Forecasting bank defaults using CDS over global financial crisis

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Abstract

The last global financial crisis (2007-2009) hit worldwide economies with an unprecedented magnitude. The forecasting power of several types of financial products reveals that CDS characteristics are the “best measure” to forecast a bank default.

We studied 50 among the TOP 100 European banks for the period from 2007 to 2013.

We use a meta-rule that took account of the lapse of time between two thresholds (based on CDS spreads) in order to forecast any significant financial distress for a bank.

This methodology is useful to regulators in order that bankers take urgent financial decisions. Hence, regulators can exert an early intervention before a bank default occurs.

Keywords: financial crisis, CDS spreads; risk; bank default; regulation

1. Introduction

This empirical paper examines how CDS should be used to forecast and prevent the potential default of a bank. We studied 50 among the TOP 100 European banks for the period from 2007 to 2013 to account for the impact of global financial crisis.

We found that the relevant thresholds could lead to an intervention when the own CDS spread of a given bank move from a bound at 100 bps to a bound at 200 bps in less than 180 days. Each bound is considered to be triggered whenever the CDS price (or spread) is above either 100 bps (or 200 bps) for at least 20 of the last 30 trading days.

This type of results appeared for the first time with this European bank sample.

This can allow regulators to make an intervention in due time before a bank defaults (provided that an ad hoc procedure is conceived).

“Bank default” is defined in terms of “financial distress”.

Credit Default Swaps or CDS are part of the credit derivative group of financial products.
They provide a type of insurance against credit risk. In 1994, CDS credit derivatives were developed by Blythe Masters of JP Morgan: they were used initially by banks to hedge credit exposures on their balance sheets.

By the end of the 90’s, the prediction of bank default is investigated. The two last decades of the past century ended with different types of banking crises everywhere in the world. Some banks can no longer perform their role as intermediates because they become insolvent.

Three-quarters of IMF countries experienced banking distresses in the period 1980-1996 state *Davis and Karim (2008 a)*. These two decades of financial liberalization have also been accompanied by an increase of new financial products with enhanced effects. This is facilitated by computerization and internationalization of financial markets. The major changes to the American Glass-Steagall Act allowed commercial banks, investments banks and insurance companies to consolidate and to become universal (as of 1999 under the Gramm-Leach-Bliley Act). This permits these new whole entities to fully diversify their investments with negative and positive effects on risk-taking as a result.

In the US, the financial crisis that peaked between 2008 and 2009 began in 2007 with the collapse of subprime mortgages. *Demyanyk and Hasan (2010)* state the subprime securitized mortgage outstanding debt of the US market amounted to $1.8 trillion in 2008 for securities issued between 2000 and 2007. In comparison, the total

of the US securitized mortgage debt was of $6.8 trillion. The grouping together of individual securities that were later repackaged to create even more sophisticated products is "catastrophic". Nevertheless, it is difficult to explain the extent of this crisis to such a level and how it impacted so heavily outside the US. *Levine (2010)* finds that major conflicts of interests appeared among Credit Rating Agencies and banks. They started to purchase a massive amount of CDS from 1996 because of the Fed's decision permitting them to reduce their bank capital, thereby encouraging risk-taking. This regulatory decision had a terrible impact on the banks. They reallocated capital to higher-risk assets and higher-expected returns, *Stulz (2010)*. Indeed, before the beginning of the financial collapse in 2007, CDS have grown dramatically from the mid-1990s to reach a notional value of $62 trillion in 2007, *Levine (2010).* The market of derivative products amounted at $615 trillion at the end of 2009 where more than 80% were OTC traded.
According to International Swaps and Derivatives Association (ISDA), the outstanding credit derivatives have increased by 128% from June 2004 to June 2005.

Taylor (2008) shows that due to lenient monetary policy, interest rates fell from 2002 to 2004. This resulted in a monetary excess that in turn contributed to the housing boom and then the subsequent burst and collapse (cf. Taylor rule). The rise of housing prices was confirmed in *Reinhart and Rogoff (2008)*. They show a far larger growth rate for the house prices in the US than in Sweden (1991), Finland (1991), Spain (1977), Japan (1992) and Norway (1987) at the time of their financial crises. A sudden lack of banking liquidity for bank credit markets must also be considered, hence leading to contagion.

