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Under the supervision of David Thesmar

Convergences and discrepancies between American Credit Default Swaps and Bond Markets: What can we learn from the CDS-bond Basis?

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Introduction

Since Credit Default Swaps (CDS) were first introduced in financial markets in 1997, CDS markets[1] have taken their full autonomy. They provide straightforward means to get protection from, or more and more exposure to, specific credit risk and as such have become very much liquid, with a number of leading market makers regularly posting daily quotes for major entities.

As such, they are now a major source of indirect information about credit components of prices in other markets, most notably equity and bond markets: for instance Longstaff, Mithal and Neis [2005] use CDS spreads, or premia, to isolate the default component of corporate bond yield spreads, so as to explain the main determinants of the residual component. More importantly perhaps, they are closely linked with other markets; CDS premia constitute a powerful channel of information or volatility transmission, which contributes to integrate bond and equity options more closely (see e.g. Collin-Dufresne, Goldstein, Martin [2001]).

We are concerned in this work with both those aspects, i.e. the CDS market's influence on corporate bond yields as well as the information we can derive about a "fair" pricing of corporate bonds from price information contained in much more liquid CDS markets: this holds all the more since, US bond markets having remained OTC and rather opaque, it is not unheard of for some bonds of major corporations not to be traded over more than one day.

In that perspective, we empirically study extremely recent CDS and bond markets data over the period ranging from January, 2006 to April, 2009. We focus on the *CDS-bond basis*, defined as the difference between two theoretically equivalent prices for an entity's n-year credit risk, i.e. the CDS premium quoted for this maturity and the credit spread of an n-year maturity bond issued by this entity. Though this quantity should theoretically be close to zero, we find after others that this is very seldom the case; as a result, the basis constitutes a link between CDS and bond markets, and its main features and determinants are crucial to explore if one seeks to acquire a better understanding of either market, *a fortiori* to take advantage of any imbalances between them.

In section 1 of this work, we give a brief description of CDS markets and explain the theoretical source of integration between CDS and bond markets. Section 2 is devoted to the description of our data. In section 3, we test the validity of a number of statistical models exploring the determinants of the CDS bond basis; we show that it follows a random walk, with the implication that no secure profit can be achieved by betting on risk pricing differentials in those two markets; finally, we study both long- and short-term discrepancies between them. Section 4 lists a number of topics and research tracks which could usefully enrich the results presented throughout this thesis, and concludes.

[1] The number and quality of agents trading CDS, the important and regular level of trades on CDS certainly justify this hasty expression, even though CDS are still contracted on an over-the-counter basis.

1 What does the CDS bond basis measure?

1.1 An Introduction to Credit Default Swaps

Credit Default Swaps (CDS) first appeared in financial markets in 1997, an innovation due to American Bank JPMorgan Chase Co, and are the greater part (over 30%) of the wider credit derivatives market, which also comprises other assets such as Total Return Swaps, Credit Linked Notes or Collateralized Debt Obligations. Though the British Bankers' Association (BBA) started publishing an annual Credit Derivatives Report as early as 1998, the growth of this market became especially dramatic after 2003, with a global market for CDS of USD 45.5 trillion by the end of June 2007 according to the International Swaps and Derivatives Association (quoted in [Baird, 2007]), versus only USD 180 billion by the end of 1997. Acharya [2009] reports USD 62 trillion by the end of August 2008. As for all derivatives, it must be stressed that outstanding amounts do by no means represent the actual amount which changes hands from one investor to another - especially since financial intermediation is common practice in these markets, with banks frequently selling protection on one side to buy it back on another one. Indeed, banks are at the same time the major buyers of protection (52 % of the global market as reported by the BBA) as well as the major protection sellers (39 %).

CDS are exclusively traded on Over-the-counter (OTC) markets, and as such heavily subject to counterparty risks. They are more often than not tailored to correspond to the parties' requirements, which results in a wide range of products being traded. In particular, amounts under USD 5 million are extremely rare, while at the other end of the scale some have gone up to USD 1 billion. Other than banks, major players in the markets include hedge funds (net protection buyers), securities firms (net protection buyers) and insurance or reinsurance companies (by far the most important net protection sellers).

CDS are contracted by two parties (respectively referred to as "protection buyer" and "protection seller") and work in exactly the same way as insurance contracts, except for the fact that, unlike in the insurance business, the protection buyer does not need to be actually exposed to a damage to have a right to compensation. Thus CDS markets allow financial agents to get direct exposure to credit risk, whether positive or negative, without bringing in any capital or having to accept exposure to interest risk. Though when they were first originated CDS were mostly used as a protection against a risk directly incurred, they are now widely used to "bet" on future defaults. Indeed, Singh and Spackman [2009] report that at least in the emerging markets, the size of outstanding CDS contracts exceeds the total volume of oustanding bond debt.

Formally, a CDS is defined by its maturity, the reference entity (i.e. the corporate or sovereign debt issuer against whose default the protection buyer requires insurance), its settlement type and its more or less broad definition of a "credit event" (e.g. the reference entity filing for bankruptcy, renoucing - possibly parts of - its outstanding debt, suffering a credit downgrade, or restructuring its debt). The protection buyer agrees to pay his counterparty a quarterly fixed fee, expressed in percentage points of the contract's nominal amount per annum, over a predetermined timespan; this fee is widely denoted as the "credit-swap spread", but we will henceforth use the equivalent (and only slightly less widespread) term of *CDS premium* to avoid any confusion with other kinds of spreads.

Should any "credit event" occur before the end of the said timespan (the CDS contract's *maturity*), then the accrued premium is paid by the protection buyer to the protection seller. They then proceed to the contract's settlement: the most usual form of it is *physical settlement*, by which the protection buyer actually delivers the protection seller one of the entity's outstanding bonds in exchange for repayment of its par value. In other terms, the protection buyer buys a put option on any bond issued by the entity, and this option is triggered by the occurrence of a credit event. The other, less widespread form of settlement, known as *cash settlement*, consists in the protection seller paying the protection buyer the difference between face value and market value of a given reference note issued by the entity. Note that under no circumstances will the protection buyer receive compensation for the accrued coupon[2].

1.2 Pricing a CDS

Duffie [1999] first offered a convincing methodology to price CDS (i.e. to determine the premium demanded by the protection seller) which shows by a no-arbitrage reasoning that under a number of hypotheses the CDS premium P_E on a given entity E is necessarily equal to the credit spread[3] CS_E of a floating-rate bond issued by E with same maturity as the CDS contract.

Assume this is not the case: say $P_E < CS_E$, denote by T the maturity of the CDS and bond alike. Consider the following strategy (henceforth strategy A) and the attached cash flows:

- Short a Treasury floating-rate bond (alternatively, since these are more than scarce in the market, enter into rolling quarterly loans with amount 100): this yields +100 at start date; $-r_t$ quarterly, with r_t the reference risk-free rate at date t (Duffie proposes to use the “general collateral rate”, of which LIBOR is a fairly good and stable approximation); and -100 at T;
- Purchase an floating-rate bond issued by entity E: this yields -100 at start date; $+r_t + CS_E/4$ quarterly and +100 at T if no credit event occurs; $+r_t + CS_E/4$ quarterly until a credit event occurs (say the next coupon date after this event T_0), and the value of the bond $B(T_0)$ at T_0;

[2]This will probably seem clearer with a concrete example. Assume a protection buyer B contracts a 1-year CDS on a reference entity E with a protection seller S on January 1st; the agreed CDS premium is 56 basis points per annum, the size of the contract 100. B pays S 14 basis points, i.e. 0.14 on April 1st. E defaults on May 15th; B then buys on the market a (defaulted]) bond issued by E whose next coupon date is June 1st and sells it to S, as is its right, for its face value of 100, minus the accrued CDS premium of 0.7 it still owes S. B is not compensated for the accrued coupon on the bond it delivers.

[3]A bond's credit spread is defined as the difference between its yield and that of a default-free (OECD government-issued) note with identical maturity and currency.

- Buy protection in a CDS: this yields $-P_E/4$ quarterly if no credit event occurs; $-P_E/4$ quarterly until T_0 and $+100 - B(T_0)$ at T_0.

Thus this portfolio yields a strictly positive return under all circumstances. It can be very easily adapted if, as is usually the norm, coupons are paid semi-annually on the bond. Of course, if $CS_E < P_E$, an arbitrage strategy (strategy B) would be to buy a Treasury, sell protection on E in a CDS and short a floating-rate bond issued by E, assuming that this is possible.

However, a number of issues are not treated in the above reasoning. First of all, the assumption that there is a tradable floating-rate note is only valid for a very small number of entities. This is resolved by Duffie, and many after him (for instance [De Wit, 2006] which gives a very comprehensive approach of what a CDS basis is), by using *asset swaps* to replace floating-rate notes in the previously explained strategies. An asset swap is basically a financial security whose effect is to "float" a fixed-rate bond, i.e. keeping an exposure to credit risk while discarding the associated interest rate risk: it consists of a portfolio with a fixed-rate corporate bond and an interest-rate swap paying fixed and receiving floating[4]. The important concept of *asset swap spread* is then defined as the amount by which LIBOR is augmented in the swap's floating leg[5]. Since asset swaps are very easily replicable, those asset swap spreads are straightforward market data.

