been termed the "CDS-bond basis negativity puzzle." We first empirically document the existence of this puzzle. We show the existence of different regimes characterizing the basis evolution through time and, more interestingly, that the post-crisis basis did not revert to its pre-crisis regime. We then investigate the cross-sectional variation in the CDS-bond basis. We test the impact of several market frictions and risks related to the negative-basis arbitrage trade. We find that the dislocation between CDS and bond markets increases with higher bond and CDS liquidity risks, counterparty risk and funding difficulties. In that sense, the observed basis can be split into two parts: the predicted basis is the part that is explained by the risk factors, and the residual basis is the remaining part, which represents the real mispricing between CDS and bond markets that can be corrected through basis arbitrage. This approach is used to check our main assumption of a defective arbitrage mechanism during the post-crisis period, causing the negative basis anomaly to persist. To the best of our knowledge, our thesis is the first to provide an explanation of the basis non-return to pre-crisis levels. Arbitrage activity being non observable, we contribute to the limits to arbitrage literature by providing a new proxy to indirectly measure the intensity of arbitrage trades. This is done by tracing the impact of the arbitrage activity on important features of the bond market: pricing and volume. We show that this impact has significantly deteriorated during the post-crisis period and, more precisely, following regulation reforms.

Future research arising from the second essay could consist of using a more direct approach to relate the decrease in arbitrage activity to regulation reforms. For instance, identifing market participants that are constrained with new regulations from those that are not and compare their relative implications in the basis trade. Another line of research could be to use a threshold vector-error correcting model to identify thresholds in the CDS-bond basis above which arbitrageurs are not eager to initiate a basis trade and, more interestingly, to show that these thresholds have considerably increased following the recent regulatory reforms.

In the third essay, we explore the impact of credit rating changes on the equilibrium between the credit-sensitive bond and CDS markets. We show that the two instruments react differently to the same credit event, resulting in a deterioration of the CDS-bond basis. The analysis of the abnormal basis behavior around event dates shows that the basis decline is amplified for illiquid bonds. The essay findings indicates that unexpected deterioration in the basis could be used as an early sign for adverse credit events. We also study the basis behavior during stress events, proxied by downgrades that make the reference entity cross the investment grade threshold. We find that the impact of a stress event on the basis is more pronounced during the regulation era compared to the pre-crisis period.

An interesting line of research related to the third essay would be to further investigate the role of liquidity in defining the magnitude of the basis abnormal behavior. One avenue could be the construction of a "liquidity basis," defined as the difference of liquidity between the bond and CDS markets, in order to investigate for abnormal changes in the liquidity basis around credit events and study the relation between the abnormal liquidity basis and the abnormal CDS-bond basis.

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