Demirgüç-Kunt and Detragiache (1998) show that a banking crisis tends to arise more often in countries that have experienced financial liberalization. They show that the related effects are reduced by a strong institutional environment. Their study during 1980 to 1994 is based on a multivariate logit model linking the likelihood of a crisis to a vector of explanatory variables. If the macroeconomic context is not strong enough, they find this: low GDP growth, high real interest rates, high inflation and an explicit deposit insurance system can lead to banking crisis.

In theory, an explicit deposit insurance system should mitigate against the fragility of banks as a self-fulfilling panic. This is described by *Diamond and Dybvig (1983)*. However, this implies some more risk-taking by bank decision makers (i.e. a moral hazard). And we are considering the years after 1999 (i.e. post the Gramm-Leach-Bliley Act). They focus mainly on macroeconomic determinants. They assert that this is partly due to a lack of data among the potential choice microeconomic variables of banking and regulation. Hence, the need to investigate further bank level information. This was confirmed by *Demirgüç-Kunt and Detragiache (2005)* for an extended period from 1980 to 2002 for this study with 94 countries and up to 77 crisis occurrences (in their enriched sample).

Another methodology was used by *Kaminsky and Reinhart (1999)*. They found that financial liberalization often results in a banking crisis. Subsequently, a currency crisis which in turn fuels the banking crisis creating a vicious circle. Their sample consisted of 20 countries and included 76 currency crises and 26 banking crises from 1970 to 1995. They find 26 currency crises and 3 banking crises for the period from 1970 to 1979 and 50 currency crises and 23 banking crises between 1980 and 1995. This major increase of banking crises is linked to the post-liberalization era, whereas that of the 70's may be attributed to a much regulated decade.

They use a non-parametric approach based on a signal extraction model to reach their conclusions.[1] With the help of a minimization of their Noise To Signal Ratio given by a Probability of Type II error / (1 – Probability of Type I error), they construct a country specific threshold and then obtain a benchmark for an Early Warning System with univariate indicator signals. Their most valid variables are among the group of capital account (reserves for instance) and financial liberalization (such as real interest rate that predicts 50% of banking crises and domestic credit / GDP that produces 100% of banking crises).
For crisis prediction, Demirgüç-Kunt and Detragiache (2000) went further revealing that this type of model produces less in-sample Type I and Type II errors regarding probability estimations than in the signal extraction model of Kaminsky and Reinhart (1999).

Using their model, the monitor selects the probability threshold that would minimize a loss function characterizing the likelihood of either the costs of taking an action should no crisis happen or the costs of no action when problems arise. Two frameworks are contemplated: the first attempts to assess how deep the fragility is in order to intervene or not, and the second involves the rating of the fragility of the banking system. They consider six banking crises that span the years 1996 and 1997 i.e. the Jamaican crisis of 1996 and the five East Asian crises of 1997, building related out-of-sample forecasted probabilities. For three of these six crises the results are too optimistic and the authors explain this by the novelty of their econometric evaluation of systemic banking crises, in particular the use of their forecasting and monitoring tools. Furthermore, as a crisis is often triggered by new phenomena, coefficients that were used inside in-sample models might be pointless out-of-sample. In addition, it is important to consider the inherent following bias for this type of study: banking crises do not occur often and so consist of rare events (36 crisis episodes only compared to 766 observations used for in-sample estimation), not to mention extreme events regulators incorporated since the previous financial crisis.

[1] Defining a specific interval of time between signals and crisis, they establish specific thresholds for each of their fifteen variables in order to compute their related time series of 1 (signal of crisis) or 0 (no-signal of crisis) measures any time their determinants go over their given threshold during the selected elapse of time. Then, they operate a reconciliation between those series and actual events (crisis or no-crisis) in order to design their measure of predictive accuracy.