Second, it is now agreed that in most cases the cost of shorting a bond, be it Treasury or corporate, is not null. Duffie [1996], empirically supported by Jordan and Jordan [1997], has shown that reverse repos[6] i.e. a widespread means to short a bond, can be concluded at rates below the "normal" riskless rate, i.e. at a cost for the borrower of the bond. The repo is then said to be "on special". In such a case, the cost of shorting is strictly greater than r_t - this results in strategy B being profitable only if $P_E > CS_E + Y_E$, where Y_E is the term repo special for a bond issued by entity E. Duffie further insists that other types of shorting costs should be taken into consideration, in particular transaction costs: an agent wishing to short a bond will necessarily sell it at the bid price and have to purchase it back at the ask price, thus incurring an additional cost, all the more important if the market's liquidity for this bond is low. Since scarcity is one of the reasons of a bond going on special, these restrictions should be most constraining when one wishes to

[4] When these asset swaps are traded as a package, their overall value is usually fixed to par at start date, so as to be as close as possible to a floating-rate note, and the fixed leg of the swap adapted to be exactly equal to coupon payments, which means that the floating leg is constituted of LIBOR plus some fixed basis points; however, it is also very easy to replicate them by purchasing separately the bond and a plain vanilla interest-rate swap, in which case the floating leg is usually LIBOR and the fixed leg rate need not be equal to the bond's coupon.

[5] As explained in the previous note, this is necessarily equal to the differential between the bond's coupon and the swap rate, or fixed leg rate, for the bond's maturity.

[6] A "repo" or repurchase agreement is a contract by which a party A sells a particular security, most commonly a bond, to a party B, and agrees to repurchase it at a particular price a later date, often as soon as the following day. Should A fail his word, B can sell the security to compensate its loss. For A, this is close to contracting a collateralized loan, and the differential between the sale and purchase prices corresponds to the interests which would have been paid in such a loan. This naturally defines a repo rate. B is said to have entered a reverse repo. Since it holds the bond over the life of the repo, it has the opportunity to sell it as long as it buys back in order to sell it back to A, which is close to a classical bond shorting.

implement strategy B, i.e. to short a corporate bond rather than a Treasury: this tends to increase P_E comparatively to CS_E.

Indeed, all authors to our knowledge cite reverse repo costs as one reason why the CDS premium should be higher than the asset swap spread. However, it is not unheard of for Treasury bonds to go on special. Apart from the two articles quoted above, Fleming and Garbade [2004] show that during the period August - November 2003, *"some dealers became willing to* pay *interest on money lent to borrow the ten-year [Treasury] note"*. In other words, borrowing a Treasury note came at an extra cost. In that case, strategy A becomes more costly to implement and, if we denote by Y_T the term repo special for a Treasury, is only profitable with certainty if $P_E < CS_E - Y_T$, i.e. if the CDS premium is significantly below the asset swap spread.

Another issue limiting this no-arbitrage logic is that of the availability of any bond issued by the entity, let alone one with a maturity corresponding with the CDS contract's. Many studies have emphasized the worrying lack of transparency and liquidity in (mostly OTC) corporate bond markets, especially as opposed to equity markets. Recently, Acharya, Schaefer and Zhang [2008] showed over a *"clinical study"* of the May 2005 Ford and General Motors downgrade, that bond markets were unable to show resiliency in stress times, especially when the credit spread between commercial paper and Treasury-Bills augments and market makers face an increasing cost of capital. Using data retrieved from TRACE (Trade Reporting and Compliance Engine, where all OTC transactions have to be reported), Edwards, Harris and Piwowar [2007] report that for all active issues listed in the TRACE master files, i.e. 40,508 bonds, the total number of reported trades over the period ranging from January 2003 to January 2005 was 17,327,033, yielding an average number of trades of 427 per bond, i.e. less than one per business day. Also, while CDS quotes are normally firm and valid on a pretty large scale, the arbitrage process may be handicapped by the fact that quotes posted by dealers in bond markets are only indicative and not necessarily obtainable for large trades.

Other hypotheses made by Duffie will be examined in section 3, as we attempt to deal with them. Let us only shortly mention his hypothesis 2: *"There is no payment of the accrued credit-swap premium at default."*. As stated above (see footnote 2), this is not in line with standard practice in the markets, and constitutes an asymmetry between protection buyers and sellers (who do not have to compensate their counterparties for the accrued coupon): protection buyers should logically demand to have the premium they pay reduced to compensate this. The amount of the said reduction, however, would be difficult to estimate since it is likely that the stochastic discount factor used to discount this accrued premium would have to be utility-adjusted and might depend upon the contract's size (not available in our data).

1.3 Definition of a CDS Basis

The previous section leads to a very natural definition of a Credit Default Swap/Bond Basis: for each couple i of maturity-matched CDS contract with premium and reference entity-issued bond, and for each date t, where by $CDSp_{i,t}$ and $ASS_{i,t}$ we denote respectively the CDS contract's premium and the bond's asset swap spread, we call *CDS basis* of this couple the value, expressed in basis points:

$$b_{i,t} = CDSp_{i,t} - ASS_{i,t}$$

This measure is the one we resort to using in the rest of this work. However, a number of other measures have been examined in the recent literature.

One might wonder why what would appear to be the most straightforward definition of a CDS basis, i.e. the difference between CDS premium and "simple" credit spread, as defined in footnote 3, is not more widely used. The answer lies probably in the fact that this simple definition of the credit spread actually fails to take into account the existence of a number of factors, other than credit, embedded in the said spread (e.g. tax issues, embedded options, policy constraints or liquidity problems). Thus Huang and Huang [2003] *"find that credit risk accounts for only a small fraction of the observed corporate-Treasury yield spreads for investment grade bonds of all maturities, with the fraction smaller for bonds of shorter maturity"*, a result fairly robust since it is little sensitive to the structural model it is based upon; in particular, they observe a discrepancy of 96 basis points between their predicted Baa four-year spread versus Treasury and the actual historical average. Similarly, though their findings are less striking, Longstaff, Mithal and Neis [2005], find that the nondefault component represents a percentage varying from 17 to 49 % of the observed spreads of corporate bonds versus Treasury curves. Asset swap spreads are also subject to the existence of non default components, but less directly so.

Indeed, Hull, Predescu and White [2003] compare CDS spreads with the spread between the yield of a par yield reference entity bond and that of a par yield riskless bond (corresponding to a "riskless rate"), adjusted for the fact that accrued interest is not paid in case of a credit event; after discussing what should be meant by "riskless", they conclude that LIBOR rates[7] provide a better fit to the data, and that the actual riskless rate consistent with the absence of arbitrage opportunities under the hypotheses they lay lies between the Treasury curve and the LIBOR curve, though decidedly closer to the latter (the average distance is between the implied riskless rate they find and the LIBOR curve is 6 basis points, versus 63 for the Treasury curve). Since asset swap spreads are computed against LIBOR, this tends to support our definition of the basis. Roberto, Brennan and Marsh [2005] obtain similar conclusions and carry out their study both about "basis over swaps" and "basis over Treasury".

De Wit [2006] reviews other possible CDS basis measures, most notably fixed-rate "I-spreads" and (more sophisticated) "Z-spreads"[8], but also chooses to define the basis as the differential between CDS premium and asset swap spreads: all in all, this seems to

[7]Hull, Predescu and White use the equivalent term of "swap zero curve" but we choose to adopt the term consistent with this work.

[8]I-spreads are defined by De Wit as *The yield-to-maturity differential between a credit-risky fixed-rate bond and the interpolated swap rate.*, while a bond's Z-spread or "stripped spread" is the number of basis points by which the Treasury Zero-coupon curve should be translated to equate the bond's price to the sum of its discounted cash flows

be the most widely adopted solution in recent literature [9].

Given the limits to arbitrage listed above, there is little reason to find the CDS basis exactly null - we can only expect it to be "close" to 0 in absolute value, and at the very least to converge[10] to a "small" value if there were a large deviation from 0. We show in the rest of this work that this is not always the case, and offer a number of explanations.

[9] De Wit quotes that *"Felsenheimer (2004) goes even further by stating that in any case the appropriate spread measure for comparing cash bonds with CDS is the asset swap spread".*; other practitioners tend to be of the same opinion

[10] Possibly relatively slowly, due to the lack of liquidity in bond markets already highlighted, and its potential contagion effects [Goyenko, 2006].

2 Data description

The data used in this thesis were exclusively supplied by Markit Group Limited, but originate from two quite different departments.

2.1 Credit Default Swaps premia

Our data consist of daily quoted mid-market single-name CDS premia for 52 reference entities for which the global market was very liquid, available for each trading day between January 2$^{\text{nd}}$, 2006, and April 15$^{\text{th}}$, 2009 (which was reduced to April 9$^{\text{th}}$ to correspond to our bond information), i.e. over a period which spans both a very prosperous year for financial markets and what already appears to be one of the most severe financial and economic crises of the past hundred years. These premia are available for a number of maturities: 6 months, or 1, 2, 3, 5, 7, 10, 15, 20 and 30 years. They are systematically labelled in USD. A few global groups (e.g. Citigroup), all of them financial institutions, are counted twice in this sample since different branches may issue bonds. Since credit events are thoroughly defined in OTC CDS contracts, this does not appear to be a major drawback.

