Limits to arbitrage and CDS-bond dynamics around the financial crisis

Preprint · April 2018
DOI: 10.13140/RG.2.2.13128.83208

CITATIONS
0

READS
31

2 authors:

George Chalamandaris
Athens University of Economics and Business
17 PUBLICATIONS 55 CITATIONS

Spyros Pagratis
Athens University of Economics and Business
21 PUBLICATIONS 31 CITATIONS

Some of the authors of this publication are also working on these related projects:

Project NPL's in the euro area View project

Project Adverse-selection Considerations in the Market-Making of Corporate Bonds View project
Limits to arbitrage and CDS-bond dynamics around the financial crisis

George Chalamandaris* and Spyros Pagratis**

Abstract: We explore the joint dynamics of CDS and corporate bond spreads around the financial crisis. An ostensibly broken cointegrating relationship between CDS and bond spreads during the crisis turns out to be the result of an omitted-variable misspecification. The stationary relationship is restored once Libor/OIS spread is included as a third component. Motivated by the limits-to-arbitrage literature and the economics of basis trade we identify a regime-switching VECM for CDS-bond dynamics that shows better in-sample fitting properties than competing models. It also improves the out-of-sample performance of hedging dynamically bond portfolios with CDS. We document destabilizing dynamics in CDS market during the crisis that originate from supply shocks in the bond market and the subsequent unwinding of basis trades.

JEL classification: G01, G12, G14, G24

Keywords: credit default swaps, basis trade, threshold cointegration, limits to arbitrage.

* Department of Accounting and Finance, Athens University of Economics and Business, e-mail: gchalamandar@aueb.gr.
** Department of Economics, Athens University of Economics and Business, e-mail: spagratis@aueb.gr.
1. Introduction

Pre-crisis literature on credit default swaps (CDS) and corporate bond spreads postulates the existence of a common stochastic trend – i.e. the price of credit risk – that implies a pricing parity condition between the two credit markets (e.g. Duffie 1999, Blanco et al. 2005). Practitioners exploited that prediction by trading the so-called basis, i.e. the difference between the CDS and the underlying bond spread. The basis trade consists of simultaneously buying the bond and CDS protection when CDS falls below the bond spread (negative basis), or the opposite positions if the basis turns positive.

Nevertheless, conventional wisdom about spread convergence towards parity was challenged during the financial crisis when the CDS-bond basis reached unprecedented levels that persisted for more than a year. During that period (2007-8) the basis moved deeply into negative territory for all but a few top-rated names, being particularly wide for those of lower credit quality. The result was a dramatic unraveling of basis trades and major losses to financial institutions in the likes of Merrill Lynch, Deutsche Bank, and Citadel.\(^1\)

An interesting aspect of this incident is that – despite the immense literature that evolved around the crisis – its empirical investigation has not yet produced conclusive evidence about its causes and, most importantly, about its implications for the continuing market practice. For instance, on the debate about the mechanism that brought it about, two papers stand out: Mitchell and Pulvino (2012) classified the basis-trade unravelling into a general category of arbitrage-crashes, all of which occurred because speculative capital was “too slow” to fill the market gap created by arbitrageurs unwinding their own positions. Bai and Collin-Duffresne (2011) tested various explanations and found that they cannot single out one factor that alone was responsible for this market dislocation. Instead, they suggested several distinct factors that pushed the CDS-bond basis into negative territory at different stages of the crisis, such as funding risk, counterparty risk and collateral quality. Notably, both papers regarded the break-down of the basis-trade in 2007-8 as an abnormal departure from the predominant equilibrium.

This paper takes a slightly different view contributing to the literature in two ways: First, it bridges the pre-crisis empirical literature with the 2007-8 events. To that aim, we consider different types

---

\(^1\) See, for example, Craig, S. and C. Mollencamp, January 24 2009, "At Merrill, Focus Is Now on Montag, Sales Chief", Wall Street Journal.
of equilibria describing the no-arbitrage relationship between the CDS and corporate bond markets, which may well have been present since the early days of the basis trade, although they were ignored in the pre-crisis literature. The key point here is that only one of these equilibria can best explain what happened in the run-up to the financial crisis and thereafter. Second, this paper probes into some of the most important implications of this incident for market participants. That is, we examine whether CDS contracts can still be considered as valid hedging instruments for corporate credit risk, even in the aftermath of the 2007-8 debacle.

The limits-to-arbitrage literature offers a plausible framework to explain the unraveling of basis trades, focusing on the liability side of arbitrageurs’ balance sheet. The idea is that clusters of stop-loss orders may force arbitrageurs to unwind spread-compressing trades en-masse once the market moves unexpectedly far against them. Price deviations from long-term equilibrium relationships will persist in this case, if exacting funding constraints prevent other investors from entering these trades and replace the withdrawn capital. Acharya, Lochstoer and Ramadorai (2013), Mitchel and Pulvino (2012) and Bai and Collin-Duffresne (2013) discuss limits to arbitrage in various markets; central theme in all cases is funding liquidity risk arising from a maturity mismatch between (long-term) assets and (short-term) liabilities of arbitrageurs.

In preliminary tests, we find evidence indicating that the ostensibly “broken” cointegrating relationship between CDS and bond spreads during the financial crisis was not really broken after all; it was instead the result of an “omitted variable” misspecification. With respect to recent literature, we find evidence that this misspecification is related to the “slow-moving capital” hypothesis of Mitchell and Pulvino (2012). Econometrically, money-market liquidity (proxied by Libor/OIS spread) turns out to be the missing variable that restores the CDS-bond equilibrium relationship.² Also, the price of credit risk across rating categories appears to share a common component that is directly linked to that same variable (Libor/OIS spread).

Motivated by the above evidence, the economics of the basis trade and limits-to-arbitrage considerations, we incorporate the linear VECM of Blanco et al. (2005), Zhu (2006) and Forte and Peña (2009) into an encompassing empirical framework that spans models with multiple regimes

---
² Libor-OIS spread is a widely used measure of stress in money markets and is indicative of the interest rate differential between unsecured and secured funding. Historically it averaged at around 10 basis points before the collapse of Bear-Sterns, reaching an all-time high of 364 basis points in October 2008, in the aftermath of Lehman crisis. Since then, it dropped considerably below 100 basis points in mid-January 2009, returning to normal levels of 10-15 basis points by September 2009.
and cointegrating vectors. “Threshold” variables are related to the basis trade Profit & Loss (P&L). Given that we work with diversified rating portfolios of bonds/CDSs rather than with single-names, it is fair to assume that normal arbitrage activity takes place inside a basis band, within which funding costs and funding risks are not high enough to deter arbitrageurs from entering a trade when the opportunity arises. Outside this band however, the breach of the threshold by the portfolio P&L typically coincides with the simultaneous breach of many individual stop-loss limits. Concurrent activation of these orders unavoidably drains the market of liquidity, while making it harder for any risk-averse speculator to enter most of those trades and thus counter the market momentum. As a result, the basis dynamics are bound to change into an error-correction mechanism that may not even be “correcting” at all. In that respect, our structure appears as quite the opposite to the standard threshold cointegration model of Balke and Fomby (1997) where error correction is triggered outside a band of inaction, around a parity condition.

Among the models spanned by this framework we find that those with two cointegrating vectors, three regimes, and a regime-switching variable related to the basis-trade’s P&L have better in-sample fitting properties than competing specifications. Most importantly we find that – despite their size – these models improve significantly the out-of-sample performance of dynamic hedging strategies. The results suggest that CDS contracts remain valid hedging instruments against the mark-to-market risk of corporate bonds even during distress periods, provided we take proper account of the shifting money-market liquidity conditions.

The regime we codify as “first” tends to coincide with normalcy periods before the onset of the financial crisis (pre-crisis normal regime). The second regime corresponds to normalcy periods in the run-up and after the eruption of the financial crisis (post-crisis normal regime). The third regime points to the peak of the financial crisis, around the Lehman failure (distressed regime).

In pre- and post-crisis normal regimes CDS and bond spreads revert to their long-term equilibrium relationship, in line with the pre-crisis literature (e.g. Blanco et al, 2005). During pre-crisis normalcy we find evidence of price discovery taking place in the CDS market for AAA and crossover – two rating categories of particular interest to speculators. For other rating categories we

---

3 It is worth noting that Acharya, Amihud and Bharath (2013) use a similar approach to study the exposure of the U.S. corporate bond returns to liquidity shocks of stocks and treasury bonds over the period 1973-2007.
find no evidence of either the CDS or bond market leading the other. In post-crisis normalcy, the CDS market no longer leads the price discovery process for any rating category.

In the distressed regime we document a complete break from the usual pattern of joint dynamics: CDS spreads are now entirely driven by random shocks and the disequilibrium error with the bond market. But instead of pulling CDS spreads back towards parity with bond spreads, deviations from equilibrium now widen the basis even further. At the same time, bond spreads appear totally unaffected by anything that is happening in the CDS market. This pattern suggests that the breakdown of negative-basis trades during the financial crisis was caused principally by supply shocks in the corporate bond market; right after that, stop-loss orders and funding constraints lead to the unwinding of CDS positions by arbitrageurs. It is worth noting that prominent market research at the time (e.g. Elizalde et al, 2009) agreed on this line of events.

From a more theoretical viewpoint, we conjecture that the dynamics of the distressed regime can be explained by an “illiquidity spiral” mechanism (Brunnermeier and Pedersen, 2009). To understand this, we need to delve into the economics of the basis trade. Typically, arbitrageurs fund the bond position (up to a haircut) in the repo market, while the remaining part (along with CDS upfront, running cost and margin) is funded unsecured. Supply shocks in the bond market lead to higher haircuts, thus reducing the portion of the bond position that is funded in the repo market. At the same time, the ability of arbitrageurs to substitute secured for unsecured funding is constrained by counterparty risk or liquidity hoarding by major dealer banks (Acharya and Mora, 2015). That leads to forced unwinding of basis trades due to stop-loss orders or limited funding to rollover the trades for another period, especially in the low-rating spectrum where repo funding is relatively scarce. As funding costs increase, basis trades incur mark-to-market losses that trigger margin calls and funding foreclosures from prime brokers, or new clusters of stop orders from investors (Shleifer and Vishny, 1997). Forced unwinding of trades then widens the basis further and mark-to-market losses feed into an illiquidity spiral à la Brunnermeier and Pedersen (2009).

4 For top-rated names such as AAA, a positive basis persisted and not arbitraged out during the crisis possibly because (lower rated) arbitrageurs were unable to sell CDS protection. It might have also been difficult to short-sell AAA bonds during the crisis due to flight to safety and scarcity of top quality bonds.

5 According to Mitchell and Pulvino (2012) such a negative feedback loop was exacerbated by rehypothecation, where prime brokers relied to intermediate funds from universal banks by recycling (rehypothecating) collateral received on repo funding to arbitrageurs.
Of course, for such destabilizing dynamics to be at play there must be lack of investors eager to replace arbitrageurs who are forced out of the market. For the trade that we examine, “slow-moving” capital conditions can be a consequence of increased funding risk, as perceived by speculators, and deteriorating money-market conditions in general. The analysis of the breakeven basis corroborates exactly this point.\(^6\) Specifically, Elizalde and Doctor (2009) show that the breakeven basis is a function not only of funding costs, but also of funding cost uncertainty; practically, the trade becomes less attractive the more funding costs and funding risk increase.\(^7\)

The rest of the paper is organized as follows. Section 2 describes the data and Section 3 presents some preliminary analysis on the stability of CDS-bond cointegrating relationship during the financial crisis. Section 4 discusses alternative specifications for structural instability under threshold cointegration to allow for limits to arbitrage. Section 5 discusses the estimation procedure and Section 6 presents the results based on the best-fitting model. Section 7 discusses hedging implications and Section 8 concludes. Annex A discusses the calculation of bond-implied par equivalent CDS spreads (PECS) that we use as a measure of corporate bond spreads.

2. Data

Our analysis draws from an extensive dataset of CDS and bond prices that covers three distinct sub-periods of comparable duration: The first sub-period (January 2005 to December 2006) corresponds to market conditions examined in the pre-crisis literature (e.g. Blanco, Brennan and Marsh, 2004). The second sub-period (January 2007 – April 2010) includes all milestones of the

\(^6\) Breakeven is the basis level that makes the trade marginally profitable, after considering funding costs.

\(^7\) Consider a buy-and-hold arbitrageur entering a basis trade that involves a purchase of bond at price \(p\) and CDS protection on same notional (100). Let the arbitrageur pay margin \(m\) to the protection seller but no upfront payment, i.e. CDS trades on full running spread. The arbitrageur faces constant funding spreads over Libor – i.e. \(R\) for secured (repo) funding and \(F\) for unsecured – as well as haircut \(h\) on funding the bond in the repo market. Suppose also the arbitrageur enters into a par asset swap to hedge any remaining interest rate exposure. It follows easily that the funding cost of implementing the basis trade is given by:

\[
\text{Basis trade funding cost} = -m \cdot F \cdot 100 - (1-h) \cdot p \cdot R - h \cdot p \cdot F - (100-p) \cdot F
\]

Recasting and dividing with notional, this gives a breakeven basis of

\[
-F - m \cdot F + (1-h) \cdot (F - R) \cdot p \cdot \frac{100}{100}
\]

Given that spreads on secured funding \((R)\) are lower than on unsecured \((F)\), the higher the bond haircut, funding costs and margin, and the lower the bond price, the more negative the breakeven basis. Uncertainty about future funding conditions would lead to more negative breakeven basis.
financial crisis, i.e. the onset of the subprime crisis and the ABCP market freeze, the failure of Bear Sterns and Washington Mutual, the Lehman crisis and the AIG bailout. The third sub-period (April 2010 – December 2012) is imbued by the crisis experience and bears the impact of regulations that were introduced as a result of it.\textsuperscript{8} We use this third sub-period exclusively for out-of-sample analysis, as a robustness check.