By comparison between the multivariate Logit models in Demirgüç-Kunt and Detragiache (2005) and the signal extraction method in Kaminsky and Reinhart (1999), Davis and Karim (2008 a) we conclude that, as far as the in-sample predictive ability is concerned, the multivariate logit model gives more acceptable results than those from signal extraction. Also, their results show that the multinomial logit model is more likely to agree with global Early Warning Systems whilst the signal extraction methodology is better for country specific Early Warning Systems. They find that changes in terms of trade and real GDP growth are the best predictors for banking crises for their sample.

Wilson (1998) and the McKinsey company proposed a model, “Credit Portfolio View”. It is based on a discrete time multi-period model and that only measures default risk. In this multi-factor model, default probabilities which are generated by a Logit model depend on macroeconomic variables (such as growth rate, level of interest rates, unemployment, etc.). These variables are specified for each country and they capture their state of economy. Furthermore, each of these independent variables is assumed to follow an autoregressive model of order 2 (AR(2)). The main idea of “Credit Portfolio View” consists of connecting those macroeconomic factors to the default and migration probabilities.

However, in order to calibrate the model, reliable default data for each country and their related industry sector are needed as mentioned by *Crouhy et al. (2000).*

Another limitation also exists because the model requires a specified procedure to adjust the migration matrix. Indeed, because of the brevity of historical past records, it is difficult to cover several credit cycles and to test the inherent model robustness in a crisis situation.

Calabrese and Giudici (2015) propose a model that deals with extreme values, applied to 783 small Italian banks (less than 20 are listed) during the period 1996-2011. Through a Generalized Extreme Value (GEV) link function, they implement the Generalized Linear Model (GLM) of *Calabrese and Osmetti (2013).* That explains the use of a dependent variable: a distress event from macroeconomic and banking oriented microeconomic explanatory variables.

Demyanyk and Hasan (2010) describe very technical and sophisticated tools. They have been developed in the empirical literature using operational research models such as Case-based reasoning, Neural Networks, Trait Recognition, Multicriteria decision aid, etc.

Interestingly, none of these methods appear to be substantially better than another. This is why it may be more efficient to combine at least two of them. Hence, *Davis and*

Karim (2008 a) or *Davis, Karim and Liadze (2011)*, depending on either the global or country / zone specific Early Warning Systems we want to focus on.

This rest of the paper is organized as follows:

- Section 2 presents the CDS forecasting power. We suggest a new indicator to optimize the forecasting power of CDS. We also present the conditions for Bank default or financial distress.
- Section 3 develops our empirical study. It presents the sample and describes the methodology and main results.
- Section 4 presents an applied study by describing the methodology and empirical results.
- Section 5 concludes the paper.
- Section 6 is the appendix.
- Section 7 deals with references.

2. The CDS forecasting power: a survey of the literature

One of the main reasons for using CDS lies in the potential of a CDS market to lead other markets in terms of information discovery. As such, it leads the stock market and the bond market *(Hart and Zingales, 2011, Chiaramonte and Casu, 2011, Flannery et al, 2010).*

Why use CDS instead of other financial products?

2.1 Why use CDS in our approach?

Portfolio strategy became more sophisticated in the early 90’s when credit derivatives first appeared. Credit risk management is now separated from the underlying asset risk.
So, because of this financial innovation, markets change e.g. risk pricing, risk transfer or risk buying have become more widespread for nearly all maturities, products or states. Thus, degrees of freedom have been increased by dividing risk factors. In doing so, they have allowed a more active risk management for asset managers.
With a more liquid market and the capacity of hedging under specific conditions, we can regard markets as complete because of credit derivatives.

By comparison the bond market tends to lack liquidity since there is a lack of standardization. Bond prices are a less reliable indicator in terms of solvency than CDS prices. CDS success results from their standardized nature.

Equity prices are not a good measure of financial distress, despite their related liquid markets. If equity is insensitive to the downside, because of limited liability, it is very sensitive to the upside. Furthermore, high prices do not mean that the SIFI (Systematically Important Financial Institutions) have no problems.