We systematically discarded Euro-labelled quotes to match my bond data sample. Also discarded were data lines where either the reference 5-year maturity quote or at least 4 quotes among the remaining maturities are missing. To test the consistency of the data, we checked that each quote (i) does not show more than a 20 % difference to the equivalent quote dated from the previous day or (ii) if it does, that the closest two quotes (e.g. for the 3-year maturity quote, 2-year and 5-year maturities) also exhibit at least a 10 % difference from their previous day equivalents. Finally, CDS for which less than half the maximum number of dates (i. e. 819) remained were also discarded. Less than 1% of data was affected by this step.

All in all, our CDS database then consisted of 41 liquid entities listed in Table 1, of which 37 had data for 800 days or more.

2.2 Bond information

We received data on a large number of bonds for the period ranging from January 3$^{\text{rd}}$, 2006 to April 9$^{\text{th}}$, 2009. All those bonds were USD-denominated and complied with Markit's minimum criteria to be part of their most liquid iBoxx Indices product range[11]: only bonds with certain cash flows were eligible (excluding for instance all index-linked bonds); minimum "averaged" rating was BBB, and minimum maturity was 1 year (though, since indices are only rebalanced once a month, bonds with a little more than 11 months to maturity may be found in the sample). To ensure liquidity, retail and private placement bonds are excluded, as well as bonds with an initial maturity below 18 months, and a minimum outstanding amount (USD 500 million for corporate or financial bonds)

[11] A detailed list of the said criteria is available online: http://www.indexco.com/download/products/guides/Markit_ iBoxx_ USD_ Guide.pdf .

for each bond is required. Moreover, we remove all bonds containing embedded options or with convertible features which may lead to a rational widening of the basis and a distortion in our measures (indeed, Blanco, Brennan and Marsh [op. cit.] state that when Fiat issued a new convertible bond, which for obvious reasons was traded at a large discount, Fiat's CDS premium jumped by a sizeable amount, creating a gap between premium and credit spread).

For the purposes of this study, we kept all bonds where there was no missing or inconsistent value in either a "fundamental" field (having no information on the bond's duration or finding a negative coupon casts a negative suspicion on data's validity) and/or those fields we were interested in (namely: pricing date, identifier, issuer, bid price[12], coupon, straight yield to maturity, asset swap spread and maturity date). For instance, a null or negative asset swap spread was considered inconsistent. Most of the time, removal was due to the bond asset swap spread not having been computed - this amounted to about 0.3 % of our data.

2.3 Matching the data

Since both data sets were originally totally unconnected, a major matching work had to be carried out before they could be used, most importantly to ascertain which bond could correspond to which CDS premium. We first had to remove from the bond database all those which could not be directly linked to the CDS available in the CDS database. To that end, we looked up the issuer of each individual bond thanks to its ISIN (International Securities Identification Number) as extra safety and compared it to the issuer filled in in the Markit data. Both sources concorded perfectly. We then retained all bonds for which both (i) the ticker (e.g. PG for Procter & Gamble) was also present in the CDS database and (ii) the issuer was clearly part of the said group, i.e. had a transparent name and/or was listed in one of the said group's two latest annual reports as a full subsidiary. We systematically removed all issuers for which there was only a possibility that a bond they issued could be delivered as a reference asset under the terms of a standard CDS contract. For global corporations with two different CDS tickers, each subsidiary was assigned to one or the other according to its nationality. Table 1 shows which reference entities were ultimately retained, the number of days for which both a CDS premium and the price of at least one bond issued by this entity or one of its subsidiaries are available, as well as the average daily number of bonds which could be matched to this entity[13]. Emphasized in bold are the entities which are also constituents of the latest version of CDX.NA.IG Index[14].

[12] Markit's standard practice is to privilege the quality of bid prices, and allow ask prices to remain void if there is a doubt on their exactness.

[13] Since bonds with too short a maturity went out of the sample and newly-issued bonds entered it, the number of outstanding bonds for each entity is not necessarily a constant through time

[14] Recall that in this index, each of the five component sectors is assigned only 25 names, which explains why many financial institutions are not included in it, very liquid though their CDS are.

[Table 1: list of CDS in our sample]

This corresponds to the following repartition by sectors: Communications and Technology (8), Consumer Stable (4), Consumer Cyclical (3), Energy (3), Financial (23).

To compute the actual basis, we use a methodology which to our knowledge has not been used in this field of study; indeed, as was explained above, a couple with both a CDS contract and a bond with the exact same maturity, which more often than not does not exist, is required for the basis to be meaningful. All authors in the recent literature we have consulted (notably De Wit [2006], Blanco et alii [2005], Hull et alii [2003]) choose to set the (usually standard 5-year, though De Wit also includes 3- and 10-year) CDS contract as reference and build, either through linear interpolation or with a simple statistical model, a 'virtual' 5-year-to-maturity (respectively 3 or 10) bond from the basket of available bonds issued by the relevant entity to compute the basis. While this may have solid motivations (most importantly in our opinion the fact that CDS are significantly more liquid than bonds), a practical objective of our work is to use more widely, and often earlier, available CDS data to price bonds; also, we believe that since CDS contracts are single-name but allow for the delivery of a number of different bonds (and many have emphasized the fact that this *cheapest-to-deliver option*, or CTD, which will be examined later on, is an important factor in pricing the basis), it is not altogether wrong to set bonds as reference and build for each of them a corresponding virtual CDS premium. A last argument lies in the fact that CDS contracts are tailored, which bonds obviously are not; hence it seems fairly reasonable to imagine that an investor holding a risky bond and willing to carry it to maturity should want to negotiate a CDS contract with maturity date matched to that of its bond.

Based on this logic, we define for each bond and each pricing date the corresponding CDS premium as the result of the linear interpolation of the two CDS premia with closest maturity[15]. We then define the basis as stated in section 1, i.e. the difference between this premium and the bond's asset swap spread as directly provided in the data.

Our final database hence consists of 464,768 data lines. Graph 1 outlines the daily mean and median values for the basis over our whole sample. Notice the mean is systematically below the median up to August 18$^{\text{th}}$, 2007, and more generally systematically higher in "crisis" times (January and February, 2008, September and October 2008,...). This signals to removing outliers, which we do with the standard criterion of the median plus or minus five times the interquartile range. Since there is definite suspicion of regime switches, and to avoid contagion from one period to another, we split our sample in three periods to do so, namely from January, 2006 to June 2007; from July, 2007 to June, 2008; and from July, 2008 onwards. Those periods are clearly suggested by Graph 1, and loosely correspond to a "prosperity time" (Graph 1a), a "classical financial crisis", and "turmoil times" immediately before, during and after Lehman's filing for bankruptcy (Graph 1b). This results in deleting a little short of 7,000 lines evenly spread across time

[15] Thus consider a bond i with maturity 2.5 years at date t. The corresponding CDS premium $CDSp_{i,t}$ is computed as the arithmetical average of 2-year and 3-year CDS premia whose reference entity is the bond's issuer.

Reference entity	Ticker	Data Length	Nr of bonds
American International Group	AIG	819	25.0
AIG - International Lease Finance Corp.	AIG-I	819	13.0
Anadarko Petroleum Corporation	APC	817	5.8
AT& T Inc.	ATTINC	819	18.7
American Express Company	AXP	819	11.4
Bank of America	BACORP	819	40.2
Barclays Bank	BACR	430	5.9
MidAmerican Energy Company	BRK-M	581	11.9
Citigroup Inc.	C	811	31.8
Caterpillar Inc.	CAT	650	2.1
Commercial Investment Trust	CIT	819	10.9
Comcast Corporation	CMCSA	818	24.2
Capital One Financial	COF	818	8.9
ConocoPhillips	COP	818	13.6
Credit Suisse	CRDSUI	810	15.9
Deutsche Bank	DB	819	4.1
Residential Capital, LLC*	GM-Re	418	1.1
Goldman Sachs Group	GS	819	25.0
HBOS, Plc.	HBOS	818	12.1
HSBC Holdings	HSBC	818	11.7
HSBC Finance Corporation	HSBC-Fin	819	19.8
International Business Machines Corporation	IBM	819	11.7
JPMorgan Chase & Co	JPM	819	27.2
JPMorgan Chase Bank, National Association	JPM-C	793	5.7
Kraft Foods Inc.	KFT	819	8.5
Lehman Brothers Holding Inc.	LEH	678	19.3
Merrill Lynch & Co Inc.	MER	819	19.9
MetLife Inc.	MET	818	8.6
Altria Group	MO	819	5.2
Morgan Stanley	MWD	819	17.4
News America Inc.	NWS-AmInc	817	6.0
Procter & Gamble Company	PG	398	8.4
Sprint Nextel Corporation*	S	614	10.3
SLM Corporation	SLMA	818	11.9
Target Corporation	TGT	818	10.7
Time Warner Inc.	TW	819	5.2
Vodafone Group, Plc.	VOD	818	10.1
Verizon Communications, Inc.	VRZN	598	23.2
Wachovia Bank, National Association	WB-Bank	701	2.6
Wells Fargo & Company	WFC	819	39.3
Wal-Mart Stores Inc.	WMT	819	12.9
Wyeth	WYE	818	8.2

*This entity is a constituent of the current CDX High Yield index periods, or about 1,5 % of the original data.