Our bond sample consists of 1,818 U.S. corporate securities that appeared in JP Morgan’s daily CDS-Basis Report during that time.\textsuperscript{9} The inclusion rules for this study are especially designed to focus on basis trades that are actively pursued in the market. These are:

- Bonds must be rated by Moody's and Standard & Poor's with issue sizes of at least $300 million.
- The corporate entity issuing the bond must have at least $1 billion of fixed rate bonds outstanding to ensure overall issuer liquidity.
- The CDS contract of the bond issuer must be a member of at least one of the CDX indices to ensure sufficient contract liquidity.
- Each bond must pay a non-zero coupon semi-annually and have a bullet (no optionality) maturity longer than 13 months from the index-beginning date but no longer than 31 years.
- All index-constituent bonds are “hand” priced daily, at least by JPMorgan’s trading desk, which is one of the largest US corporate bond dealers.

Our sample selection process guarantees that the prices we use are close to the actual market quotes. CDS spreads refer to mid-spreads on senior unsecured debt with modified restructuring clause, were obtained from Markit/Datastream at 1, 2, 3, 5, 7, and 10-year maturities and quoted for $10 million notional as of close of business.\textsuperscript{10} Bond pricing data refer to senior unsecured bonds with no embedded options, were obtained from Bloomberg and completed where necessary with prices from Datastream\textsuperscript{11}.

\textsuperscript{8} For example, the new capital regulations introduced at the aftermath of the 2008 crisis (e.g. Volcker Rule and Basel III requirements) raised the costs of negative basis trades, as the upkeep of bond inventories became more capital-demanding. At the same time, as almost all CDS contracts adopted upfront payment structure since 2008, they became more capital-intensive instruments compared to the pre-crisis period. Last not least, the adoption of more conservative rehypothecation practices, especially in the UK, in line with U.S. Federal Reserve Board’s Regulation T and SEC Rules 15c3-3 have increase the funding cost of bond purchases in negative basis trades.

\textsuperscript{9} CDS-Basis report was distributed to JP Morgan’s customers through its Morgan Markets platform by the Credit Research Department.

\textsuperscript{10} This is approximately 5:15pm New York time.

\textsuperscript{11} Datastream is now part of Eikon Thompson Reuters service.
Using the full CDS curve that corresponds to the issuer of each bond, we calculate the bond-implied CDS spread, as discussed in Appendix A. This method was first proposed by Doctor, Elizalde and Sultak (“Par-Equivalent CDS Bond Spreads”, JP Morgan 2005) and has since then been applied in various academic papers (including Bai and Collin-Duffresne (2013) which is most relevant to our study). We then pair bond-implied and CDS spreads by interpolating on the CDS-fitted forward hazard rate. The number of pairs each date is time-varying, ranging from a minimum of 411 to a maximum of 1,448 (median of 822). For each trading day we construct 8 rating pairs of bond portfolios. Each bond portfolio consists of equally weighted positions in bonds, coupled with a corresponding CDS portfolio in the same positions. Unlike Bai and Collin-Duffresne (2013) who take a cross-sectional approach to measure basis risk constituents, we focus on the dynamics of rating portfolios and investors’ ability to hedge effectively their short-term risk.

3. Preliminary results for linear specifications during the financial crisis

In this section we explore the existence and stability of a cointegrating relationship between the CDS and bond market during the financial crisis. To this purpose, we examine the properties of those series specifically for the period 3/1/2007 – 17/4/2010. We find evidence of instability in the cointegrating relationship, partly attributable to a money-market liquidity component.

It is worth noting that the application of standard unit root/cointegration tests on the whole sample (3/1/2005 to 17/12/2012) is not appropriate as it “hides” effectively many of the dislocations that affected the market during financial crisis and are central to our analysis. For example, although LIBOR/OIS spread is found to contain unit root in all 3 subsamples, it appears as almost stationary when testing for unit roots on the whole sample. The problem in this case is one of scale: Figure 1 shows that LIBOR/OIS starts from a low-volatility/low-level environment and returns to a similar one in 2009, which biases tests towards rejecting the null of a unit root.

[Figure 1]

However, it would be a rather poor attempt at consolation for, say a trader who lost millions on basis-converging trades during the crisis, to remind that money-market dislocations are transitional, and liquidity will eventually return to normal levels. Indeed, once we add in our null hypothesis the assumption that there is also a structural break at some point during the examination period (i.e. using the more appropriate Perron Break-point Unit root test, 1989) we confirm that
Libor/OIS spread does contain a unit root throughout the entire sample. Therefore, we focus first on the crisis period and then reconcile our evidence with pre- and post-crisis data using models adapted to structural breaks.

3.1. Unit root /Cointegration analysis

We start by applying a battery of unit root/stationarity tests (ADF, ERS and KPSS) on the CDS, bond and Libor/OIS series to verify the presence of unit roots for the sub-period 3/1/2007 – 17/4/2010. As expected, the results of these tests point to the existence of unit root in all series.

We then apply Johansen’s cointegration test to examine the existence of stationary linear relationships for the pair of spreads (CDS, bond), (bond, Libor/OIS), (CDS, Libor/OIS), and also for the triplet (CDS, bond, Libor/OIS). Cointegration test results are shown in Table 1 (Panel A) for all rating portfolios during the crisis period.

[Table 1]

For (CDS, bond) the null of “no cointegration” is rejected in only half of the rating categories. This finding shows that the long-term stationary relationship between CDS and bond spreads, which was recognized in the pre-crisis literature, is questioned for the crisis period. For (bond, Libor/OIS) the null is rejected in only 3 out of 8 rating categories, and specifically in those placed in the middle of the rating spectrum (A, BBB, BB). Finally, for (CDS, Libor/OIS) evidence for a long-term equilibrium relationship between CDS and money market liquidity exists only for the CCC-C rating portfolios. In all these cases, the rejection of the null is indicative of a common stochastic trend in each pair of spreads.

For rating categories that fail to reject the null of Johansen’s cointegration test in the pair (CDS, bond) – i.e. for AA, BBB, XOVER, and BB – we investigate if failure to reject can be attributed to a structural break in their long-term equilibrium relationship. To this aim we apply the ADF* test of “no cointegration” of Gregory and Hansen (1996), the alternative of which stipulates “a structural break in an existing cointegrating relationship” affecting the constant, the trend, or both (full break). Table 1 (Panel B) shows that the null of “no cointegration” is strongly rejected in 3

---

12 To economize on space, we omit the presentation of unit root results. These are available from the authors upon request.

13 We choose the number of lags using the Akaike Information Criterion (AIC).
out of 4 rating categories tested – i.e. for AA, BBB, and BB – once we assume a full break in the (CDS, bond) cointegrating vector. In effect, this test leaves only the cross-over rating case failing both Johansen’s and Gregory-Hansen’s cointegration tests.

Intuitively, this result implies that assuming a “final” break in the relationship between the two markets during the sub-period 3/1/2007 – 17/4/2010 is not a satisfactory interpretation for the lack of cointegration in our data. Far from it, it suggests that this relationship continues to exist, albeit distinctly different from what it was before the break. It must be noted here that the Gregory-Hansen test takes a rather general view, assuming a structural break that is “exogenous” in nature. For all we know, the structural break could be an “omitted variable” problem.

Repeating the cointegration test for the triplet (CDS, bond, Libor/OIS) we reject the null of “no cointegration” in all rating portfolios. Most importantly, we also reject the null of “at most one cointegrating vector” (for the alternative of two cointegrating vectors) in 5 out of 8 rating categories. The first observation is a key result as it shows that money-market liquidity is indeed the abovementioned “omitted variable”; the one capable to restore the equilibrium relationship between the CDS and bond markets, even during the financial crisis. The second observation of two cointegrating vectors is also very significant, considering that the common stochastic trend in the two-variable system of (CDS, bond) spreads captures the “price of credit risk” (Blanco et al, 2005). We add to this intuition by further identifying a common component among all stochastic trends across rating categories that is directly linked to the state of money market liquidity (Libor/OIS spread).

Summarizing, our results confirm the existence of a long-term equilibrium relationship between CDS and bond spreads, even during the financial crisis of 2007-2009. However, this equilibrium relationship is described more efficiently once it includes Libor/OIS spread as a third component. In theory, the presence of cointegration between CDS and bond spreads is indicative of arbitrage activity spanning the two markets.14 In practice, it provides us with a useful guide to impose restrictions on VECM models that may lead to more efficient estimation, forecasting, or hedging.

---

14 The inverse does not necessarily hold as various factors influencing the arbitrage trade may contain unit roots (see for example, Brenner and Kroner 1995).
4. **An encompassing view: Structural instability under threshold cointegration**

As the focus of this paper is to improve our understanding about the disruption of basis trades during the financial crisis, we need to delve deeper into the mechanisms causing the change in the joint dynamics of CDS and bond spreads that became evident in the previous section. In theory, constraints that deter agents from exploiting arbitrage opportunities between the two markets are bound to lead to persistent deviations from the long-term equilibrium relationship, and – in extreme circumstances – even to the breakdown of the no-arbitrage relationship (i.e. self-reinforced deviations from equilibrium). To account for such limits to arbitrage, we extend the linear VECM specification to a framework of regime-switching models. Econometrically, this approach allows us to describe distinct sets of market conditions with a single model. Most importantly, by scrutinizing the structural differences between regimes and the nature of the transition mechanism, we gain deeper insight into limits to arbitrage between the two markets and possibly improve the efficiency of dynamic hedging.

The threshold cointegration model of Balke and Fomby (1997) permits non-linearity in standard cointegrating relationships. The basic idea is that a given error-correction mechanism applies only for specific ranges of values that a given threshold variable can take. Beyond this range, dynamics change into a different error-correction setting, which incidentally may not be “correcting” at all.

Applications of threshold cointegration in the financial literature include the law of one price, the transmission of prices between substitute markets and the detection of arbitrage opportunities. In most cases there is a band of inaction in the error-correction mechanism where small deviations from equilibrium are not corrected unless the potential benefit of correction outweighs the cost.\(^{15}\)

In a limits-to-arbitrage world however, threshold cointegration appears to operate almost the opposite way, as the focus shifts from a band of inaction to a zone lying outside “normal” trading conditions. Indeed, seen at a larger scale, outside the now broader band within which arbitrageurs are normally active (when the basis exceeds the break-even point),\(^{16}\) there exist new thresholds that roughly correspond to clusters of stop-loss limits. Beyond those basis levels, arbitrageurs are forced to unwind existing trades because capital invested in basis bets is withdrawn (Shleifer and Vishny, 1997) and new capital capable of filling the gap to exploit the emerging opportunity arrives

---


\(^{16}\) For an excellent description of the calculation of the break-even point in basis trades see Elizalde et al. (2009).
with great delay, if at all (Mitchell and Pulvino, 2012). Put otherwise, we use threshold cointegration as a tool for identifying circumstances under which normal cointegration dynamics are obstructed or even disrupted due to funding constraints.

More specifically, let \( z_1, z_2, \) and \( z_3 \) denote the deviations of CDS, bond, and Libor/OIS spreads from equilibrium relationships we tested in the previous section:

\[
\begin{align*}
    z_{1t} &= CDS_t - b_0 - b_1 \cdot Bond_t, \\
    z_{2t} &= Bond_t - c_0 - c_1 \cdot Libor / OIS, \\
    z_{3t} &= CDS_t - d_0 - d_1 \cdot Bond_t - d_2 \cdot Libor / OIS_t
\end{align*}
\]  

(1)

where \( b_i, c_i, d_i \) (\( i=1,2 \)) are cointegrating vector coefficients.

Based on disequilibrium errors (1) we discuss alternative models of the joint dynamics of CDS, bond, and Libor/OIS spreads. These models vary from the simplest (linear) VECM to more structured (regime switching) specifications, as summarized in Table 2. To explain the basis disruption during the financial crisis we select the best fitting model using AIC and BIC.

[Table 2]

Model 1: Bivariate linear VECM with 1 cointegrating vector. This is the benchmark model used, among others, by Blanco et al. (2005) and Zhu (2006). It assumes the existence of a cointegrating relationship between the CDS and bond spreads that is stable over time and is not affected by any third variable, such as money-market liquidity.

\[
\begin{bmatrix}
    \Delta CDS \\
    \Delta Bond
\end{bmatrix}_t =
\begin{bmatrix}
    a_1 \\
    a_2
\end{bmatrix}
\cdot
z_{1,t-1} + \sum_{k=1}^{2} \Phi_{t-k} \begin{bmatrix}
    \Delta CDS \\
    \Delta Bond
\end{bmatrix}_{t-k}
\]  

(Model 1a)

where, \( a_i \) (\( i=1,2 \)) are mean-reversion coefficients towards the long-term equilibrium relationship, \( \Phi \) is coefficient matrix capturing short-term dynamics, and \( z_1 \) is defined in (1).