If we consider CDS as relevant products, we can proceed using a specific trigger based on CDS followed by the appropriate intervention action: should the trigger be activated, the default of a bank could be prevented.

Are CDS spreads a good indicator of a bank default or the best one *(Chiaramonte and Casu, 2011, Sundaresan and Wang, 2011, Flannery et al, 2010, Chabot, Bertrand and Thorez, 2019)*?
Empirical studies attempted to answer this question as well as the specific CDS type of trigger to choose.
What level of spread is required to activate the trigger?
What are CDS and how they operate to predict bank default?

Hart and Zingales (2011) have found that the following condition would make sense in order to detect the right time to intervene:
"Trigger intervention whenever the CDS price is above 100 bps for at least 20 of the last 30 trading days"**.** This rule will be safer for manipulations than one that states that the CDS price could never go above 100.

We could also examine the need to use a trigger of 100 bps rather than for example 50 or 150 and try to justify the choice with a qualitative study. It may also be interesting to reveal cases where CDS did not react as we would have expected.

Based on evidence from the financial crisis, *Chiaramonte and Casu (2011)* focus on the field of bank CDS spreads on a true international level in comparison to other less specialized studies.

Their approach is original in that they focus specifically on balance sheet ratios, because these provide brief and direct information on a firm's financial health. Their paper also includes recent events of the financial crisis starting in July 2007.

Their analysis appears to be sufficiently extensive as it consists of three time periods which are a pre-crisis period (1 January 2005 / 30 June 2007), a crisis period (1 July 2007 / 31 March 2009) and its less acute phase period (1 July 2007 / 31 March 2010).

The study was based on a sample of 57 mid-tier to top-tier international banks (in terms of assets) and with senior CDS spreads of 5 years.

The results come from a fixed-effects panel regression and the explanatory variables are essentially balance sheet variables relating to Asset quality, capital, liquidity, and earning potential. Their main conclusions are:

- Bank CDS spreads reflect the risk captured by the bank balance sheet ratio and this becomes more sensitive over the two crisis periods.

- During the two crisis periods, the relationship between balance sheet ratios and bank CDS spread became stronger because there was a growth in the number of significant explanatory variables.

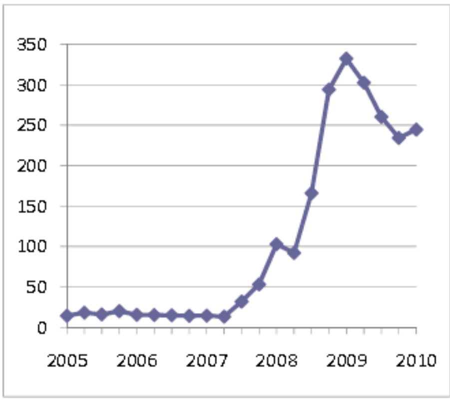
Furthermore, the ratio "loan loss reserve" to "gross loans" (an asset quality determinant) is basically a unique ratio which is appropriate for all three periods.

Indeed, there is an increase of the probability of default for those banks which obtain poor quality loan portfolios.

We also learn from their results that the crisis made the change in sign for liquidity (cf. liquidity variable and its relationship with CDS spreads, their dependent variable that measures the probability of default). Thus, the authors can assert that the financial crisis led finally into a liquidity crisis.

Hence with these conclusions their results in the following chart are hardly surprising.

<u>Illustration 0</u>: trend of average CDS spread values (in bps i.e. basis points) for the 57 sample banks chosen world-wide



(Source: Datastream database).

Their conclusion and results serve to confirm and support the authors with the aim "not to predict, but to explain credit spreads".

2.2 Choice of a possible second indicator to complement CDS spreads

In addition, we could also build a dynamic indicator instead of using a static "barrier" like the previous one of 100 bps. It happens that CDS use may not always be efficient using a fixed level. Why not compare or mix two indicators i.e. the first one based on CDS and the second one on another type of financial indicator (or index of CDS)? Then, establish a decision rule based on the interpretation of this comparison?