The most striking result obtained here is that the bases we find are negative in their large majority (more precisely in 74.78 % of cases), a finding which is surprising in light of all previous studies, showing that the basis is as a rule positive[16], which will be investigated in the next two sections. This remains true, though less strikingly so (65.27% of negative bases), if we focus on a sample more directly comparable to that used in previous studies, i.e. restrained to maturities lying between 4.5 and 5.5 years. Blanco and alii, however, did find an average negative basis of -41 basis points when they used the swap against government yields as reference credit spread, and a small positive basis (+6 basis points) when they used LIBOR rates, which led them to conclude that the real basis lay probably somewhere in between; in that light, then, the average basis of -11.43 basis points we obtain over the first 18 months of data is not totally inconsistent with what other works have shown. Last, we observe that negative bases are slightly more frequent[17] in 2006 to Mid-2007 than afterwards and that, though we take this period as benchmark against crisis periods during the rest of the study, we must not forget that it also exhibited some very peculiar features. Most notably, interest rates and bond spreads were historically very low in 2006, even though they are on the long term quite high relatively to the risk implied by equity markets. This may mean that the true benchmark basis which should be computed from our definition lies below the -11.43 basis points we find for period 1.

Other results are more in line with what we expected, most notably that the times were the basis is largest in absolute value are also those where markets were most stressed and arbitrage most difficult to carry out, either because of funding or liquidity issues or, more simply, because arbitrageurs had too much to deal with otherwise. Table 2 shows a number of descriptive statistics for the basis, both over the whole sample and split up by periods (all figures are expressed in basis points). We also show some statistics for financial institutions only.

[Table 2: Descriptive statistics about the basis]

Sample	Mean	Median	Standard deviation
Full sample	-40.35	-14.29	119.0
Period 1	-11.43	-7.38	18.56
Period 2	-23.52	-20.8	58.98
Period 3	-116.95	-116.78	206.2
Financials, full sample	-32.44	-9.9	130.72
Financials, period 3	-147.07	-136.76	109.5

Notice that in period 1, the figures we obtain are quite close in absolute value to that obtained by De Wit for the years 2004-2005 (mean of 9.9 and median of 6.5 after excluding emerging markets sovereign issuers), and even closer if we focus on the year 2005 only.

[16] Recall however the *caveat* that the basis is not computed in the same way.

[17] ... but much less important in absolute terms!

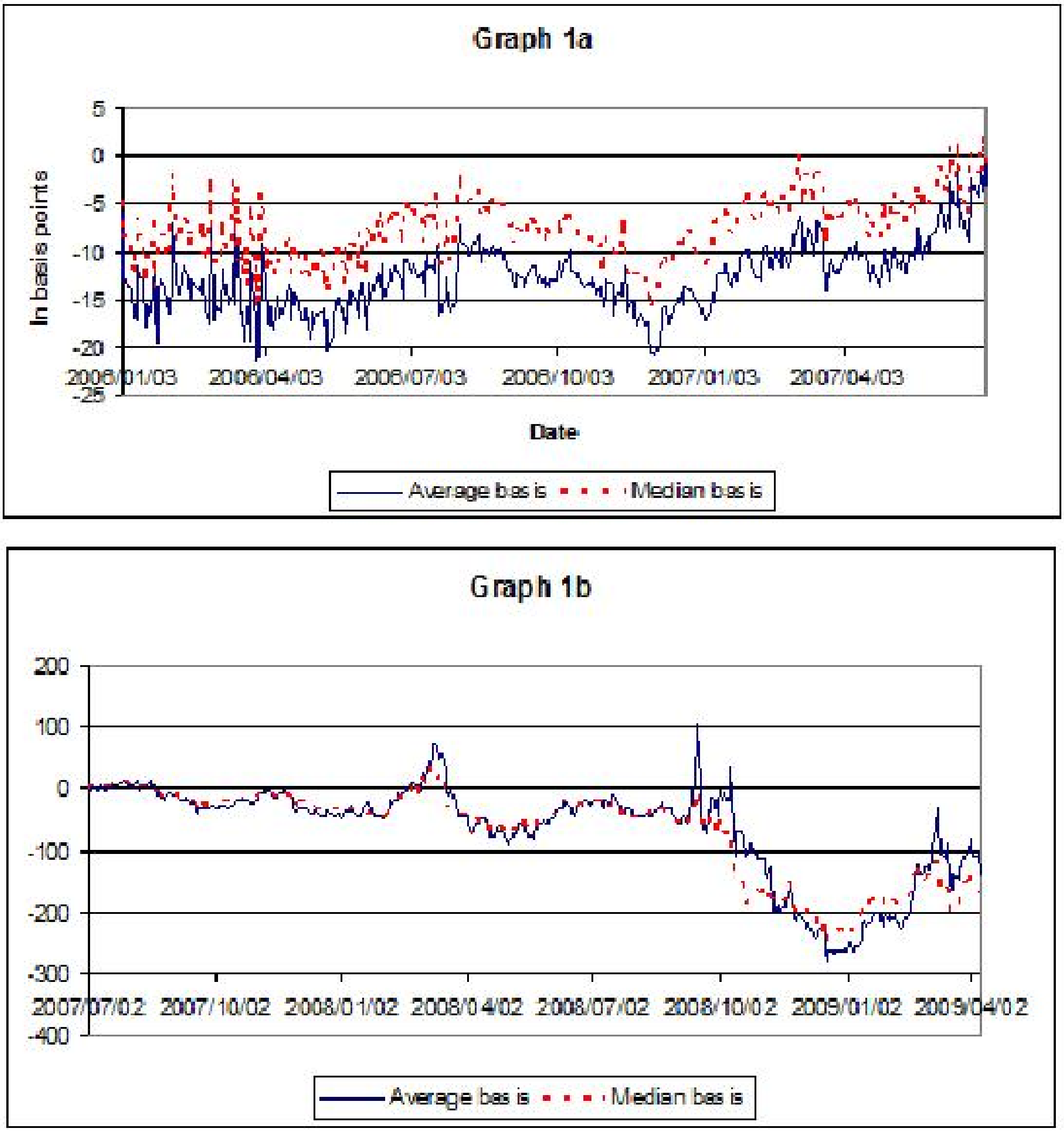

Figure 1: - average and median basis, January, 2006 to April, 2009

It is also interesting to examine the standard deviation of basis computed day per day: it oscillates between 16.12 and 20.1 over period 1 (excluding the second fortnight of June, 2007, where it begins to rise slowly up to 24.9); rises sharply in the beginning of August, 2007 to reach 40 and again in November, 2007 - it then fluctuates between 49.9 and 65 (with one to two weeks peaks) until the end of our second period; and remains invariably above 150 after September 10^{th}, 2008. The average basis per entity and per week does not seem to be highly significative (it is more often than not smaller than its standard deviation in absolute terms), but varies sizeably from one issuer to the other.

3 Predicting and using the basis

3.1 Various predictive models of the CDS basis

A "basis" model

By analogy to the well-known market or single-index model, we first estimate a statistical model in which the basis is driven by a common market factor approximated by either the average or the median basis. Formally, we say that

$$b_{i,j,t} = \alpha_i + \beta_i b_{M,t} + \epsilon_{i,j,t}$$

where by $b_{M,t}$ we denote the average (respectively median) for the basis computed over our whole sample for day t, by i a reference entity and by j a bond issued by this entity: that is, we allow the parameters to vary entity per entity (another choice would be sector by sector, but the "financial" sector is probably too widely defined to be homogenous).

Since one of this thesis' major aims is to ascertain how predictable the basis is, we compute each model's R^2 as a measure of its predictability. In the current case, this model's R^2 amounts to 37.0 % when estimated over our full sample with reference mean, all estimates of the β_i being statistically significant at the 0.1% confidence level, with the notable exception of the coefficient for Residential Capital, LLC; indeed, since General Motors (Residential Capital's parent company) experienced heavy turmoils as early as 2005 when the rest of the market was still bolstering, this is not altogether surprising - a similar result would probably have been observed if we had had Ford data in our sample. Of the estimates for α_i[18], 19 out of 42 are positive. We obtain the following results:

[Table 3: Regression 1: common basis variation]

Sample	Type	R^2	Fisher test	Positive α	5^{th} lowest β	5^{th} highest β	Significative betas
Full	mean	37.0%	3,239	19	0.376	1.86	41
Period 1	mean	25.14%	801	19	0.543	1.67	39
Period 2	mean	33.6 %	934	15	0.70	1.35	42
Period 3	mean	38.1 %	881	12	0.515	2.05	40
Full	median	37.9 %	3358	19	0.242	1.7	41
Period 1	median	24.87 %	789	11	0.54	1.58	38
Period 2	median	32.97 %	908	17	0.71	1.35	41
Period 3	median	37.2 %	848	14	0.55	1.85	41

We provide the 5^{th} highest and lowest betas because they are more emblematic that the minimum and maximum would be, as illustrated by the example of Residential Capital, LLC. Thus this model seems to have a fairly good predictive power, which means that all bases vary along a common average daily variation with more or less pronounced intensity, but would probably be more meaningful if it could be estimated over longer periods (it does not necessarily require to be performed on daily data)).

[18] More precisely, we estimate the following model:

$$b_{i,j,t} = \lambda_0 + \sum_{k=1}^{42} \mu_k 1_k + \sum_{k=1}^{42} \beta_k b_{M,t} * 1_k + u_{i,j,t}$$

which yields $\alpha_i = \lambda_0 + \mu_i, \forall 1 \leq i \leq 42$.