To capture the possibility of money-market liquidity causing transient supply/demand shocks in the CDS and bond market, we augment Model 1a to include lagged changes in Libor/OIS spread.

\[
\begin{bmatrix}
    \Delta CDS \\
    \Delta Bond \end{bmatrix}_t =
\begin{bmatrix}
    a_1 \\
    a_2
\end{bmatrix}
\cdot
z_{1,t-1} + \sum_{k=1}^{2} \Phi_{t-k} \begin{bmatrix}
    \Delta CDS \\
    \Delta Bond \\
    \Delta (Libor / OIS)
\end{bmatrix}_{t-k}
\]  

(Model 1b)
Model 1b assumes no limits to arbitrage. The model is consistent with the idea of high speed of capital where arbitrageurs unable to implement the basis trade are swiftly replaced by others. Thus money-market shocks affect only the short-term dynamics of CDS and bond spreads.

**Model 2: Bivariate linear VECM with 1 cointegrating vector including Libor/OIS spread.** It builds on Model 1 recognizing that Libor/OIS spread is necessary component of the long-term equilibrium relationship between CDS and bond spreads.

\[
\begin{bmatrix}
\Delta CDS \\
\Delta Bond
\end{bmatrix}_{t} = \begin{bmatrix}
a_1 \\
a_2
\end{bmatrix} \cdot z_{3,t-1} + \sum_{k=1}^{2} \Phi_{t-k} \begin{bmatrix}
\Delta CDS \\
\Delta Bond
\end{bmatrix}_{t-k} + \sum_{k=1}^{2} \Phi_{t-k} \begin{bmatrix}
\Delta Libor \\
\Delta OIS
\end{bmatrix}_{t-k}
\]

(Model 2)

where, \(a_i (i=1,2)\) and \(\Phi\) are defined as in Model 1, and \(z_3\) is defined in (1).

Model 2 assumes no limits to arbitrage between the CDS and bond market and high speed of capital as in Model 1. The main novelty about this model is that it recognizes money-market liquidity as an important variable affecting the long-term equilibrium relationship between CDS and bond spreads. As shown in the previous section, practitioners and researchers that ignore it may mistakenly believe there is a structural break in the CDS-bond arbitrage relationship when, in fact, it is only the level of the Libor/OIS that has become abnormally large.

Besides our preliminary testing procedure, ample motivation for this model can also be found in practitioners’ research. For instance, Doctor and Elizalde (2009) argue that there is a break-even level for every basis trade that is specific to the funding costs of the arbitrageur: A negative basis trade that is sensible for a prime-broker with deep pockets, may not be as such for a hedge fund with tight funding constraints. As a result, among arbitrageurs interested on a given basis trade, the equilibrium relationship between the CDS and bond markets will be conserved by those financing their positions at the relatively lowest funding cost. That said, a systematic shift in funding costs will affect the break-even levels of negative basis trades in general, pushing them to a territory of significantly wider spreads. It is worth noting that this effect was ignored in pre-crisis
literature, possibly because of ample liquidity and nearly homogenous funding conditions across institutions and basis trades.

**Model 3: Bivariate linear VECM with 2 cointegrating vectors.** It allows for a cointegrating vector exclusively between CDS and bond spreads while it also includes Libor/OIS in a second cointegrating vector for a more complete description of the long-term relationship.

\[
\begin{bmatrix}
\Delta CDS \\
\Delta Bond
\end{bmatrix}_t = \begin{bmatrix} a_{11} & a_{12} \\
a_{21} & a_{22}
\end{bmatrix} \begin{bmatrix} z_1 \\
z_2_{t-1}
\end{bmatrix} + \sum_{k=1}^{2} \Phi_{t-k} \begin{bmatrix}
\Delta CDS \\
\Delta Bond \\
\Delta (Libor / OIS)
\end{bmatrix}_{t-k}
\]  

(Model 3)

where, \(a_{ij}\) (i,j=1,2) are mean-reversion coefficients towards long-term equilibrium relationships, \(\Phi\) is coefficients matrix capturing short-term dynamics, and \(z_i\) (i=1,2) are defined in (1).

Model 3 assumes no limits to arbitrage between the CDS and bond market, very much like Models 1 and 2. The main difference with Model 2 is that it also brings in a second long-term relationship / “attractor” pulling towards it the joint dynamics of the two variables without affecting the “pull” exercised by the first long-term relationship.\(^{17}\) For example, it now becomes possible that CDS/Bond returns respond much faster (slower) to a deviation from the first equilibrium relationship compared to a similar deviation from the second. In that sense, Model 3 nests as special cases Models 1 and 2, which may still be valid, yet partial, descriptions of the true dynamics. Again, this model is motivated by our preliminary results in section 3.1 indicating the presence of two cointegrating vectors in the (CDS, Bond, Libor/OIS) system.

[Figure 2]

With respect to this model, previous literature paid scant attention on the impact of long-term relationship between bond spreads and funding costs on basis dynamics. A look at Figure 2 can help explain this apparent omission. For example, prior to 2007, the disequilibrium error \(z_t\)

\(^{17}\) Although the “attractor” terminology was initially borrowed from the field of control systems, it is now a standard name for cointegrating relationships in econometric textbooks (e.g. Enders, 2010).
(between CDS and bond spreads) exhibits much higher volatility and persistence than \( z_2 \) (between bond and Libor/OIS spreads), thus dominating effectively the joint CDS-bond dynamics. Since the onset of financial crisis in 2007 however, both the volatility and persistence of \( z_2 \) increased markedly, as shown in that figure for portfolios of AA and A rated bonds thus making its impact felt.

**Model 4: Bivariate threshold VECM with 1 cointegrating vector and 2 regimes.** This is the non-linear extension of benchmark Model 1 with two regimes, as in Hansen and Seo (2002).

\[
\begin{bmatrix}
\Delta CDS \\
\Delta Bond
\end{bmatrix}_{t} = \begin{bmatrix}
a_1^{(i)} \\
a_2^{(i)}
\end{bmatrix} \cdot z_{1,t-1} + \sum_{k=1}^{2} \Phi_{t-k}^{(i)} \begin{bmatrix}
\Delta CDS \\
\Delta Bond
\end{bmatrix}_{t-k},
\]

(Model 4)

\[
i = \begin{cases}
1, & \text{if } z_{1,t-1} \leq \gamma \\
2, & \text{if } z_{1,t-1} > \gamma
\end{cases}
\]

where, \( \gamma \) is threshold value that determines regime \( i \) at time \( t \), \( a_j^{(i)} \) \( (j=1,2) \) are mean-reversion coefficients towards the long-term equilibrium relationship, \( \Phi^{(i)} \) is coefficient matrix capturing short-term dynamics, and \( z_1 \) is defined in (1).

Model 4 introduces limits-to-arbitrage in our analysis as it assumes two regimes, one of which can possibly refer to “abnormal” market conditions. The underlying hypothesis is that the joint dynamics of CDS and bond markets shift radically from a “normal” to a “distressed” regime, right after the basis crosses a given threshold \( \gamma \). From the market practitioner’s perspective, changes of this kind are often observed on price levels around which cluster large volumes of stop-loss orders. Typically, when orders of this type are activated demanding immediate liquidation, the market experiences liquidity shocks of varying severity.

In our setup, arbitrageurs are forced to unwind spread-converging trades *en masse* when the basis widens beyond a certain level and that could lead to a break-down in the CDS-bond arbitrage relationship. In the break-even framework of Doctor and Elizalde (2009), this break-down occurs when the trade becomes unaffordable for all arbitrageurs, i.e. when the break-even level of the negative basis trade becomes too high for everyone. Having said that however, Model 4 is clearly lacking in that respect: As it does not explicitly account for the impact of money-market liquidity.
on the long-term equilibrium relationship between the two markets, the underlying arbitrage constraint remains unspecified.

**Models 5-6: Bivariate threshold VECM with 1 cointegrating vector and 3 regimes.** This is an extension of Model 4 to the direction of including money-market liquidity effects (represented by Libor/OIS spread) both in short-term dynamics and in the long-term equilibrium relationship between CDS and bond spreads. The inclusion of the third regime in our hypothesis allows us to discern between the scenario of an *abrupt* change from normalcy to distress and the scenario supporting a more *gradual* deterioration of market conditions. Specifically, if a third regime is necessary for the explanation of the observed dynamics, it follows that there must be an intermediate stage that is distinct from both the normal and the highly distressed regimes.

\[
\begin{bmatrix}
\Delta CDS \\
\Delta Bond
\end{bmatrix}
= \begin{bmatrix}
a_1^{(i)} \\
a_2^{(i)}
\end{bmatrix}
\cdot z_{t/3,t-1} + \sum_{k=1}^{2} \Phi_k^{(i)}
\begin{bmatrix}
\Delta CDS \\
\Delta Bond
\end{bmatrix}
+ (Libor/OIS)_{t-k}
\]

(Models 5-6)

where, \(\gamma_i\) (i=1,2) are threshold values, \(d\) the lag of threshold variable that determines regime \(i\) at time \(t\), \(a_j^{(i)}\) \((j=1,2)\) and \(\Phi_k^{(i)}\) are defined as in Model 4, and \(z_1, z_3\) defined in (1).

When \(z_1\) is used as threshold variable, the model (Model 5) assumes that the joint dynamics of CDS and bond markets enter the distressed regime once the basis widens beyond a certain level. Intuitively, this could be the result of stop-loss orders placed on the level of the basis as in Model 4. When \(z_3\) is used as the threshold variable (Model 6), arbitrage constraints become also associated with funding-liquidity constraints as implied by the breakeven basis described in Doctor and Elizalde (2009). As in Model 5, we could now argue that stop-loss limits seem to be placed *on the P&L* of the basis trade itself, of which funding costs are an important part.

**Models 7-9: Bivariate threshold VECM with 2 cointegrating vectors and 2 endogenous breaks**
This is a non-linear extension of Model 3 allowing for different regimes in the joint short-term dynamics between CDS and bond spreads. It also extends Models 5-6 to the direction of including one cointegrating vector exclusively between CDS and bond spreads, and a second one between bond and Libor/OIS spreads for a more complete description of the long-term relationship.

\[
\begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond}
\end{bmatrix}_t =
\begin{bmatrix}
a_{11}^{(i)} & a_{12}^{(i)} \\
a_{21}^{(i)} & a_{22}^{(i)}
\end{bmatrix}
\begin{bmatrix}
z_t \\
z_{t-1}
\end{bmatrix}
+ \sum_{k=1}^{2} \Phi_{i-k}^{(i)}
\begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond} \\
\Delta(\text{Libor / OIS})
\end{bmatrix}_{t-k}
\]  

(Models 7-9)

\[
i = \begin{cases} 
1, & \text{if } z_{m,i-d} \leq \gamma_1 \\
2, & \text{if } \gamma_1 < z_{m,i-d} \leq \gamma_2 \\
3, & \text{if } z_{m,i-d} > \gamma_2 
\end{cases}
\]

where, \(a_{ij}^{(i)} (i,j=1,2)\) and \(\Phi^{(i)}\) defined as in Model 3, \(\gamma_i (i=1,2)\) and \(d\) determine regime \(i\) at time \(t\) as in Models 5-6, and \(z_m (m=1,2,3)\) defined in (1).

Threshold variable \(z_m (m=1,2,3)\) allows for structural breaks in the CDS-bond arbitrage relationship to depend on stop-loss limits based on the level of basis \((z_1)\), on bond-funding costs \((z_2)\), or on a combination of both \((z_3)\).

**Model 10: Bivariate threshold VECM with 2 cointegrating vectors and 2 exogenous breaks.**

This model is very similar to Models 7-9, except that regimes are now determined by *exogenous* structural breaks, corresponding to two specific points in time. Equivalently, in this model we define as threshold variable time \(t\).

\[
\begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond}
\end{bmatrix}_t =
\begin{bmatrix}
a_{11}^{(i)} & a_{12}^{(i)} \\
a_{21}^{(i)} & a_{22}^{(i)}
\end{bmatrix}
\begin{bmatrix}
z_t \\
z_{t-1}
\end{bmatrix}
+ \sum_{k=1}^{2} \Phi_{i-k}^{(i)}
\begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond} \\
\Delta(\text{Libor / OIS})
\end{bmatrix}_{t-k}
\]

(3d – Model 10)

\[
i = \begin{cases} 
1, & \text{if } t \leq t_1 \\
2, & \text{if } t_1 < t \leq t_2 \\
3, & \text{if } t > t_2 
\end{cases}
\]

where, \(a_{ij}^{(i)} (i,j=1,2)\) and \(\Phi^{(i)}\) defined as in Model 3.
For the purpose of our analysis, Model 10 serves as a robustness check. It enables us to examine whether the threshold variables $z_m (m=1,2,3)$ we assumed in Models 4-9 are indeed informative. If it proves more successful than previous regime-switching models, it implies that we have not yet specified adequately the reasons for which arbitrage has indeed broken down in our sample. As in Model 3, money-market liquidity is assumed to affect both the long-term equilibrium relationship between CDS and bond spreads and their short-term dynamics.

5. Estimation procedure

Before proceeding with model estimation, we estimate cointegrating vectors and their respective disequilibrium errors $z_1$, $z_2$ and $z_3$ using Hansen’s Fully Modified OLS.\(^{18}\) Only exception is Model 4 where $z_1$ and threshold $\gamma$ are estimated jointly using a double grid-search procedure that maximizes the log-likelihood function.

Threshold effects are tested in two ways: For Model 1, we test the null hypothesis of “no-threshold effects” (single regime) against the alternative of a single threshold (2 regimes) using the LM test of Hansen and Seo (2002). Hansen-Seo LM test is a formal model-based statistical test that is heteroskedasticity-robust with higher power than comparable non-parametric tests.\(^{19}\) However, it cannot be applied on larger specifications, i.e. with more than 2 endogenous variables and/or more regimes. Therefore, for multiple regime extensions of Models 1-3 we apply the threshold test of Tsay (1998) in the following successive steps: First we reject the null hypothesis of “no-threshold effects” for the alternative of a single threshold. Then we repeat the test on each of the two subintervals to examine if there is a second threshold in either of them. The procedure ends when the null is not rejected. To economize on space, we only present model comparisons that pass this multistage procedure.

Test results for all three specifications (Models 1-3) suggest rejection of the null of “no-threshold effects” at 0.01 confidence level for all rating portfolios and for all values of $d$ (delay in the threshold variable) ranging from 1 to 7. It is worth noting that the alternative hypothesis of threshold effects implies both the existence of regime effects and the ability of the assumed threshold variable to distinguish between the two regimes. While we cannot formally test for the

\(^{18}\) Notice that when both $z_1$, $z_2$ are included in the same model, they are estimated orthogonal to each other.

\(^{19}\) For a discussion, see Balke and Fomby (1997) and Lo and Zivot (2001).
existence of three regimes against the null of two regimes, our procedure is able to distinguish if the basis dynamics are indeed better explained by a three- rather than two-regime process.

An indication that a three-regime process is possibly more accurate representation of CDS-bond dynamics than a two-regime process is shown in Figure 3. It plots AIC values of a two-regime specification of Model 3 against alternative threshold levels (in basis points).\textsuperscript{20} We observe a wide range of threshold values (between -150 and -40 basis points) corresponding to almost equally informative models, i.e. with very low AIC values. This could be interpreted as absence of an undisputable global minimum, indicating the existence of more than two regimes.

[Figure 3]

Following Tong (1990) and Tsay (1998) we estimate Models 5-10 using the AIC approach for threshold cointegration. According to this approach, we first fix the number of lags and regimes and then select the model based on AIC. In practice, this approach is asymptotically equivalent to selecting the model with the smallest generalized residual variance using the conditional least squares method. Tsay (1998) shows that the estimates obtained by this method are strongly consistent and independent of threshold value priors.

[Table 3]

Table 3 presents model comparisons for each rating portfolio based on AIC and BIC, with ranking 1 corresponding to best fit and 11 to worst.\textsuperscript{21} If the two criteria give conflicting results, then we consider it as tie. Overall, we find that in all cases both information criteria point to the same model ordering, with the exception of the cross-over rating category for Models 2 and 3.

6. Results

Our main results (Table 3) can be summarized as follows:

Specifications with two cointegrating vectors are generally superior to single cointegrating vector models, other things being equal (e.g. number of regimes). In other words, as already expected

\textsuperscript{20} Figure 3 refers to the portfolio of AA rated bonds, using $z_1$ as threshold variable.

\textsuperscript{21} Even though the usual information criteria (AIC, BIC, HQ) require all candidate models to belong to a single parametric family, previous empirical research suggests that they can be very effective for the purpose we use them. For example, Kapetanios (2001) shows that AIC, BIC are better able to choose the appropriate threshold model compared to other criteria (e.g. ICOMP or GIC), which - at least in theory - are not subject to similar constraints.
from our preliminary tests in Section 3, the inclusion of the second cointegrating vector between bond and Libor/OIS spreads offers a more accurate description of the joint CDS-bond dynamics for all rating categories.

Multiple-regime Models 4-10 exhibit consistently better fit than linear (single-regime) Models 1-3, pointing towards the limits-to-arbitrage hypothesis we discussed previously. Econometrically this result is rather expected given our earlier test results that indicate threshold effects for all rating portfolios.

Among multiple-regime models, regime-switching mechanisms that are linked to dynamic threshold variables $z_i, i=1,2,3$ exhibit better fit across all rating categories, compared to the alternative of Model 10. While the former mechanism implies a link to financing costs and the break-even level of basis trades, the latter is “agnostic” to the transition mechanism between regimes assuming static break points in time. Intuitively, this result confirms our conjecture that the unravelling of the basis trade during the 2007-09 crisis was a direct product of its very economics. Furthermore, the fact that $z_1$ and $z_3$ are more successful choices for the threshold variable than $z_2$ (except for the CCC rating category), points to a regime-switching mechanism that is better described by stop-loss limits rather than by funding constraints alone.

All 3-regime specifications (Models 5-9) turn out to dominate the 2-regime Hansen-Seo model (Model 4), indicating the need to account for more structure than just a normal and distressed regime. In particular, Figures 4-6 show (in shade) the in-sample estimates of regimes 1 to 3 across rating categories based on Model 9, where $z_3$ is used as threshold variable. Regime 1 tends to coincide with normalcy periods before the eruption of financial crisis in 2007 (pre-crisis normal regime). Regime 2 roughly corresponds to an intermediate stage, to normalcy periods after the onset of financial crisis in 2007 (post-crisis normal regime). Regime 3 points to the peak of the financial turmoil, right before and after the Lehman failure (distressed regime).\footnote{\begin{enumerate}
\item Bai and Collin-Duffresne (2013) refer roughly to the same periods as “Before Crisis” for regime 1, “Crisis I” and “Post-Crisis” for regime 2, and “Crisis II” for regime 3.
\item Interestingly, for the AAA rating category the distressed regime includes also the early sample period in 2005. This could be due to proliferation of collateralized debt obligation (CDO) structures during that period.
\end{enumerate}}

\begin{figure}
\centering
\caption{Figure 4}
\end{figure}

\begin{figure}
\centering
\caption{Figure 5}
\end{figure}
Notice that $z_3 > \gamma_2$ implies “pre-crisis normal regime” for all rating categories except AAA, for which it implies “distressed regime”. For $z_3 \leq \gamma_1$ the basis is most negative and implies “distress regime” for all rating categories except AAA, for which it corresponds to “pre-crisis normal regime”. The “post-crisis normal regime” corresponds to $\gamma_1 < z_3 \leq \gamma_2$ for all rating categories.

Tables 4 and 5 present estimated coefficients for CDS and bond spread dynamics using Eicker-White heteroskedasticity robust estimates of the 3-regime model using as threshold variable the disequilibrium error $z_3$ (Model 9).\textsuperscript{24}

Tables 4 and 5 show that in normalcy regimes (1 and 2) CDS and bond spreads tend to revert towards their long-run equilibrium relationship, in line with the pre-crisis literature. This is indicated by the negative and statistically significant effect of disequilibrium error $z_1$ on CDS dynamics. Furthermore, the effect of liquidity-related disequilibrium error $z_2$ on bond spreads is mostly negative and statistically significant implying that an increase in Libor/OIS spread (i.e. a fall in money market liquidity) relative to its long-term equilibrium relationship with the bond market tends to push bond spreads higher. Yet, short-term (possibly offsetting) effects of money-market liquidity obscure the economic interpretation of spread dynamics in normal regimes, except for causality effects that we discuss below.

Pre-crisis normalcy also coincides with periods of “low risk premia”, as indicated by the mostly negative and statistically significant trend (constant) across the rating spectrum, especially in the CDS market (Table 4). In the post-crisis normal regime this negative trend flattens out, or moves into positive territory, especially for the BB rating category where it increases markedly (0.47 and 0.28 for CDS and bond spreads, respectively). The distressed regime is associated with a clear trend of widening spreads, especially in the CDS market.

The distressed regime is the most interesting of the three, presenting a complete break from the usual pattern of joint dynamics. Table 4 shows that changes in CDS spreads are now entirely driven by random shocks and the disequilibrium error with the bond market, as the effect of $z_1$ is the only

\textsuperscript{24} Similar results obtain when $z_1$ is used as threshold variable (Model 7).
The positive coefficient of $z_1$ signifies that a widening of the basis drives CDS spreads away from the long-run equilibrium relationship with bond spreads, widening the basis even further. A plausible explanation for such destabilizing dynamics is the forced-unwinding of basis trades due to activation of stop orders or funding-liquidity constraints.

Of course, for stop orders to accelerate the momentum of CDS spreads away from its normal equilibrium with bond spreads there must be a lack of investors eager to replace the arbitrageurs who are being forced out of the market. Under normal market conditions, a wide basis would have attracted enough capital to slowdown the market movement and even push the basis towards its regular levels. But under conditions of exceedingly slow-moving capital the activation of stop orders accelerates the markets towards new clusters of stop orders, creating a virtual snowball effect (Shleifer and Vishny, 1997; Mitchell and Pulvino, 2012; and Bai and Collin-Duffresne 2013). When this happens, the basis goes on increasing almost uncontrollably.

CDS spreads for AAA names in the distressed regime are not affected by $z_1$. By contrast, the component with the highest impact is short-term changes in money-market liquidity: For every basis point widening in Libor/OIS there is a fourfold reduction in CDS spread. This is possibly due to reduced demand for CDS protection against AAA names at the height of the financial crisis when protection sellers considered not safe enough and sell protection at a lower spread. This effect is moderated by the negative coefficient (-0.32) of disequilibrium error $z_2$ (between bond and Libor/OIS spreads), which falls as Libor/OIS spread increases.

Also in the distressed regime the effect of $z_1$ on bond spreads is mostly statistically insignificant, as well as the effect of short-term changes in money-market liquidity. A special case is CCC-C rated bonds where short-term increases in Libor/OIS seem to reduce bond spreads substantially. Although this effect is rather counterintuitive, it is worth keeping in mind that quoted prices for CCC-C bonds in the distressed regime may be quite far from accurate.

Overall, the observed pattern in distress regime supports the hypothesis that the basis breakdown was caused by bond supply shocks contaminating the CDS market through the unraveling of basis

---

25 The AAA rating category is the only exception and we discuss below.
26 Tightening money-market conditions during the financial crisis also coincides with broader unwinding of synthetic CDO structures that led to increased supply of CDS protection against AAA names and lower spreads.
trades: CDS spreads are almost exclusively driven by the P&L of basis trades, whereas bond spreads seem completely impervious to anything that is happening in the CDS market.

We also consider the extent to which price discovery takes place in the CDS market. During pre-crisis normalcy, spread innovations in the CDS market transmit into the bond market for AAA and cross-over portfolios, but not the other way round. This is shown by the positive and statistically significant effect of short-term changes in CDS spread on AAA and cross-over rated bonds (0.15 and 0.28, respectively) in Table 5. Such causality is suggestive of price discovery taking place in the CDS market for rating categories that are of special interest to speculators. In particular, AAA bonds attract a liquidity premium due to their special role of acting as collateral in a wide array of financial transactions. On the other hand, the cross-over rating category is affected by funding discontinuity in repo market. It is also particularly sensitive to rating downgrades as it defines the investment-subinvestment dichotomy.

For AA and A rating categories we find no evidence of causality during the pre-crisis normal regime, where bond spreads appear unaffected both by short-term changes in CDS spreads and disequilibrium error $z_1$. Moreover, changes in CDS spreads are driven by disequilibrium error $z_1$ (-0.13 and -0.48, respectively) with the A rating category depending also on short-term changes in money-market liquidity proxy (0.69). Therefore, while the two markets are cointegrated and basis trades seem to play a key role in CDS convergence towards bond spreads, we find no evidence of price discovery taking place primarily in any of the two markets, in line with Zhu (2006). Also, we find no one-way causality effects for BBB, BB and CCC-C portfolios during pre-crisis normalcy. Instead, we observe (two-way) feedback effects between the CDS and bond spreads, where innovations in one market are transmitted into the other and vice versa.

In the post-crisis normal regime, causality effects disappear also for the AAA and cross-over rating category, indicating that the CDS market no longer leads the price discovery process for any rating category. This coincides with a substantial drop in notional amount of outstanding CDS contracts (from around $58tn in 2008 down to $30tn in 2010), constraints to rehypothecation, and widespread distrust of CDS contracts to deliver on their intended purpose of insuring against default.\(^\text{27}\)

\(^{27}\) For example, according to FT article “Credit default swaps: a $10tn market that leaves few happy” (July 25, 2017) distrust on the outcome of auctioning defaulted bonds to determine CDS payouts weighs negatively on CDS market.
7. **Hedging implications: an out-of-sample exercise**

The analysis so far has focused on models estimated in-sample. In this section we examine model performance in an out-of-sample framework. More specifically, we investigate if a threshold model governed by disequilibrium error \( z_3 \) (Model 9) provides practical gains for the purpose of dynamically hedging a diversified portfolio of bonds of given credit rating.

Although there is a long empirical literature on estimating optimal hedge ratios between cash and forward markets, to the best of our knowledge this is the first study to consider dynamic hedging between bonds and CDS. At the same time, and in addition to usual measures of hedging efficiency such as RMSE and maximum draw-down, we compare dynamic out-of-sample hedge ratios using popular tools of the forecasting literature, such as the Diebold-Mariano test.