With 5 exceptions out of 336 altogether, all betas are strictly positive, which indicates that the difference in credit risk apprehension between CDS and bond markets has a common feature, though the latter's effect is more or less pronounced according to the entity. Interestingly enough, while financial institutions are overrepresented in our sample (which can for this reason not be considered as representative of the broader market), the average beta for financial institutions is systematically slightly above 1 (ranging from 0.967 to 1.322 according to the model type and the chosen period), while that for entities in the Consumer Stable sector, for what it can mean with only 4 observations, is significantly below 1, ranging from 0.67 to 0.83).

A simple multifactor model with common factors

It has been known for some time now that simple models are not always the least performing: since we are concerned in this section with a statistical approach to predicting the basis, we first test the adequacy of a basic linear multifactor model using macroeconomic variables as factors. Indeed, drivers of the basis include, as explained in section 1, the cost of shorting either a corporate bond or a riskless bond (which loosely corresponds to borrowing money - its cost is therefore approximated by that of gross interest rates): we therefore include 3 short-term LIBOR rates in our factors, namely the daily one-week, 6-months and one-year LIBOR rates; since repos or rolling loans are very unlikely to last beyond one year, we do not find it necessary to include longer-term rates.

Also, it is very disputable to assume (as is the case in the standard theoretical no-arbitrage reasoning) that arbitrageurs can fund themselves precisely at LIBOR - however, "funding difficulty" is unobservable, and very probably correlated with the level of LIBOR rates, which means we are facing a measurement error inconsistency, since the true underlying model is

$$b_{i,j,t} = \alpha + \beta_1 r_{1week,t} + \beta_2 r_{6months,t} + \beta_3 r_{1year,t} + \gamma \text{ funding issue}_t + \epsilon_{i,j,t}$$

A first straightforward solution would be to plug in the model a proxy for funding issue. We have two such variables available, namely the daily average bond yield as well as the daily average CDS spread on financial institutions (which reflects what the market thinks of their soundness and is likely to be correlated with their willingness to loan at advantageous rates). Note that we would expect these variables' coefficients to be negative, or at least that their combined effect be negative (since they are both proxies of the same unobserved variable, we find them very highly correlated, with a correlation coefficient of 92.11 %). However, there is a high probability that those proxies are not only "imperfect", but also correlated with LIBOR rates, and that the measurement error is itself correlated with the level of our proxies[19], which would result in biasing the coefficient we obtain for funding issues. We therefore use the fact that we have two distinct measurements of funding issues and assume that their mismeasurement errors are uncorrelated (one refers to the CDS market and financial institutions specifically and is defined in absolute terms, the other one is obtained through the bond market, over various sectors, and is defined in relative value): this allows us to resort to a multiple indicator solution, and

[19] Consider for instance the possibility that when funding issues increase, even slightly, above a certain threshold, investor's apprehension of the credit risk of financial institutions worsens dramatically.

use the average bond yield as an instrumental variable for the average financial spread: $fin - spread_t = a + bmean - bond - yield_t + \epsilon_t$. We then plug the estimate for the financial spread obtained from this equation into the model in the stead of funding issue.

[Table 4: Regression 2: estimation of a simple multifactor model]

Sample	Intercept	1-week Libor	6-months Libor	1-year Libor	financial spread	R^2
Full sample	-56.52	65.76	-106.1-	52.23	-0.08	0.18
	0.89	0.58	1.6	1.2	0.002	24,703
Period 1	-16.11	15.96	-29.07	10.14	1.31	0.006
	1.4	0.76	2.1	1.72	0.13	285.8
Period 2	659.39	23.07	-57.47	47.02	-6.52	0.002
	121.2	4.4	10.66	8.66	1.09	54.5
Period 3	-289.24	64.7	-339.18	357.96	-0.1	0.104
	8.04	1.49	11.32	12.39	0.006	3,264

We proceed to the estimation of this model both on the whole sample and period by period. Results are shown in table 4, with the standard error of each parameter indicated below this parameter's estimate. The model's Fisher test is indicated below its R-square. Results are extremely contrasted: in particular, this model performs acceptably well over the whole sample, but is almost non-explicative when split up period by period - most astonishingly for period 1, since this period is marked by a relatively low volatility of the basis - but possibly an even smaller volatility of the endogenous variables, rendering them unable to correctly explain any of this low volatility. This is actually strong evidence in favour of regime switches.

However, it remains interesting to notice that strictly all parameters estimated are significatively not null and that, with the one exception of period 1's estimate for the coefficient of the average financial spread, their sign does not vary with the sample on which the estimation is performed. In particular, we may note that, as was expected, the coefficient applied to our proxy for funding issues is negative, though small; and that it seems to be fairly robust, i.e. invariant to periods, to find positive coefficients for both 1-week and 1-year LIBOR rates, and a negative coefficient for 6-months rates - which is doubly puzzling, since we could not *a priori* imagine any reason why the sign of this coefficient should vary so dramatically, and above all since it would seem more intuitive to find negative coefficients (higher interest rates mean that borrowing a Treasury note is more costly, and should result in a lower basis).

The explanation to this apparent puzzle probably lies in the fact, explored by Hull and White [2000], that the relationship between CDS premium and bond yield is more accurate when interest rates are low, but also when the Treasury curve (which they use as a reference) is flat. Hence if as here we estimate an equation of the type

$$b_{i,t} = \alpha + \beta_1 r_{1week} + \beta_2 r_{6months} + \beta_3 r_{1year}$$

it may well be that the correct model is actually

$$b_{i,t} = \alpha + \beta_1 r_{1week} + \beta_2 r_{6months} + \beta_3 r_{1year} + \gamma_1 (r_{6months} - r_{1week}) + \gamma_2 (r_{1year} - r_{6months})$$

resulting in biased coefficients: $E(\hat{\beta}_1) = \beta_1 - \gamma_1$, where by $\hat{\beta}_1$ we denote our estimate of β_1 in the first equation above. As a result, if we accept that the yield curve's slope has an effect on the CDS basis, then the estimate $\hat{\beta}_2$ is actually an estimate of the sum $\beta_2+\gamma_1-\gamma_2$, while $E(\hat{\beta}_3)=\beta_3-\gamma_3$. Thus, assuming that the γ_i are positive (as to expect) and have more or less the same absolute value[20], an appealing explanation is that $\gamma_1-\gamma_2$ is close to zero, so the "real" β_2 is indeed negative, while $|\gamma_1|>|\beta_1|$ (and similarly for γ_3 and β_3), which would explain the positive estimates for β_1 and β_3.

Augmented multi-factor models

Since the previous paragraph showed that a basic version of a common factor model is very disappointing in terms of predictability and that this can be traced to the lack of variability in the exogenous variables, we add further variables to more accurately predict the basis.

First of all, we include the (CDS contract, bond) couple's maturity, and expect it to be affected by a negative coefficient, based on the following observation: as a reaction to problems arising in summer 2000 when Conesco had to restructure its debt and protection sellers found themselves obliged to accept bonds with very long maturity to remain, the ISDA (International Swaps and Derivatives Association) implemented on May 11$^{\text{th}}$, 2001 the so-called "Modified Restructuring" prohibiting the delivery of such long-term bonds. This means that long-term bonds actually carry greater risk than equivalent shorter-lived bonds, since their credit risk can only be partially hedged through CDS contracts (this is all the truer since CDS contracts with large maturities are more subject to counterparty risk). On the other hand, long-term CDS contracts are not affected by this clause - this induces an asymmetry between CDS and bond markets which can explain lower basis levels for high maturities.

This effect could, however, be compensated by a structural excess of CDS demand for longer maturities; but this does not seem very likely, since it is fairly common for big fund managers, who are major actors on this market (usually to buy a long-term bond and carry it to maturity, as part of an ALM strategy[21]), to be restricted on entering CDS contracts, out of both regulatory and professional constraints. Also, since most hedgers do not have a particular interest in such long-run deals (recall that a typical hedge fund's life expectation is a mere 5 years), they do not correct this asymmetry either.

Second, we take into account De Wit's observation that protection sellers are exposed to a bond's full face value while an investor acquiring it when it trades below par has less at stake, which increases the CDS risk relatively to that of the bond and hence should result in increasing the basis. Consequentially, we introduce a dummy for bonds trading above par in our model and expect its coefficient to be negative.

[20] In other words, and since as a rule the yield curve is steeper at its very beginning, we assume that the yield curve's steepness for very short maturities has an altogether greater impact that its steepness for 6 months to 1 year maturities, but that any variation in those slopes has the same effect.

[21] Asset-Liability Management consists in matching a company's cash inflows to its outflows as much as possible.

Last, we try to consider the often raised issue of the CDS cheapest-to-deliver option: since reference entities often have many bonds outstanding, a number of which can be delivered in case of credit events, a protection seller is almost certain to find himself stuck with those worth least at the time of the event and will augment the premium he requires to incorporate this additional risk. As De Wit emphasizes, *"the wider the spectrum of deliverable bonds and loans in terms of covenants, maturities and coupons, the more valuable this delivery option may be"*: we test this by including a variable equal to the number of bonds in our sample for the reference entity on each particular day. Note that the restrictions underlined in section 2 apply, i.e. that our bond sample cannot claim exhaustivity - however, this variable can be considered as an acceptable, though far from perfect, proxy for the number of (at least reasonably) liquid, plain bonds outstanding for any entity. The coefficient for this variable, which we expect to find positive, should therefore be interpreted with all due caution.

.