We consider 5 competing hedging strategies:

Strategy 1 (Naïve Static Hedging) stipulates a hedging ratio of \([1, -1]\) for the pair of par CDS and bond-implied par-equivalent CDS contracts. It assumes that the hedger is concerned only about the default scenario where bond losses are fully covered by the protection seller. However, this strategy implies either an infinite trading horizon (e.g. a buy-and-hold investor not subject to mark-to-market accounting), or infinite stop-loss limits for the hedger.

Strategy 2 (Rolling Regression Hedging) is estimated by the slope coefficient \( \beta \) in

\[
\Delta Bond_t = a + \beta \cdot \Delta CDS_t
\]

Despite the absence of time index in the slope coefficient in (2), in practice this hedge ratio is time-varying given that is estimated on a daily basis using the sample of changes in CDS and bond spreads over the preceding year (260 daily observations). However, as the variance-covariance matrix practically changes very little from day to day, this model produces hedge ratios that are significantly autocorrelated by construction.

The next three hedging strategies stem from the Kroner and Sultan (1991) bivariate GARCH approach. It assumes a cointegrated pair of prices for which the joint dynamics of the mean vector are described by a VECM.

Strategy 3 (VECM-CV1) relies on a mean VECM, similar to Model 1b in Section 4, but with \( L \) lags to describe the short-term dynamics.
\[
\begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond}
\end{bmatrix}_{t} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} + \sum_{k=1}^{L} \Phi_{t-k} \begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond} \\
\Delta (\text{Libor} / \text{OIS})
\end{bmatrix}_{t-k} + \begin{bmatrix} \varepsilon_{\text{CDS}} \\ \varepsilon_{\text{Bond}} \end{bmatrix}_{t}
\]

(3)

Strategy 4 (VECM-CV2) is based on Model 3 with \(L\) lags for the short-term dynamics.

\[
\begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond}
\end{bmatrix}_{t} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} + \sum_{k=1}^{L} \Phi_{t-k} \begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond} \\
\Delta (\text{Libor} / \text{OIS})
\end{bmatrix}_{t-k} + \begin{bmatrix} \varepsilon_{\text{CDS}} \\ \varepsilon_{\text{Bond}} \end{bmatrix}_{t}
\]

(4)

Strategy 5 (T-VECM) is based on Model 9 with three regimes and \(L\) lags for the short-term dynamics.

\[
\begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond}
\end{bmatrix}_{t} = \begin{bmatrix} a_{11}^{(i)} & a_{12}^{(i)} \\ a_{21}^{(i)} & a_{22}^{(i)} \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} + \sum_{k=1}^{L} \Phi_{t-k} \begin{bmatrix}
\Delta \text{CDS} \\
\Delta \text{Bond} \\
\Delta (\text{Libor} / \text{OIS})
\end{bmatrix}_{t-k} + \begin{bmatrix} \varepsilon_{\text{CDS}} \\ \varepsilon_{\text{Bond}} \end{bmatrix}_{t}
\]

(5)

\[
i = \begin{cases} 
1, & \text{if } z_{3,t-1} \leq \gamma_1 \\
2, & \text{if } \gamma_1 < z_{3,t-1} \leq \gamma_2 \\
3, & \text{if } z_{3,t-1} > \gamma_2 
\end{cases}
\]

Kroner and Sultan (1991) propose as “optimal” hedge ratio \(\beta^*\) the ratio of conditional covariance \(h_{\text{CDS/Bond}}\) between changes of the two series divided by the conditional variance \(h_{\text{CDS}}\) of the hedging instrument’s changes (here, the CDS contract).

\[
\beta_{t-1}^* = -\frac{h_{\text{CDS/Bond},t}}{h_{\text{CDS},t}}
\]

(6)

Both numerator and denominator of the hedge ratio in (6) are elements of the conditional covariance matrix \(H_t\) of the residual series \(\varepsilon_{\text{CDS}}\) and \(\varepsilon_{\text{Bond}}\) in (5). In every application of this method \(H_t\) is assumed to follow a bivariate GARCH specification. Given the apparent skewness of spread changes, we estimate \(H_t\) using the asymmetrical BEKK GARCH(1,1) model of Brooks et al (2002). This model captures any asymmetric response of volatility to positive or negative innovations of equal magnitude and describes the dynamics of the conditional covariance matrix as follows.

\[
H_t = C_0C_0 + A_{11}\varepsilon_{t-1}^r \varepsilon_{t-1}^r + A_{11} + B_{11}H_{t-1}B_{11} + D_{11}^{11}\varepsilon_{t-1} \varepsilon_{t-1}^r D_{11}^{11}
\]

(7)
where, \( \bar{\xi}_t = \begin{bmatrix} \min(\varepsilon_{CDS,t}, 0) \\ \min(\varepsilon_{Bond,t}, 0) \end{bmatrix} \), 
\[ C_0 = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}, \quad A_1 = \begin{bmatrix} a_{11} & a_{12} \\ a_{11} & a_{22} \end{bmatrix}, \quad B_1 = \begin{bmatrix} b_{11} & b_{12} \\ b_{11} & b_{22} \end{bmatrix}, \quad D_1 = \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{11} & \delta_{22} \end{bmatrix} \]

We start the iterative procedure by estimating the size (number of lags \( L \), number of regimes) and coefficients for each model over the 2-year period 3/1/2005-3/1/2007. The number of lags ranges from 0 to 10 (usually 2 or 3) and is determined on the basis of minimizing AIC. The number of regimes ranges from 1 to 3 and is determined by the Tsay (1998) testing procedure discussed in Section 5. At this stage we are not particularly concerned about model parsimony or the robustness of estimated coefficients, but rather about the model’s ability to “whiten” the residual series by removing all possible auto/cross-correlations. Thus we may end up with models of more than 2 lags that we assumed in Section 5 for in-sample analysis. First we estimate the mean model to generate the residuals and, at a second stage, we estimate the conditional covariance matrix of the residual vector series. As long as the residual series are clean of auto/cross-correlation, the produced hedge ratios are unbiased.

Having estimated the last incidence of conditional covariance matrix \( H_t \) for each strategy during the 2-year period, we calculate and record the hedge ratio \( \beta_t^* \) on the last trading day \( t \) of the period and the realized hedged portfolio return \( R_{t+1} \) on the next trading day \( t+1 \). We repeat this process 1,553 times recording each time the estimated hedge ratio and hedged-portfolio return for each strategy. In each iteration the estimation sample increases by one trading day, until 16/12/2012. Clearly the quality of estimated hedge ratios depends on the quality of conditional covariance matrix estimates. In that sense, our model comparisons are essentially comparisons of forecasts of the true daily covariance matrix and, by extension, of the “optimal” hedge ratio.

Since any out-of-sample forecasting exercise requires an in-sample (ex-post) benchmark to evaluate different forecasts against, we derive the ex-post “optimal” hedge ratio using Kalman filter fixed-interval smoothing. Kalman smoothing runs only in off-line mode because to produce smoothed estimates of state variables at any point in time \( t \) requires not only processing of prior
observations but also those that follow. Its main benefit is that yields the “optimal” estimate of a state variable, in a least squares sense, as long as the system is well-defined and identifiable. But when this process is used to forecast the state variable in “real time”, predictions are nowhere near as successful. As in all out-of-sample forecast exercises, Kalman-Filter covariance forecasts are no more but imperfect predictions of the true (unknown) covariance matrix.

Therefore, to filter the “optimal” hedge ratio in off-line mode we assume that the true hedge ratio $\beta_t$ is an unobservable state variable in the following state-space setup that we estimate using maximum likelihood over the entire sample period 3/1/2005-17/12/2012.

$$\Delta Bond_t = \Delta CDS_t \cdot \beta_t + v_t$$

$$\beta_t = \beta_{t-1} + w_{1,t}$$

$$v_t = \phi v_{t-1} + w_{2,t}$$

(8)

The first equation denotes the so-called “measurement equation” in the state-space formulation and links the first state variable (i.e. the hedge ratio $\beta_t$) with the observed variable ($\Delta Bond_t$) through a linear time-varying relationship. The second equation describes the dynamics of state variable $\beta_t$ which is the “optimal” hedge ratio, assuming that it follows a random walk. The random walk assumption is imposed not only for identification purposes, but also for the hedge-ratio process to have the highest possible persistence. Given that persistent hedge ratios yield lower daily turnover compared to less persistent ones, we restrict our solutions to most economical in terms of transaction costs. The third equation describes the dynamics of state variable $v_t$ that captures any first-order autocorrelation in measurement error, compensating for any short-term dynamics left unspecified in (8). Finally, we assume that $w_{1,t}$ and $w_{2,t}$ follow a bivariate normal distribution with diagonal covariance matrix.

We also define turnover ($TO_i$) of strategy $i$ as the sum of absolute daily changes in hedge ratios.

$$TO_i = \sum_{t=1}^T |\beta_{i,t+1} - \beta_{i,t}|$$

(9)
Turnover provides a measure to compare transaction costs of different hedging strategies. For example, if the average transaction cost for a particular CDS contract is 3 basis points (bps) then the total transaction cost of the hedging strategy over the whole forecasting period is roughly equal to $3 \text{bps} \times TO \times (\text{Bond Notional}) \times (\text{Spread Duration})$.

Table 6 shows descriptive statistics of daily returns and turnover of different strategies for hedging portfolios of bonds of a given credit rating with CDS contracts, for the out-of-sample period 3/1/2007-16/12/2012. The out-of-sample hedging strategies considered are the naïve static hedging assuming hedging ratio $[1 - 1]$, the rolling regression hedging based on a 1-year window, and the three Kroner-Sultan dynamic hedging strategies assuming one cointegrating vector (VECM-CV1), two cointegrating vectors (VECM-CV2), and two cointegrating vectors and three regimes (T-VECM) for the joint CDS-bond dynamics. Descriptive statistics for the unhedged position and the in-sample Kalman-filter strategy benchmark are presented for comparison. For that purpose, turnover of each out-of-sample hedging strategy is expressed as a fraction of the turnover produced on the basis of the Kalman filter strategy.

To start with, we observe that all strategies reduce the variance of hedged portfolio returns compared to the unhedged position. This is despite the fact that the out-of-sample period (3/1/2007-16/12/2012) contains the Lehman failure and the ensuing turmoil in financial markets. This clearly shows that hedging bonds with CDS reduces mark-to-market risk compared to the unhedged portfolio, regardless of hedging strategy. Moreover, the in-sample Kalman filter smoothed estimates exhibit, as expected, the best performance in terms of daily return statistics (lowest standard deviation, kurtosis) compared to out-of-sample hedging strategies. This is also true in terms of total turnover, with the obvious exception of rolling regression that, by definition, is a low turnover strategy albeit with significant bias.
Regarding out-of-sample comparisons, the Kroner-Sultan strategies (VECM-CV1, VECM-CV2, T-VECM) clearly outperform static and rolling regression strategies, both in terms of daily-return volatility and kurtosis. It is also obvious that T-VECM performs better than VECM strategies in terms of total turnover, with only (slight) exception the AA rating portfolio.

However, by the basic statistics alone we cannot conclude if T-VECM is better hedging strategy than VECM. Therefore, we consider the hedge ratios produced by the out-of-sample hedging strategies as predictors of the “true” hedge ratio. As a proxy of the latter we use the in-sample Kalman-filter benchmark. To compare between forecasts of different hedging strategies we employ the Diebold-Mariano modified statistic based on the RMSE of forecast errors. The null of this test can be expressed as “neither of the two hedging strategies produces better hedge ratio forecast than the other”. A statistically significant positive statistic implies rejection of the null in favor of the second series of predictions (second strategy). In contrast, a statistically significant negative statistic implies rejection of the null in favor of the first series (first strategy). A non-statistically significant statistic implies that we cannot reject the null either way.

Table 7 shows comparisons of out-of-sample hedging strategies based on their Diebold-Mariano modified statistic and assuming error autocorrelation of 5 lags. The first column compares the rolling regression (strategy 2) against VECM-CV2 (strategy 4), in which case the null is soundly rejected in favor of VECM CV2. The second column shows that T-VECM (strategy 5) produces better hedge ratio forecasts than the rolling regression (strategy 2). The BB category is the only exception. The third column shows that VECM-CV2 (strategy 4) turns out to have better out-of-sample hedging performance than VECM-CV1 (strategy 3) for 5 out of 8 rating categories. Notice also that none of the remaining 3 categories shows an inverse relationship (i.e. negative Diebold-Mariano statistic). Finally, T-VECM (strategy 5) turns out to have better out-of-sample hedging performance than VECM-CV2 (strategy 4) in 4 out of 8 rating portfolios. In other words, assuming a threshold mechanism improves the out-of-sample hedging performance of VECM with two
cointegrating vectors. Only for the BB rating category VECM-CV2 is clearly superior predictor than T-VECM.

Overall, our out-of-sample results corroborate the main points of the in-sample analysis regarding the need of a richer and regime-oriented description of the CDS-bond dynamics compared to the pre-crisis paradigm. Moreover, the use of two cointegrating vectors (i.e. both disequilibrium errors $z_1$ and $z_2$) improves the out-of-sample prediction of the “optimal” hedge ratio relative to a Kroner-Sultan framework with only one cointegrating vector.

8. Conclusions

The dramatic unraveling of the negative basis trade during the financial crisis led to a common perception that a well-documented cointegrating relationship between CDS and corporate bond spreads undergone a “final” or structural break. Market participants attributed the widening of the basis to elevated costs of funding for arbitrageurs in money markets that resulted in a retraction of the breakeven basis deep into negative territory.