[Table 5: Regression 3: augmented multifactor models]

Sample	Intercept	financial spread	maturity	Above par	No. of bonds	R^2
Full	-25.75	-0.07	-1.99	4.67	- 0.52	20.6 %
	1.02	0.00	0.02	0.33	0.02	16,185
Period 1	6.34	1.27	-1.29	-6.02	-0.05	34.8 %
	1.14	0.11	0.00	0.07	0.00	14,489
Period 2	702.69	-6.69	-1.96	-4.37	0.00	0.3 %
	124.85	1.12	0.11	2.04	0.09	74
Period 3	-248.69	-0.10	-2.46	29.07	-1.92	13.35 %
	8.13	0.01	0.07	1.31	0.05	2,464

All results are shown in table 5 (estimates for LIBOR rates, not shown here, are fairly similar to those obtained with a simpler model - see table 5 above). The model we estimate is the following:

$$b_{i,j,t} = \alpha + \beta_1 r_{1week,t} + \beta_2 r_{6months,t} + \beta_3 r_{1year,t} +$$

$$\gamma \times fspread_t + \delta \times maturity_{i,j,t} + \zeta \times nrbonds_{i,t} + \theta \times abovepar_{i,j,t} + \epsilon_{i,j,t}$$

Two coefficients exhibit a surprizing sign: that for the dummy that the bond trades above par (but this sign is not extremely robust, since it is different in period 2), always significative, which means this dummy probably captures a hidden variable and could very well reflect a regime change, not unheard of in CDS or bond markets (see Ellul, Lundblad and Jotikasthira [2009]); and that for the number of bonds outstanding for the entity. This reinforces the suspicion expressed above that this variable is not an excellent proxy for the value of the cheapest-to-deliver option. Solutions to this issue might be the inclusion of a dummy for the sector, since by nature financial institutions are much more likely to have issued more bonds *ceteris paribus*, and/or the replacement of the variable "number of bonds" by one equal to the maximum yield between those of the bonds issued by the entity, which would give an idea of how cheap the cheapest-to-deliver bond might be.

3.2 Meaning and value of "basis returns"

We turn to examining basis autocorrelations, both to improve basis predictability and to explore how the basis converges towards 0, or at least towards its constant long-term level. All in all, the most effective predictive model turns out to be the simplest one: if we test the validity of the model

$$b_{i,j,t} = \alpha + \beta b_{i,j,t-1} + \epsilon_{i,j,t}$$

, we obtain a very good fit to the data:

[Table 6: Regression 4: a simple autoregressive model]

Sample	Intercept	previous basis	R^2
Full	-1.283	0.973	93.54 %
	0.058	0.000	6,525,227
Period 1	-0.333	0.971	94.29%
	0.01	0.001	3,133,021
Period 2	-0.833	0.967	92.8 %
	0.044	0.001	1,920,099
Period 3	-4.21	-0.968	92.69 %
	0.19	0.001	1,453,405

In that case, adding common factors hardly improves predictability at all, since those factors themselves vary in general only slightly from one day to another and their previous value is already incorporated in $b_{i,j,t-1}$.

It is probably even more instructive to allow the two parameters of the equation estimated above to vary according to the reference entity (according to the model $b_{i,j,t} = \alpha_i + \beta_i b_{i,j,t-1} + \epsilon_{i,j,t}$). In that case, we find that only 5 α_i are significatively different form zero, while the null hypothesis that $\beta_i = 1$ cannot be rejected for 14 reference entities out of 42, while the others are almost all very close to 1 (of the 42 β coefficients, only that for Procter & Gamble lies below 0.9, and 38 stand between 0.952 and 1.015). This leads to the hypothesis that bases actually follow a standard martingale process, very widespread in the financial markets, and thus we may wonder how much bases can be assimilated to asset prices.

This seems *a priori* to be meaningless: a CDS basis is not a price (as it does not allow to buy any asset and is not even quoted by dealers), but a difference between two (implicit) prices[22], i.e. the price for risk in CDS markets on the one hand, in bond markets on the other hand. Assume however that you want to bet on an increase of the basis, i.e. that you believe that quoted CDS premia will decrease more (respectively increase less) than quoted asset swap spreads in absolute value. You can implement the following strategy:

- Sell protection in a CDS contract (i.e. enter a contract by which you will be receiving the CDS premium $CDSp_t$ in exchange for default guarantee);
- Sell an asset swap on bond markets for the corresponding amount;
- The position can then be unwinded by buying protection in a CDS contract and selling back the asset swap.

[22] Though a basis is not a price in itself, it would not be altogether surprizing that it be a martingale, as the difference between two implicit prices which are likely to be martingales.

If your forecasts were accurate, the gain realized on the CDS trades (respectively the asset swap trades in case of a decrease) will more than compensate the loss made on the asset swap trades (respectively the CDS trades). The specificity of such a strategy is that the bet is made solely on the basis itself, *not* on CDS premia and bond spreads, since those can both increase or decrease without jeopardizing the strategy. As a result, the CDS basis fills one of the main functions of a price in financial markets, i.e. to compute the reward for an investor betting on a successful strategy.

It does not, though, fill another major function of prices: to measure the initial capital needed to get exposure to this strategy. Indeed, this is a major reason why what we shall call "returns" on CDS basis[23] for lack of a better word are meaningless, and why we observe such dramatic deviations: while the mean of those returns is -0.40 (i.e. an already impressive -40 %), its standard deviation amounts to 162! Amazing though those figures look, recall that they are more often than not computed on values close to zero, and that when, say, $b_{i,j,t-1} = -2$, a variation of 0.8 basis points is enough to reach this 40 %. We denote this return $r_{i,j,t}$ in the following section.

Still, it is interesting to study those returns to ascertain whether bases follow martingale processes and may be considered as random walks, which would have the exciting meaning that *it is impossible to predict whether, and in which direction, the difference between the appreciation that CDS markets and bond markets have of an entity's credit risk is going to change*, i.e. that one cannot as a rule hope to win by playing one market's appreciation of credit risk versus the other's. We will test this hypothesis in the remaining part of this section.

We first try regressing basis returns on models similar to the ones used in the previous section when trying to statistically predict the basis itself:

- A simple common factor model: as previously, we regress the basis return on one-week, six-months and one-year LIBOR rates as well as our sample's average financial spread. Not only do we find absolutely no fit of this model to the data, but also that no coefficient, including the intercept, is significatively not null. The same remarks apply if we allow the parameters to vary according to the entity: in spite of the number of exogenous variables, this model's R^2 remains below 0.05 % (i.e. hardly above the value it would "artificially" achieve if the exogenous variables had no predictive power at all on the endogenous). Moreover, here again, virtually none of the coefficients is different from zero.

- As above again, we augment these models (with common or varying parameters) by adding in to the common factors a number of entity and bond-specific exogenous variables, maturity, dummy for price above par and level of the basis observed at the previous date. Results are just as before and indicate that this model is incapable of fitting the data. Those remarks remain valid when we split the sample in three periods as before.

[23] As would be computed from the fraction $\frac{b_{i,j,t}-b_{i,j,t-1}}{b_{i,j,t-1}}$.

- We also try performing a model where each individual basis return depends upon our sample's median or average basis return, similarly to what we improperly called earlier a "market" model. Again, this has no predictive power.
- Last of all, we compute for each entity the correlation between the vector $r_{i,j,t}, \forall j$, and $r_{i,j,t-1}$. This is for no entity and bond significatively different from zero, suggesting that if successive returns are not independent, they are at the very least uncorrelated.

To test this formally, we follow some of the methods described by Campbell, Lo and MacKinlay [1997] to test various versions of Random Walk hypotheses. As they do, we assume covariance-stationarity for the series $r_{i,j,t}$. For each entity and bond i, j, for each $1 \leq k \leq 20$, we compute estimates for [24].

$$\gamma(k) = Cov(r_{i,j,t}, r_{i,j,t+k})$$
$$\rho(k) = \frac{\gamma(k)}{\sigma_{r_{i,j,t}} \times \sigma_{r_{i,j,t+k}}}$$

We study the strongest Random Walk assumption, i.e. what Campbell, Lo and MacKinlay denote "Random Walk 1", under which all returns are independently and identically distributed, we compute Box and Pierce's [1970] Q-statistic:

$$Q(m) = T \sum_{k=1}^{m} \hat{\rho}(k)^2$$

Since the choice of m can be important for the meaning of this statistic[25], we compute Q for $m \in \{5, 14, 20\}$. Under Random Walk 1, the estimates $\hat{\rho}(k)$ are all Gaussian with zero mean and variance $1/T$, and as a result $Q(m)$ follows a $\chi^2(m)$. We can then test the assumption by comparing $Q(m)$ to the critical value for 95% of a Chi-square distribution with m degrees of freedom. We find that we can reject the null hypothesis with a 95% confidence level only for 22 to 27% of bonds in our sample - in other words, there is evidence in favour of the strongest form of Random Walk for about three bonds out of four.

3.3 Can the basis (always) tell us anything about relationships between the CDS and bond markets?

In the rest of this section, we replicate the part of the article by Blanco, Brennan and Marsh [op. cit.] in which they study relation between Credit Default Swaps and Credit Spreads[26]. Since their data run from January, 2001 to June, 2002, we try to ascertain whether their findings still hold 6 years later.

[24] There is actually virtually no difference between those two standard deviations, and we could just as well use $Var(r_{i,j,t})$ as the denominator in this fraction.

[25] *"if too few [autocorrelations] are used, the presence of higher-order autocorrelation may be missed; if too many are used, the test may not have much power due to insignificant higher-order autocorrelations".*

[26] Their measure of credit spreads is more straightforward than the asset swap spread we study in this work.

Cointegration: do long-term prices of credit risk in the CDS and bond markets converge?

Based on the observation that both credit spread and CDS premium are measures of an entity's credit risk (and that, since the basis between them is not null, at least one of the said measures is biased), they assume that there is a "true" unobservable efficient price of credit risk $m_{i,t}$ (we denote as usual by i a reference entity), and this price follows a random walk, i.e. $m_{i,t} = m_{i,t-1} + u_{i,t}$, where $u_{i,t}$ is a sequence of i.i.d. white noises. Then

$$CDSp_{i,t} = m_{i,t} + s_{i,t}^{CDS} + d_{i,t}^{CDS}$$

$$ASS_{i,t} = m_{i,t} + s_{i,t}^{ASS} + d_{i,t}^{ASS}$$

with $s_{i,t}$ a market-specific transient noise reflecting the market's microstructure and $d_{i,t}$ a market-specific noise component reflecting other factors, some of which may be permanent.

In this framework, under the assumption that both markets priced credit risk equally in the long run, CDS premia and bond credit spreads should be cointegrated[27]: indeed, the difference $CDSp_{i,t} - ASS_{i,t}$ is equal to the transient factor $s_{i,t}^{CDS} - s_{i,t}^{ASS}$ which can be neglected in the long run, plus the remaining factor $d_{i,t}^{CDS} - d_{i,t}^{ASS}$. If cointegration is not valid, then either this latter factor has a permanent non-stationary component which is not directly linked to credit risk (or it would be incorporated in $m_{i,t}$); or at least one of our measures for risk prices is permanently and time-varyingly biased; or, quite simply, the assumption that both markets price credit risk equally does not hold.

We test cointegration without restriction for all reference entities, first only in the first period, where daily price variations were mild and markets had time to take them into account exhaustively. For each entity, we first perform Dickey-Fuller tests for the existence of unit roots (line 2 of table 7), and proceed to testing cointegration only if those tests are positive both for the CDS premium and the asset swap spread (line 3). We estimate the cointegrating vector with the Johansen procedure, and normalize the coefficient for CDS premium to 1[28]: as a result, we expect the coefficient for asset swap spread to be equal to -1 (lines 4 & 5). If there is evidence of cointegration, we perform another Johansen procedure with the additional restriction that the constant in the cointegration vector be null. Finally (last line), we test whether the basis (i.e. the difference between CDS premium and asset swap spread, which would correspond to a [1 -1 0] cointegrating vector) is stationary with yet a Dickey-Fuller test (this time we are interested not in the null, but in the alternative hypothesis) - note that since we only tested cointegration on non-stationary series, the number of entities for which the basis is stationary may be consistently greater than the number of entities with cointegration. We repeat these steps over the whole sample. Individual results for those entities for which we find evidence of cointegration are listed in table 8.

[27] Consider two variables following an integrated process, i.e. such that exogenous shocks might have an effect on their levels, but not on their first difference. Those variables are said to be cointegrated if there exists a stationary linear combination of those variables.

[28] This normalization does not reduce the validity of our results: if two variables are cointegrated, i.e. the process $a_1 y_1 + a_2 y_2 + b$ is stationary, then the process $\alpha a_1 y_1 + \alpha a_2 y_2 + \alpha b$ is likewise stationary.

[Table 7: Cointegration test results]

	Period 1	Full sample
Reference entities	42	42
Unit roots for both series	23	27
Of which, cointegrated	22	23
Average coefficient for the asset swap spread	- 0.99	-0.6
Standard deviation of the ASS coefficients	0.31	0.32
Stationary basis at the 5 % confidence level	34	17

When we restrict ourselves to period 1, i.e. the one which is closest to the period studied by Blanco et alii, or any other researchers to our knowledge, we find results that are wholly similar to theirs: cointegration indeed exists for almost all entities for which it is meaningful to look into it; furthermore, the basis is stationary for 34 entities out of 42, but we do not in general find evidence that the constant in the cointegration is zero - in other words, while over this period CDS and bond markets react similarly to long-term shocks in credit risk, there is a constant excess price of credit risk in bond markets relatively to CDS markets.

When we proceed to studying cointegration over the timespan January, 2006 to April, 2009[29], we find that the number of bonds with stationary basis is divided by 2, dropping to a mere 17 out of 42, and that the coefficient for asset swap spreads, far from its theoretical -1, is now on average equal to -0.6: CDS markets react more strongly than bond markets. This points to the impression that while our results support those obtained by Blanco et alii, i.e. that for most entities, CDS and bond markets have the same long-run apprehension of credit risk as long as it is merely "risky", they also suggest those results do not necessarily hold when those entities' credit situation has become radically "uncertain", in the sense of Frank Knight.

Price discovery: does any market have the lead in the incorporation of new information?

Lehmann [2002] stated that *"Prices for the same asset in different markets should tend to converge in the long run but might deviate from one another in the short run due to trading frictions"*. After studying this long-run convergence in the previous paragraph, we now turn to those possible short-term deviations. Hasbrouck [1995] defined "price discovery" to be *the incorporation of new information* and studied, when a security is traded on more than one market, which of these effectively fills this role as a leader.

Following Blanco et alii's application of the Gonzalo and Granger [1995] method for price discovery to CDS and bond markets, we estimate the following Vector error correction model (where Δ stands for the difference between two consecutive values taken by a variable):

$$\Delta_{CDSp_{i,t}} = \lambda_1(CDSp_{i,t-1} - \alpha_0 - \alpha_1 ASS_{i,t-1}) + \sum_{j=1}^{p} \beta_{1j}\Delta_{CDSp_{i,t-j}} + \sum_{j=1}^{p} \delta_{1j}\Delta_{ASS_{i,t-j}} + \epsilon_{1,i,t}$$

[29] An alternative method would have been to look separately at all three periods as we did previously, but this would have brought up some issues, considering that period 2 and 3's lengths are respectively 12 and 10 months, i.e. too small a timespan for our various tests to be meaningful.

$$\Delta_{ASS_{i,t}} = \lambda_2(CDSp_{i,t-1} - \alpha_0 - \alpha_1 ASS_{i,t-1}) + \sum_{j=1}^{p} \beta_{2j}\Delta_{CDSp_{i,t-j}} + \sum_{j=1}^{p} \delta_{2j}\Delta_{ASS_{i,t-j}} + \epsilon_{1,i,t}$$

The underlying assumption is that a market is the place of price discovery if the other market "takes into account" its price changes (assumed, in conformity with the Efficient Market Hypothesis, to be the result of new information); in the above framework, the bond market contributes significantly to the price discovery if λ_1 is negative and statistically significant, while the CDS market contributes to price discovery if λ_2 is positive and statistically significant. In other terms, we try to ascertain how much, whean a market undergoes a significant move in price, the other one "catches up" with this change.

We perform the estimation only for the entities for which we have shown in the previous paragraph that there was cointegration, with $p = 5$. We restrict α_1 to be equal to one, but let α_0 be not null since there is no evidence that the constant in the cointegrating vector is null - this has however the result of putting a larger weight on period 2 and 3 observations, when the basis was structurally very negative. We denote by * the coefficients with 5 % significativity, by ** those with 1 % significativity. In fact, most coefficients for the full sample are highly insignificant, the majority exhibiting a t-value above 30 %.

[Table 8: Price discovery, full sample and first period]

	Full sample				First period			
Entity	Cointegration coef.	λ_1	λ_2	GG	Cointegration coef.	λ_1	λ_2	GG
AIG	-0.6	0.016	0.04	1.67	-0.93	0.005	0.08**	1.07
APC	-0.49	-0.01**	0.006	0.375	-0.95	-0.05*	0.107**	0.68
ATTINC	-0.46	0.0004	0.006	1.07	-0.85	-0.062*	-0.005	-0.09
AXP	-0.76	-0.015	0.023**	0.605	-0.98	-0.003	0.037	0.925
BACR					-1.08	-0.005	0.041*	0.89
BRK-M	-0.22	-0.001	-0.003	1.5				
C					-1.08	-0.046*	0.06*	0.567
CAT	-0.58	-0.014	-0.003	-0.27	-0.55	-0.038	0.031	0.45
CIT	-1.06	-0.008	0.02*	0.714	-1.38	-0.004	0.077**	0.951
CMCSA	-0.42	-0.002	-0.003	3	-0.68	-0.007	0.025*	0.781
COF	-0.46	0.001	0.007*	1.17	-0.91	-0.027*	0.013	0.325
COP	-0.31	-0.001	0.006	0.857				
CRDSU	-0.21	-0.002	-0.003	3	-0.71	0.009	0.058*	1.18
GS					-1.51	0.009	0.062**	1.17
HSBC-	-1.14	0.000	0.03**	1	-0.82	0.013	0.099**	1.15
KFT					-1.95	0.014	0.079**	1.21
JPM	-0.45	-0.007	0.003	0.3				
LEH	-1.08	-0.035	0.225**	0.865				
MER	0.49	-0.013*	0.003	0.1875				
MET	-1.31	-0.012	0.022**	0.647				
MO					-0.9	-0.019*	0.021	0.525
NWS-A					-1.16	-0.216**	0.012	0.053
PG	-0.73	-0.013	0.021	0.618	-0.75	-0.076	0.079	0.51
S	-1.07	-0.037**	0.022	0.373	-1.24	-0.013	0.094*	0.879
SLMA					-1.19	0.019	-0.035**	0.648
TGT	-0.57	0.003	0.013*	1.3				
VOD	-0.4	0.003	0.002	-2	-1.38	-0.005	0.049**	0.907
VRZN	-0.33	0.000	-0.001	0.99				
WFC	-0.39	-0.005	0.000	0.001				
WMT	-0.57	-0.003	-0.012	1.33				
WYE					-0.88	-0.023	0.055	0.705

Whenever the λ_j are significative, which is not always the case, we find them to be of the expected sign, with the one exception of λ_2 for Sallie Mae in the first period. Like Blanco et alii, we find that our estimates for λ_2 are more frequently significative than those for λ_1. The Gonzalo-Granger measure for the CDS market's contribution to price discovery is equal to $GG = \frac{\lambda_2}{\lambda_2 - \lambda_1}$. Like Blanco et alii, we sometimes (i.e. when at least one of the λ_j does not have the expected sign) find this to be greater than 1 or negative, particularly when we include the full sample.