In this paper, we examine the joint dynamics of CDS and corporate bond spreads at a rating portfolio level based on an extensive dataset covering the financial crisis and normalcy periods around it. At a preliminary stage we largely confirm the findings of previous research suggesting the existence of a long-run equilibrium between the two markets, while at the same time we highlight the importance of a money-market liquidity variable – the Libor/OIS spread – in describing the joint dynamics of the two markets. This is in line with practitioners’ view that money-market liquidity was a key contributor to the unraveling of the basis trade.

Based on this preliminary evidence, we detract from the linear model paradigm to explore threshold effects in the joint dynamics of the two markets using a threshold VECM specification. Comparison of the in-sample fitting properties of a suite of alternative linear and non-linear VECM models supports the existence of a dynamic threshold mechanism with three regimes (pre- and post-crisis normalcy, and a distressed regime) for the period January 2005 to April 2010. Also the dynamics of the two markets appear to be influenced by deviations from two distinct cointegrating
vectors: one that directly links CDS and bond spreads, and a second that relates bond spreads to money-market liquidity.

Contrary to the common perception, the results confirm the existence of a cointegrating relationship between the CDS and corporate bond market under all regimes, even during the liquidity-crisis in the aftermath of Lehman failure. But at the peak of the financial crisis, bond market spreads appear weakly exogenous to the system, while CDS spreads are entirely driven by random shocks and the disequilibrium error with the bond market. More important, deviations from the equilibrium relationship between the two credit markets push CDS spreads further away from bond spreads, widening the basis even further. This is in line with practitioners’ view that the breakdown of negative-basis trades during the financial crisis was caused by supply shocks in the corporate bond market, higher funding costs and a more negative breakeven basis.

In line with pre-crisis literature, we find evidence that price discovery takes place in the CDS market for key rating categories such as the AAA and cross-over. But in post-crisis normalcy, the CDS market no longer leads the price discovery process for any rating category. This coincides with a drop of around 50 percent in the notional amount of outstanding CDS contracts between 2008 and 2010. It also adds to evidence by Bai and Collin-Dufresne (2013) of a declining contribution of the CDS market to price discovery as the financial crisis deepened.

Finally, we show that CDS contracts remain valid hedging instruments against mark-to-market risk of corporate bonds in the post-crisis era. Taking into account money-market liquidity effects, our threshold VECM specification leads to enhanced out-of-sample performance of dynamic strategies for hedging corporate bond portfolios with CDS contracts for the period April 2010 - December 2012. This is a key result as the out-of-sample period still has recent memories from the crisis and also bears the impact of new regulations and market practices, such as Basel III, a wider adoption of upfront CDS payments and limits to collateral rehypothecation.

References


Appendix A: Calculating bond-implied par-equivalent CDS spreads

CDS spreads are paid on quarterly or semi-annual frequency until either contract maturity or default of the reference entity, whichever occurs first. Duffie (1999) shows that only a floating rate note issued by the reference entity at par and in conjunction with a very liquid repo market. Structures that are common in practice involve asset swapped or futures-hedged bullet bonds that produce very different credit risk profiles than CDS. The more a bond deviates from the assumptions of Duffie (1999) the more incompatible the metric of bond spreads (yield spread, zero spread or asset-swap spread) with the CDS spread.

To address this issue we use a survival-based valuation approach to derive the “bond-implied CDS spread”, similar to “par-equivalent CDS spread” of JP Morgan and the “arbitrage price difference” (APD) of CFSB. By deriving the bond-implied CDS spreads within the same framework we employ a consistent relative value measure across the bond and CDS market, which does not

28 Even in that case some divergence in payoffs is still expected. For example, in case of default, the protection buyer will receive payment of the bond, but the protection seller will not receive the accrued premium.

29 For a more detailed description of the various spread metrics see for example Jersey et al. (2007).

30 Par-equivalent and APD are discussed in Beinstein and Scott (2006) and Jersey et al. (2007).
depend on bond characteristics. Furthermore, it is a consistent metric for arbitrage-free interpolation between different CDS maturities.\(^\text{31}\)

At inception of the CDS contract, arbitrage-free pricing implies the expected stream of CDS spread and protection payments are equally priced:

\[
S_N \sum_{i=1}^{N} PS(t_i) \cdot \Delta_i \cdot d(t_i) + AI = (1 - R) \cdot \sum_{i=1}^{N} [PS(t_{i+1}) - PS(t_i)] \cdot d(t_{i+1}) \tag{A1}
\]

where, \(S_N\) is the CDS spread, \(\Delta_i\) is the CDS payment period, and \(R\) the recovery rate of par value in case of default. The survival probability from time 0 to time \(t_i\) is denoted as \(PS(t_i)\), while the risk-free discount factor as \(d(t_i)\).\(^\text{32}\) Finally, \(AI\) stands for the accrued interest on default.

Similarly, the dirty price of a bullet bond issued by the same corporate entity, with \(M\) remaining coupons until maturity, is given by:

\[
\text{Bond Price} = C \cdot \sum_{i=1}^{M} \Delta_i \cdot PS(t_i) \cdot d(t_i) + PS(t_M) \cdot d(t_M) + R \cdot \sum_{i=1}^{M} [PS(t_{i+1}) - PS(t_i)] \cdot d(t_{i+1}) \tag{A2}
\]

where, \(C\) denotes the bond coupon rate.

For obvious reasons, a function of maturity \(f(t)\) can be a survival probability curve \(PS(t)\) only if is strictly positive, decreasing and satisfying \(PS(0) = 1\). To avoid the impositions of such constraints when fitting a parametric curve to bond prices or CDS spreads, we fit instead of \(PS(t)\) the market-implied forward hazard rate curve \(H(t, t_{i+1}, t_i)\) in the spirit of Schonbücher (1999) and Houweling and Vorst (2005), which only needs to be positive. Berd et al. (2004) note that violation of this constraint usually signals violations of arbitrage conditions.

In a variant of their reduced-form model approach, we model the observed at time \(t\) forward hazard rate \(H(t, t_1, t_2)\) that spans the interval \(t_2-t_1\) as a deterministic piecewise-constant function,\(^\text{33}\) which remains constant between monthly intervals, and whose monthly value follows the Nelson and Siegel (1987) parametric form:

\[\ldots\]

\(^{31}\) An arbitrage-free interpolation scheme is conducted at the level of the hazard rate. It is arbitrage-free because it coincides with the market-practice that is used for calculating forward CDS spreads.

\(^{32}\) These discount factors are bootstrapped from the Libor/Swap curve following Blanco et al. (2005), and Hull et al. (2004) among others.

\(^{33}\) As Schonbücher (2003) notes, the use of a stochastic hazard rate process that is independent of the interest rate process, while more complicated, will offer no clear advantage to a deterministic specification of the hazard rate curve when pricing bullet bonds or credit default swaps with no embedded optionality.
The forward hazard rate \( H(t, t_i, t + \frac{1}{12}) = b_0 + b_1 \cdot \exp\left( -\frac{t}{b_3}\right) + b_1 \cdot \exp\left( -\frac{t}{b_3}\right) \) (A3)

The forward hazard rate \( H(t, t_i, t + \frac{1}{12}) \) corresponds to the conditional probability that the issuer will default in the interval \([t, t_i + \frac{1}{12}]\) given that she has survived until \(t_i\).

Our method produces relatively “smooth” and intuitive shapes of the survival probability function. This is in sharp contrast with the CDSW method in Bloomberg, which often yields coarse grids of implausible forward hazard rates and highly discontinuous survival probabilities.

Having defined the forward hazard rate curve, it is easy to calculate the survival probability that is implied by it from

\[
PS(t = t_n) = \prod_{i=1}^{n} \frac{1}{1 + \delta_i H(t, t_{i-1}, t_{i+1})}
\]  

(A4)

We define the bond-implied CDS spread similarly to par-equivalent spread of JP Morgan and arbitrage price difference (APD) of CSFB’s, following three steps:

First, we use all available CDS maturities to fit through equations (1) and (4) the forward hazard curve described in (A3). Second, we use this curve to price any bond of the same issuer and seniority. To do this, we shift the forward hazard rate curve in parallel until we obtain the correct market price. With the “adjusted” hazard rate curve in hand, we calculate the bond-implied CDS spread from (A1) and (A4), having the same maturity and default risk and the reference bond.

The above-described algorithm provides a credit spread metric for a specific bond that takes into account both the term structure of default probabilities implied by the CDS market and the recovery rate of the bond’s par value at default. An important advantage of this approach is that the CDS-bond basis is not affected either by bond characteristics or discontinuities of the bootstrapped hazard rate. The latter could potentially cause sudden shifts in the interpolated CDS when seeking to match a particular bond.

34 Berd et al. (2004) propose a smooth instantaneous hazard rate which requires numerical integration when fitting it to market prices. This imposes quite a computational burden without offering any clear advantage in the results. Indeed, our results show that both methods produce fitting errors in CDS spreads that are fractions of a basis point.

**Panel A: Johansen cointegration test**

<table>
<thead>
<tr>
<th>Null hypothesis (trace statistic):</th>
<th>(CDS, bond)</th>
<th>(bond Libor/OIS)</th>
<th>(CDS, Libor/OIS)</th>
<th>(CDS, bond, Libor/OIS)</th>
<th># Lags</th>
</tr>
</thead>
<tbody>
<tr>
<td>no cointegration</td>
<td>25.94*</td>
<td>17.15</td>
<td>16.20</td>
<td>43.03**</td>
<td>17.41</td>
</tr>
<tr>
<td>at most one cointegrating vector</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>AAA</td>
<td>15.95</td>
<td>10.94</td>
<td>10.56</td>
<td>47.95**</td>
<td>13.99</td>
</tr>
<tr>
<td>AA</td>
<td>39.73**</td>
<td>24.00*</td>
<td>9.81</td>
<td>132.50**</td>
<td>22.85*</td>
</tr>
<tr>
<td>A</td>
<td>18.88</td>
<td>66.38**</td>
<td>18.16</td>
<td>137.77**</td>
<td>32.12*</td>
</tr>
<tr>
<td>BBB</td>
<td>13.31</td>
<td>7.04</td>
<td>7.42</td>
<td>38.23**</td>
<td>13.75</td>
</tr>
<tr>
<td>XOVER</td>
<td>17.52</td>
<td>32.47**</td>
<td>18.22</td>
<td>72.95**</td>
<td>24.54*</td>
</tr>
<tr>
<td>B</td>
<td>22.80*</td>
<td>19.76</td>
<td>14.99</td>
<td>67.36**</td>
<td>26.72*</td>
</tr>
<tr>
<td>CCC-C</td>
<td>51.09**</td>
<td>19.90</td>
<td>21.03*</td>
<td>73.38**</td>
<td>23.22*</td>
</tr>
</tbody>
</table>

**Panel B: Gregory-Hansen cointegration test for (CDS, bond)**

<table>
<thead>
<tr>
<th>Break in Constant</th>
<th>Break in Trend</th>
<th>Full Break</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADF* statistic</td>
<td>Breakpoint</td>
<td>ADF* statistic</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ADF* statistic</td>
</tr>
<tr>
<td>AA</td>
<td>-4.40</td>
<td>16/1/2009</td>
</tr>
<tr>
<td>XOVER</td>
<td>-2.36</td>
<td>10/2/2009</td>
</tr>
<tr>
<td>BB</td>
<td>-5.09*</td>
<td>30/6/2008</td>
</tr>
</tbody>
</table>

Panel A shows Johansen cointegration test results for the null hypothesis of “no cointegration” for the pairs (CDS, bond), (bond, Libor/OIS), (CDS, Libor/OIS), and the triplet (CDS, bond, Libor/OIS), where the number of lags used is determined on the basis of AIC. For the triplet (CDS, bond, Libor/OIS) we also test the null hypothesis of “at most one cointegrating vector”. Panel B shows Gregory-Hansen ADF* test results for the null of “no cointegration” against the alternative of “a structural break in an existing cointegrating relationship” affecting the constant, the trend, or both (full break). It refers to rating categories that failed the Johansen cointegration test in the (CDS, bond) pair, aiming to investigate if failure to reject the null of “no cointegration” was due to a structural break in cointegrating relationship. Breakpoints indicate the dates of estimated structural break. Statistical significance at 1% and 5% confidence level is denoted by ** and * respectively.
Table 2: Basic features of linear and non-linear VECM specifications for the joint dynamics of CDS and bond spreads.

<table>
<thead>
<tr>
<th>Model index number:</th>
<th>1a,b</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>(CDS, bond) single equilibrium</td>
<td>✓</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(CDS, bond, Libor/OIS) single equilibrium</td>
<td>√</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(CDS, bond) and (bond, Libor/OIS) independent equilibria</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Money-market dislocations have transitory effect</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Money-market dislocations have permanent effect</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Arbitrage may break down when:</td>
<td>✓</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>… stop-loss limits lead investors to retract capital</td>
<td>✓</td>
<td>✓</td>
<td>√</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>… funding-liquidity constraints become binding</td>
<td>√</td>
<td></td>
<td>√</td>
<td>√</td>
<td>√</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>… no explicit reason</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Pre- and post-crisis dynamics differ</td>
<td>✓</td>
<td>✓</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
</tbody>
</table>

This table shows basic features of linear and non-linear VECM specifications indexed 1-10, as discussed in Section 4. Such features include long-term (equilibrium) relationships for the pairs (CDS, bond), (bond, Libor/OIS) and the triplet (CDS, bond, Libor/OIS), transitory and permanent effects of money-market dislocations, possible break-down in CDS-bond arbitrage relationship due to funding constraints, stop-loss, or other reasons, and differences in pre- and post-crisis joint dynamics of CDS and bond spreads.
**Table 3:** Comparison of linear and non-linear VECM specifications for the joint dynamics of CDS and bond spreads.