All in all, we find that price discovery, when measurable, preponderantly takes place in the CDS market relatively to the bond market: this suggests that movements observed on CDS premia can help predict immediately future movements in bond prices[30]. There are a number of reasons why this should be true: the main one is probably in our opinion that agents trading often in the CDS markets are more sophisticated and more specialized in credit risk than those in the bond markets - indeed, Blanco et alii show that bond markets tend to react more effectively to new macroeconomic information, while CDS markets are more concerned with firm-specific information. Also, since CDS markets are more liquid, they are the primary market to "run to" when you want to take advantage of a new information, while by attempting to trade on bonds you may lose your first-mover advantage.

[30] This is not inconsistent with our finding that the basis follows a random walk.

4 Further issues to explore

We have studied in this work, which is only a first exploration calling for further development of an astonishingly rich database, a number of topics related to the CDS bond-basis.

Most importantly, we find it to be almost systematically negative; we also showed it was reverting to a long-term constant, but could exhibit very long periods of high absolute value, mostly because events rushed into another and made effective mean-reversion impossible. Though it is sensitive to certain exogenous macroeconomic factors, we find that the basis is best predicted by a linear function of its previous value and effectively follows a random walk: as a result, it is impossible to predict whether, and in which direction, the difference between the appreciation that CDS markets and bond markets have of an entity's credit risk is going to change. Thus the relationship between CDS and bond markets, though fluctuating, is ever present.

We also find that CDS and bond markets exhibit both long-term and short-term convergences in times when the volatility remains low, but that those convergences can be long to appear when an important quantity of information has to be incorporated over a short period of time. We find evidence that CDS markets usually are the privileged place for price discovery, which means that CDS can effectively be used to correctly predict bond prices, though this result is yet again less valid in high volatility times.

The most puzzling result we have obtained remains that, unlike what others have found on previous data, the CDS bond basis exhibits on average a small, but decisive negativity over the period January, 2006 to July, 2007, which then takes wider proportions, still remaining negative. A number of phenomena may account for this feature. We list below a few of them, as well as possible tracks to inquire into them as part of further research projects:

- As emphasized in section 2, this work is to our best knowledge the only one in which bonds, and not CDS quotes, were used as references to build a maturity-matched (CDS premium, bond asset swap spread) couple. We have stated above that when we use a possible proxy for the cheapest-to-deliver option, it does not exhibit the (positive) effect on the basis we would normally have expected, and that this might be accounted for by the imperfection of this proxy. Another, in our opinion rather convincing, explanation, lies in the fact that in a sample where bonds are taken as references, this cheapest-to-deliver option is by construction compensated for in our definition of the basis, and that as a result it is not driven upwards as is the case when CDS premia are taken as reference.

- Still related to the previous point is the fact that we chose, for obvious simplicity reasons[31] to build "virtual" CDS quotes with linear interpolations, while the curves plotting CDS premia against maturities, like standard yield curves, actually tend to be closer to logarithms or splines. In that light, our estimations for CDS premia

[31]With 42 entities and 819 days of data, we would have had to build over 34,000 curves...

may be biased downwards, accentuating the basis' negativity. Symetrically, since De Wit, whose definition of the basis is closest to ours, computes asset swap spreads through linear interpolation, his measure of the basis is likely to be slightly biased upwards.

- While most researchers focus on actual transactions to obtain CDS premia, we rely on data supplied by market makers, i.e. based on quotes, which results in an overrepresentation of long maturities in our sample relatively to others'. Since transactions rather infrequently occur on longer maturities (i.e. beyond 10 years), which is probably due to the counterparty risk becoming too great a worry, there might be an excess of supply on those maturities, driving CDS premia and bond bases downwards. This is another factor explaining why we found maturity to have a negative impact on the basis.

- De Wit lists *"synthetic CDO issuance"* as one technical factor driving the CDS basis down; the dramatic development of Collateralized Debt Obligation [32], which has now come to a halt, meant that originators had to get a direct exposure to credit risks for their CDO vehicles, and selling protection in CDS was the easiest way to do so. This has resulted in shifting the supply-demand for protection equilibrium towards lower CDS spreads, with the collateral effect of depressing the bond basis. Likewise, being included in global Credit Derivatives Index such as Markit's CDX can seriously affect the CDS premia for an entity, since those indices are equally-weighted.

- Finally, recall that financials tend to exhibit lower bases than corporates, which is a fairly robust result across studies; the proportion of financial institutions in our sample is extremely high: not only do they represent over half the entities about which whe have obtained data, but they also tend to issue many more bonds that non-financial corporate institutions, which increases their over-representation.

Effects of liquidity on bond bases It is now an established fact that liquidity issues can affect market prices very significantly (see for instance Amihud and Mendelson[1991]), hence a change in the differential between liquidities on CDS and bond markets can account for a potentially sizeable change in their credit risk price differential, i.e. in the basis. Driessen and De Jong [2006] show that for corporate bonds, the liquidity premium can be equivalent to the price of credit risk; also, they conclude that CDS premia are lower than corporate bond spreads, which is consistent with our finding of a negative basis. Thus if liquidity has increased in CDS bond markets relatively to bond markets, thus increasing CDS premia relatively to bond spreads, this provides an explanation for the decrease in basis we observe. Since stylized facts on liquidity include that it is related

[32] Quarterly CDO issuance increased from USD 20 billion in the first quarter of 2004 to an all-time high of over 900 billion three years later, according to the Securities Industry and Financial Markets Association.

to market volatility, this assumption is testable.

More generally, liquidity is treated by De Wit as one factor whose effect on basis is uncertain. In our opinion, Acharya and Pedersen's Liquidity-CAPM [2005] provides theoretical support for a negative effect of liquidity problems on the basis, even if those are evenly distributed across all markets: indeed, they show that assets which are in positive net supply (as bonds are by definition, while CDS contracts are not) always exhibit lower prices in cases of illiquidity. In other words, whenever illiquidity arises, bond spreads should go up - thus lowering the basis.

Finally, we provide two examples of research projects who in our opinion could contribute to broaden our knowledge of the CDS bond basis, and thus more generally of both CDS and bond markets.

We have emphasized at the end of section 3 that CDS markets seemed to be the primary place for price discovery over the period January, 2006 to April, 2009. While those results hold on average, they are much more pronounced over the period January, 2006 to July, 2007, i.e. when little information had to be incorporated at a time by the markets. Also, it must be stressed that the current work has treated all price changes equally, and the perspective could be different if the interest lay mostly in knowing where price discovery occurs for most valuable information (i.e., according to the Hasbrouck [1995] framework, information resulting in a high increase in price volatility). Indeed, Barclays (October 20, 2008) writes: "In recent financial institutions bankruptcies, CDS levels were clearly not the leading indicator. Lehman Brothers provides the best example, as its CDS remained in spread running the week of its bankruptcy filing. This actually resulted in some of the best basis trades ever in the credit market as the bonds cratered well before CDS.". Note however that Barclays' remarks hold for financial institutions mostly, where conflicts of interests (recall that banks are leading actors on the CDS markets) might be burning: quoting very high CDS premia for an institution with whom you have many contracts outstanding and intertwined increases other agents' defiance towards this institution, and hereby its financing difficulties, thus jeopardizing its ability to repay whatever it owes you. An exhaustive study of bankruptcies, or more simply of significant credit rating downgrade, of both non-financial corporations might shed an exciting light in this matter.

Furthermore, recall that our study of price discovery is made under the standard assumption that changes in price reflect new information. However, this information (in a very broad sense) need not necessarily be correct. A refinement would then be to concentrate on major price deviations by a market (as always, relatively to the other one: say for instance, to fix ideas, that both CDS premium and asset swap spreads augment significantly, the former by 50 basis points, the latter by 30 only), resulting in the basis dramatically widening, and ascertain which of the two markets has correctly priced the new information (i.e. in the example above, was it serious enough to justify an augmentation of this entity's credit risk price by 50 basis points, or "merely" 30?) by either computing the new long-term mean-reversion levels of both markets or assuming them to be their levels when the basis returns to its long-term mean. It is then possible to compute the frequency of times when each market worked as a "pioneer", i.e. underwent a major deviation relatively to the other market because it correctly priced the new information (which was in turn underpriced by the other market), and that of times when each market proved to be "overreactive", i.e. cases when the credit risk price in the most reactive market actually converged back to the price in the other market. This would give a useful insight into the relative efficiency of both markets.

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