<table>
<thead>
<tr>
<th></th>
<th># of Regimes = 2</th>
<th></th>
<th># of Regimes = 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(CDS, bond)</td>
<td>(CDS, bond)</td>
<td>(bond, Libor/OIS)</td>
<td>(CDS, bond) &amp; (bond, Libor/OIS)</td>
</tr>
<tr>
<td>Cointegrating Vector(s):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>z1</td>
<td>z1</td>
<td>z3</td>
<td>z3</td>
<td>t</td>
</tr>
<tr>
<td>Model index number:</td>
<td>1a 4</td>
<td>1b 5 2 6 3 7 8 9 10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AAA</td>
<td>(11) (7)</td>
<td>(9) (4) (8) (5) (10) (2) (3) (1) (6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AA</td>
<td>(11) (6)</td>
<td>(9) (2) (8) (4) (10) (1) (5) (3) (7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>(11) (6)</td>
<td>(8) (4) (10) (3) (9) (1) (5) (2) (7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BBB</td>
<td>(9) (7)</td>
<td>(11) (4) (10) (3) (8) (1) (5) (2) (6)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>XOVER</td>
<td>(11) (6)</td>
<td>(10) (2) (8) (4) (8) (1) (3) (5) (7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BB</td>
<td>(9) (5)</td>
<td>(11) (3) (10) (4) (8) (1) (6) (2) (7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>(11) (6)</td>
<td>(10) (4) (9) (3) (8) (2) (5) (1) (7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC-C</td>
<td>(9) (6)</td>
<td>(11) (5) (10) (4) (8) (3) (1) (2) (7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimation Method:</td>
<td>Johansen Hansen-Seo Johansen Tsay Johansen Tsay Johansen Tsay Tsay Tsay</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table shows comparisons of linear and non-linear VECM specifications with model index number 1a,b-10, as discussed in Section 4. The ordering is based on AIC and BIC, with ranking (1) corresponding to best fit and (11) to worst.
Table 4: Eicker-White estimated coefficients of Model 9 for changes in CDS spread under regimes $i=1,2,3$

$$\Delta CDS_{i} = a_{t-1}^{(i)} + a_{t+1}^{(i)} + \sum_{k=1}^{2} \phi_{1}^{(i)} \Delta CDS_{r,k} + \phi_{2}^{(i)} \Delta Bond_{r,k} + \phi_{3}^{(i)} \Delta (Libor/OIS)_{r,k}$$

<table>
<thead>
<tr>
<th>Lag ($k$)</th>
<th>Const.</th>
<th>$\Delta CDS_{t-k}$</th>
<th>$\Delta Bond_{r-k}$</th>
<th>$z_{1,t-1}$</th>
<th>$z_{2,t-1}$</th>
<th>$\Delta (Libor/OIS)_{r-k}$</th>
<th>Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AAA</td>
<td>-0.20**</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.20</td>
<td>-0.09</td>
<td>-0.45**</td>
<td>1.94</td>
</tr>
<tr>
<td>AA</td>
<td>-0.07**</td>
<td>0.31**</td>
<td>-0.12</td>
<td>-0.13</td>
<td>0.07</td>
<td>-0.13**</td>
<td>0.00</td>
</tr>
<tr>
<td>A</td>
<td>-0.21**</td>
<td>-0.12</td>
<td>-0.10</td>
<td>-0.01</td>
<td>0.07</td>
<td>-0.48**</td>
<td>0.00</td>
</tr>
<tr>
<td>BBB</td>
<td>-0.02**</td>
<td>0.03</td>
<td>0.07</td>
<td>-0.23**</td>
<td>-0.06</td>
<td>-0.16**</td>
<td>-0.01**</td>
</tr>
<tr>
<td>XOVER</td>
<td>-0.10**</td>
<td>0.03</td>
<td>-0.06</td>
<td>-0.22</td>
<td>-0.02</td>
<td>-0.10**</td>
<td>-0.01**</td>
</tr>
<tr>
<td>BB</td>
<td>-0.10**</td>
<td>-0.12**</td>
<td>-0.17**</td>
<td>-0.16**</td>
<td>0.10</td>
<td>-0.40**</td>
<td>-0.05**</td>
</tr>
<tr>
<td>B</td>
<td>-0.35**</td>
<td>-0.16</td>
<td>0.19**</td>
<td>0.13</td>
<td>-0.28**</td>
<td>-0.57**</td>
<td>-0.11**</td>
</tr>
<tr>
<td>CCC-C</td>
<td>-8.29**</td>
<td>0.47</td>
<td>0.01</td>
<td>-1.84**</td>
<td>-0.49</td>
<td>-0.98**</td>
<td>-0.30**</td>
</tr>
</tbody>
</table>

Pre-crisis normal regime ($i=1$)

| AAA       | 0.00   | 0.07**            | -0.17**           | 0.09**     | 0.25**     | -0.03**           | -0.02** |
| AA        | 0.00   | 0.06              | 0.09**            | -0.08      | -0.16**    | -0.16**           | -0.03** |
| A         | 0.00   | 0.11**            | 0.05              | -0.21**    | 0.08**     | -0.11**           | 0.00    |
| BBB       | 0.05** | -0.03             | 0.00              | -0.24**    | -0.07      | -0.75**           | 0.01** |
| XOVER     | 0.06** | -0.18**           | -0.05             | 0.01       | 0.09       | -0.19**           | 0.03** |
| BB        | 0.47** | -0.26**           | -0.33**           | 0.26       | 0.51**     | -1.09**           | -0.01** |
| B         | 0.09** | 0.02              | -0.33**           | -0.59**    | 0.23**     | -0.37**           | -0.01** |
| CCC-C     | -0.08**| 0.04              | 0.05              | -0.66**    | -0.35**    | -0.22**           | -0.14** |

Post-crisis normal regime ($i=2$)

| AAA       | 0.01** | 0.24              | -0.39             | 1.04       | 0.05       | -0.24             | -0.32** |
| AA        | 0.31** | -0.03             | -0.16             | 0.10       | 0.40       | 0.50**            | 0.16** |
| A         | 0.40** | -0.35             | 0.53              | 0.34       | -0.41      | 0.55**            | 0.02    |
| BBB       | 0.12** | -0.19             | 0.17              | 0.17       | -0.17      | 0.20**            | 0.00    |
| XOVER     | 2.45** | 0.17              | -0.66             | 0.56       | 0.54       | 1.14              | 0.17   |
| BB        | 1.10** | 0.05              | -0.22             | -0.28      | -0.13      | 0.91**            | 0.01   |
| B         | 1.81** | -0.08             | -0.25             | -0.37      | 0.39       | 0.69**            | 0.09   |
| CCC-C     | 30.73**| -0.39             | -0.21             | 1.28       | -0.96      | 0.39              | 1.23   |

Distressed regime ($i=3$)

This table shows Eicker-White heteroskedasticity robust estimates for CDS spread dynamics across rating categories using the 3-regime model with threshold variable $z_3$ (Model 9). Disequilibrium errors $z_1$, $z_2$, and $z_3$ are defined as $z_1=CDS_{t-1}-Bond_{t-1}$, $z_2=Bond_{t-1}-CDS_{t-1}-LIBOR_{t-1}$, and $z_3=CDS_{t-1}-Bond_{t-1}-LIBOR_{t-1}$, where $b_n$, $c_n$, $d_i$, ($i=1,2$) are cointegrating vector coefficients. “Pre-crisis normal regime” ($i=1$) tends to coincide with normalcy periods before the eruption of financial crisis. “Post-crisis normal regime” ($i=2$) tends to coincide with normalcy periods around the full-blown financial crisis. “Distress regime” ($i=3$) tends to coincide with the heights of the financial crisis, before and after the Lehman failure. Statistical significance at 1% and 5% confidence level is denoted by ** and * respectively.
Table 5: Eicker-White estimated coefficients of Model 9 for changes in bond spread under regime $i=1,2,3$

\[
\Delta \text{Bond}_t = a_1^{(i)} z_{1,t-1} + a_2^{(i)} z_{2,t-1} + \sum_{k=1}^{2} \left[ \phi_{1,k}^{(i)} \Delta \text{CDS}_{t-k} + \phi_{2,k}^{(i)} \Delta \text{Bond}_{t-k} + \phi_{3,k}^{(i)} \Delta (\text{Libor / OIS})_{t-k} \right]
\]

<table>
<thead>
<tr>
<th>Lag ($k$)</th>
<th>Const.</th>
<th>$\Delta \text{CDS}_{t-k}$</th>
<th>$\Delta \text{Bond}_{t-k}$</th>
<th>$z_{1,t-1}$</th>
<th>$z_{2,t-1}$</th>
<th>$\Delta (\text{Libor / OIS})_{t-k}$</th>
<th>(\text{Obs.})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$-$ 1 2</td>
<td>$-$ 1 2</td>
<td>$-$ 1 2</td>
<td>$-$ 1 2</td>
<td>$-$ 1 2</td>
<td></td>
</tr>
<tr>
<td>AAA</td>
<td>0.13**</td>
<td>0.15** 0.03</td>
<td>-0.48** -0.17</td>
<td>-0.07*</td>
<td>-0.29**</td>
<td>0.91 -2.58**</td>
<td>662</td>
</tr>
<tr>
<td>AA</td>
<td>0.04*</td>
<td>0.14 -0.01</td>
<td>0.03 0.09</td>
<td>0.05</td>
<td>-0.02</td>
<td>-0.04 0.12</td>
<td>610</td>
</tr>
<tr>
<td>A</td>
<td>-0.10</td>
<td>-0.14 -0.02</td>
<td>0.07 -0.01</td>
<td>-0.22</td>
<td>0.00</td>
<td>0.38 0.87**</td>
<td>556</td>
</tr>
<tr>
<td>BBB</td>
<td>-0.01**</td>
<td>-0.06 0.17**</td>
<td>-0.22** -0.06</td>
<td>-0.05**</td>
<td>-0.01**</td>
<td>-0.17** -0.05</td>
<td>714</td>
</tr>
<tr>
<td>XOVER</td>
<td>-0.03</td>
<td>0.28** -0.02</td>
<td>-0.50** -0.05</td>
<td>-0.04*</td>
<td>-0.01</td>
<td>-0.10 0.05</td>
<td>602</td>
</tr>
<tr>
<td>BB</td>
<td>-0.06**</td>
<td>0.15** 0.05</td>
<td>-0.37** -0.09</td>
<td>-0.25**</td>
<td>-0.04**</td>
<td>0.02 0.61**</td>
<td>639</td>
</tr>
<tr>
<td>B</td>
<td>-0.11**</td>
<td>0.10 0.29**</td>
<td>-0.19* -0.45**</td>
<td>-0.22**</td>
<td>-0.06**</td>
<td>0.01 0.44</td>
<td>466</td>
</tr>
<tr>
<td>CCC-C</td>
<td>-0.44</td>
<td>0.26* 0.05</td>
<td>-1.07** -0.41</td>
<td>0.01</td>
<td>-0.13*</td>
<td>-3.13 -0.71</td>
<td>635</td>
</tr>
</tbody>
</table>

|                  |         | $-$ 1 2         | $-$ 1 2         | $-$ 1 2    | $-$ 1 2    | $-$ 1 2         |             |
| Post-crises normal regime ($i=2$) |
| AAA       | -0.02** | 0.15** 0.01     | -0.26** 0.03    | 0.16**     | -0.01*     | 0.01 -0.05      | 386         |
| AA        | 0.00    | 0.24** -0.01    | -0.20** -0.06   | 0.03**     | -0.02**    | -0.11* -0.36**  | 402         |
| A         | 0.00    | 0.12** 0.04     | -0.23** 0.05    | 0.03*      | -0.02**    | -0.36** -0.10*  | 484         |
| BBB       | 0.03**  | -0.11 -0.01     | -0.20** -0.11   | -0.41**    | -0.01      | 0.22* 0.11      | 261         |
| XOVER     | 0.00    | 0.08 0.05       | -0.23** -0.02   | 0.00       | -0.01      | -0.48* -0.79*   | 453         |
| BB        | 0.28**  | -0.11 -0.27**   | 0.07 0.43**     | -0.66**    | -0.01      | 0.15 0.03       | 356         |
| B         | 0.02    | 0.21** -0.12*   | -0.80** -0.04   | -0.10**    | -0.01*     | 2.05** -0.46    | 556         |
| CCC-C     | -0.01   | 0.01 0.01       | -0.38** -0.20** | -0.05**    | -0.03**    | -0.04 0.20      | 418         |

|                  |         | $-$ 1 2         | $-$ 1 2         | $-$ 1 2    | $-$ 1 2    | $-$ 1 2         |             |
| Distressed regime ($i=3$) |
| AAA       | -0.02   | 0.06 -0.12      | 0.85** -0.14    | 0.12*      | -0.07**    | -0.48 0.84*     | 329         |
| AA        | 0.01    | 0.03 -0.08      | -0.09 0.40*     | 0.00       | -0.01      | 0.04 0.59**     | 365         |
| A         | 0.06    | -0.27 0.94**    | 0.28 -0.67**    | -0.07      | 0.05       | 0.42 0.27       | 337         |
| BBB       | 0.05**  | -0.22 0.17      | 0.29* -0.10     | -0.02      | -0.01      | 0.09 0.36*      | 402         |
| XOVER     | 0.61    | 0.29 -0.38      | 0.34 0.24       | -0.14      | -0.06      | -1.72 0.78      | 322         |
| BB        | 0.52**  | 0.27** 0.03     | -0.59** -0.51** | -0.37**    | -0.02      | 0.66 -0.65      | 382         |
| B         | 0.65**  | -0.01 -0.08     | -0.36 0.07      | -0.09      | -0.10      | 1.77 -0.81      | 354         |
| CCC-C     | 1.92    | -0.07 -0.08*    | 0.46* 0.66*     | 0.11       | -0.85**    | -34.01** -24.21 | 321         |

This table shows Eicker-White heteroskedasticity robust estimates for bond spread dynamics across rating categories using the 3-regime model with threshold variable $z_3$ (Model 9). Disequilibrium errors $z_1$, $z_2$, and $z_3$ are defined as $z_{1i}=\text{CDS}_{i}-\text{Bond}_{i}$; $z_{2i}=\text{Bond}_{i}-\text{CDS}_{i}$; $z_{3i}=\text{Libor/OIS}_{i}$, where $\phi_n$, $c_0$, $d_i$ $(i=1,2)$ are cointegrating vector coefficients. “Pre-crisis normal regime” ($i=1$) tends to coincide with normalcy periods before the eruption of financial crisis. “Post-crisis normal regime” ($i=2$) tends to coincide with normalcy periods around the full-blown financial crisis. “Distress regime” ($i=3$) tends to coincide with the heights of the financial crisis, before and after the Lehman failure. Statistical significance at 1% and 5% confidence level is denoted by ** and * respectively.
<table>
<thead>
<tr>
<th></th>
<th>AAA</th>
<th>AA</th>
<th>A</th>
<th>BBB</th>
<th>XOVER</th>
<th>BB</th>
<th>B</th>
<th>CCC-C</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unhedged bond portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>0.15</td>
<td>0.09</td>
<td>0.05</td>
<td>0.04</td>
<td>0.08</td>
<td>0.05</td>
<td>0.06</td>
<td>0.13</td>
</tr>
<tr>
<td>Skewness</td>
<td>-1.98</td>
<td>-1.89</td>
<td>-0.32</td>
<td>0.19</td>
<td>0.44</td>
<td>0.26</td>
<td>-0.12</td>
<td>-1.27</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>63.40</td>
<td>166.88</td>
<td>23.11</td>
<td>36.12</td>
<td>21.44</td>
<td>20.55</td>
<td>16.65</td>
<td>55.99</td>
</tr>
<tr>
<td><strong>Kalman filter (in-sample)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>0.06</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.70</td>
<td>-0.14</td>
<td>-0.32</td>
<td>1.48</td>
<td>0.39</td>
<td>-0.42</td>
<td>0.32</td>
<td>0.04</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>13.76</td>
<td>7.71</td>
<td>8.52</td>
<td>17.99</td>
<td>8.40</td>
<td>4.55</td>
<td>5.42</td>
<td>21.09</td>
</tr>
<tr>
<td>Turnover (% of Kalman filter)</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td><strong>Strategy 1: Naïve static</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>0.14</td>
<td>0.07</td>
<td>0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.05</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.71</td>
<td>0.79</td>
<td>1.60</td>
<td>1.00</td>
<td>0.27</td>
<td>0.27</td>
<td>-0.35</td>
<td>-0.06</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>66.08</td>
<td>151.65</td>
<td>28.35</td>
<td>21.00</td>
<td>8.81</td>
<td>5.92</td>
<td>18.60</td>
<td>43.52</td>
</tr>
<tr>
<td>Turnover (% of Kalman filter)</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td><strong>Strategy 2: Rolling regression</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>0.14</td>
<td>0.06</td>
<td>0.04</td>
<td>0.02</td>
<td>0.04</td>
<td>0.02</td>
<td>0.03</td>
<td>0.04</td>
</tr>
<tr>
<td>Skewness</td>
<td>2.85</td>
<td>-0.36</td>
<td>1.21</td>
<td>1.81</td>
<td>0.71</td>
<td>0.12</td>
<td>-0.21</td>
<td>6.40</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>62.65</td>
<td>179.77</td>
<td>18.15</td>
<td>20.41</td>
<td>9.08</td>
<td>5.05</td>
<td>20.38</td>
<td>147.28</td>
</tr>
<tr>
<td>Turnover (% of Kalman filter)</td>
<td>16%</td>
<td>11%</td>
<td>18%</td>
<td>42%</td>
<td>16%</td>
<td>50%</td>
<td>18%</td>
<td>23%</td>
</tr>
<tr>
<td><strong>Strategy 3: VECM-CV1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>0.09</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Skewness</td>
<td>2.10</td>
<td>-6.97</td>
<td>0.58</td>
<td>1.80</td>
<td>0.77</td>
<td>-0.01</td>
<td>0.02</td>
<td>0.82</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>48.03</td>
<td>210.05</td>
<td>18.30</td>
<td>18.38</td>
<td>13.98</td>
<td>6.73</td>
<td>9.92</td>
<td>33.71</td>
</tr>
<tr>
<td>Turnover (% of Kalman filter)</td>
<td>202%</td>
<td>126%</td>
<td>153%</td>
<td>515%</td>
<td>226%</td>
<td>567%</td>
<td>197%</td>
<td>282%</td>
</tr>
<tr>
<td><strong>Strategy 4: VECM-CV2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>0.09</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Skewness</td>
<td>2.11</td>
<td>-3.18</td>
<td>0.79</td>
<td>1.48</td>
<td>0.78</td>
<td>-0.22</td>
<td>0.45</td>
<td>1.03</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>48.34</td>
<td>99.01</td>
<td>19.15</td>
<td>21.09</td>
<td>14.04</td>
<td>5.04</td>
<td>6.89</td>
<td>32.85</td>
</tr>
<tr>
<td>Turnover (% of Kalman filter)</td>
<td>203%</td>
<td>109%</td>
<td>154%</td>
<td>561%</td>
<td>230%</td>
<td>162%</td>
<td>199%</td>
<td>277%</td>
</tr>
<tr>
<td><strong>Strategy 5: T-VECM</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Std.Deviation</td>
<td>0.09</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.26</td>
<td>-3.78</td>
<td>0.26</td>
<td>1.47</td>
<td>0.76</td>
<td>0.88</td>
<td>0.41</td>
<td>0.54</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>42.41</td>
<td>121.73</td>
<td>10.48</td>
<td>20.89</td>
<td>12.68</td>
<td>8.60</td>
<td>7.02</td>
<td>23.99</td>
</tr>
<tr>
<td>Turnover (% of Kalman filter)</td>
<td>177%</td>
<td>128%</td>
<td>144%</td>
<td>434%</td>
<td>211%</td>
<td>155%</td>
<td>168%</td>
<td>247%</td>
</tr>
</tbody>
</table>

This table shows descriptive statistics of daily returns and turnover of hedging strategies for bond portfolios with CDS contracts, for the out-of-sample period 3/1/2007-16/12/2012. Out-of-sample hedging strategies considered are the naïve static hedging assuming hedging ratio [1 -1], rolling regression hedging based on a 1-year window, and three Kroner-Sultan dynamic hedging strategies assuming one cointegrating vector (VECM-CV1), two cointegrating vectors (VECM-CV2), as well as two cointegrating vectors and three regimes (T-VECM) for the joint CDS-bond dynamics. Descriptive statistics for the unhedged position and the in-sample Kalman-filter strategy benchmark are shown for comparison.
Table 7: Comparisons of out-of-sample hedging strategies for bond portfolios with CDS contracts per rating category, based on Diebold-Mariano modified statistic for the period 3/1/2007-16/12/2012.

<table>
<thead>
<tr>
<th>Null hypothesis:</th>
<th>Neither rolling regression nor VECM-CV2 is better</th>
<th>Neither rolling regression nor T-VECM is better</th>
<th>Neither VECM-CV1 nor VECM-CV2 is better</th>
<th>Neither VECM-CV2 nor T-VECM is better</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAA</td>
<td>2.394**</td>
<td>3.282**</td>
<td>0.500</td>
<td>4.047**</td>
</tr>
<tr>
<td>AA</td>
<td>4.484**</td>
<td>4.029**</td>
<td>0.228</td>
<td>-0.228</td>
</tr>
<tr>
<td>A</td>
<td>2.388**</td>
<td>5.243**</td>
<td>1.867*</td>
<td>0.891</td>
</tr>
<tr>
<td>BBB</td>
<td>1.760*</td>
<td>2.136*</td>
<td>4.968**</td>
<td>4.734**</td>
</tr>
<tr>
<td>XOVER</td>
<td>3.491**</td>
<td>2.209*</td>
<td>1.681*</td>
<td>-0.030</td>
</tr>
<tr>
<td>BB</td>
<td>3.152**</td>
<td>-4.495**</td>
<td>2.199*</td>
<td>-4.496**</td>
</tr>
<tr>
<td>B</td>
<td>2.226*</td>
<td>3.885**</td>
<td>1.607</td>
<td>3.467**</td>
</tr>
<tr>
<td>CCC-C</td>
<td>-0.917</td>
<td>1.069</td>
<td>1.690*</td>
<td>1.805*</td>
</tr>
</tbody>
</table>

This table shows comparisons of out-of-sample hedging strategies for bond portfolios with CDS contracts, based on Diebold-Mariano modified statistic for the period 3/1/2007-16/12/2012, using as a proxy of the “true” hedge ratio the in-sample Kalman-filter benchmark. It tests the null of “neither of the two hedging strategies produces better hedge ratio forecast than the other”. A statistically significant positive statistic implies rejection of the null in favor of the second strategy. A statistically significant negative statistic implies rejection of the null in favor of the first strategy. The strategies considered are rolling regression hedging based on 1-year window, and three Kroner-Sultan dynamic hedging strategies assuming one cointegrating vector (VECM-CV1), two cointegrating vectors (VECM-CV2), and two cointegrating vectors and three regimes (T-VECM) for CDS-bond dynamics. Statistical significance at 1% and 5% confidence level is denoted by ** and * respectively.
Figure 1: Three-month Libor/OIS spread, for the period 3/1/2005 to 17/12/2012

This figure shows the Libor/OIS spread for three distinct sub-periods of the data sample: i) the first sub-period (3/1/2005-31/12/2006) corresponds to market conditions discussed in the pre-crisis literature; ii) the second sub-period (3/1/2007-17/4/2010), shown in shade, includes the global financial crisis, the breakdown of normal market conditions, the peak of financial distress and the return to a new “steady state”; ii) the third sub-period (17/4/2010 - 17/12/2012) corresponds to the post-crisis “normalcy”, which differs from the pre-crisis one in various institutional aspects, such as limits to rehypothecation and new capital adequacy rules for financial institutions (Basel III).
Figure 2: Disequilibrium errors $z_1$ and $z_2$ (in basis points) for portfolios of bonds rated AA and A.

Panel A: Portfolio of bonds rated AA

Panel B: Portfolio of bonds rated A

This figure shows disequilibrium errors $z_1$ (between CDS and bond spreads) and $z_2$ (between bond and Libor/OIS spreads) for portfolios of bonds rated AA (Panel A) and A (Panel B). Prior to 2007, $z_1$ shows higher volatility and persistence than $z_2$, which appeared to be stationary. But since 2007, both volatility and persistence of $z_2$ increased markedly, with a possible effect on basis.
Figure 3: AIC values of two-regime specification against alternative threshold levels.

This figure plots the AIC value for testing a two-regime specification of Model 3 against alternative threshold levels (in basis points) for the portfolio of AA rated bonds, using $z_1$ as threshold variable. A wide range of threshold values (between -150 and -40 basis points) correspond to almost equally informative models, i.e. with very low AIC values. The absence of an undisputable global minimum is indicative of the existence of more than two regimes.
Figure 4: In-sample estimates of regime 1 (pre-crisis normal regime) per rating category, for the period 3/1/2005-17/4/2010.

This figure shows (in shade) in-sample estimates of regime 1 across rating categories, based on Model 9 where $z_1$ is used as threshold variable. They mostly coincide with normalcy periods before the eruption of financial crisis in 2007, thus regime 1 is referred as “pre-crisis normal regime”.

49
Figure 5: In-sample estimates of regime 2 (post-crisis normal regime) per rating category, for the period 3/1/2005-17/4/2010.

This figure shows (in shade) in-sample estimates of regime 2 across rating categories, based on Model 9 where $z_1$ is used as threshold variable. They mostly coincide with normalcy periods in the run-up and after the eruption of crisis in 2007, thus regime 2 is referred as “post-crisis normal regime”.
Figure 6: In-sample estimates of regime 3 (distressed regime) per rating category, for the period 3/1/2005-17/4/2010.

This figure shows (in shade) in-sample estimates of regime 3 across rating categories, based on Model 9 where $z_3$ is used as threshold variable. They mostly coincide with the heights of financial crisis right before and after the Lehman failure, thus regime 3 is referred as “distressed regime”.