Hart and Zingales (2011) illustrated that we could use CDS contracts to monitor banks' solvency. We would like to show that the observation of CDS (combined with another indicator) is a better measure for an increasing probability of default. With the addition of a smart trigger, it could also result in an efficient way to take steps when a rescue is still possible.

Market price CDS is based on the risk-neutral distribution of the underlying risk. According to *Jarrow (2010)*, CDS spreads can be decomposed into 4 pieces: an expected loss, a default risk premium, a liquidity risk premium, and asymmetric information monitoring costs.[2]

So, any of these four factors could have an impact on changes over time observed in CDS spreads. There is little possibility that the last three factors are always stable and come from a rise in spreads that the underlying corporate's probability of default (PD) had increased (even if these factors are obviously interrelated).

The reliance upon CDS spreads for the purpose of macro-prudential regulation is likely to be misguided. Or an adapted control for the change in spreads (entirely resulting from changes in the markets' pricing of credit risk) is needed.

Monitoring CDS spreads on banks might not be enough to provide a complete explanation for bank solvency and a potential default.
We want to produce a combined approach to monitor banks' solvency based on both observations of CDS and another indicator as well as their interrelation.

The credit triangle relation (simple case of CDS valuation) correlates with the previous conclusions of *Jarrow (2010)* and *Raunig (2011),* i.e.

1YearCDS_Spread = 1YearDefault probability x (1 - Expected Recovery Rate)[3]

Expected recovery rates and default probabilities are often unobservable but the CDS spread is observable. It can be used to calculate default probabilities given a recovery rate assumption.

2.3 Factors that create conditions for a trigger

As stated by *Hart and Zingales (2011)* concerning a trigger, we do not want to get a static barrier such as 100 bps, because it could lead to a bias obtained using triggers based on market price, (or induce potential market price manipulation).

It may be better to look for a dynamic trigger. *Prescott (2012)* proposes four properties of Contingent Capital. He concludes the trigger is the main disadvantage of contingent capital. A trigger built around on market price would be even more disadvantageous.
Furthermore, it is not acceptable to price contingent capital, whether the trigger is a fixed one or a regulator's intervention based on a signal.

Sundaresan and Wang (2011) illustrated why contingent capital with a market equity trigger did not produce an obvious solution.

[2] The expected loss can be seen as the market's assessment of the physical default distribution (PD, LGD). Note that LGD stands for Loss Given default and all those characteristics are interconnected.
[3] Where 1-Expected Recovery Rate = Loss Upon Default (or Loss Given default).

Indeed, most of the time we do not obtain a unique equilibrium in the prices (for contingent capital and the bank's equity).
Depending on the design of the contingent capital, unique, multiple or even no equilibrium may result: if conversion strongly dilutes equity, then there are multiple equilibria. If conversion increases the equity value, then there is no equilibrium.
Based on the research above, we make two fundamental points:

1. To generalize the example of the non-efficient market price trigger, we looked at with Contingent Capital. It appears that a fixed trigger is certainly not totally reliable, sufficiently independent of regulators' intervention, objective enough, timely or even difficult to manipulate.
2. Thus, instead of a market price, Credit Default Swap could be the convenient indicator in the light of the previous findings.

We want to establish conditions for a dynamic trigger used with CDS as indicators. A trigger that prevents Capital Contingent with a market equity trigger from not leading to a unique equilibrium or that gives minor inefficiencies would be perfect.
Unfortunately, this is not realistic and these results may apply to all triggers if they depend on market value of equity (directly or indirectly).

Sundaresan and Wang (2011) (quoting *Pennachi (2010), McDonald (2011), Glasserman and Nouri (2010)*) conclude that under the conditions that the trigger's variables should not be affected by the capital conversion i.e. are exogenous we obtain a unique equilibrium. Hence, we get a price for Contingent Capital.

2.4 Suggesting a new indicator to optimize the forecasting power of CDS

We use the Markit 5-year iTraxx Senior Financial index given by the Bloomberg company (by default we call it iTraxx or iTraxx SF) in order to build our trigger mechanism. It comprises 25 equally weighted CDS on investment grade European entities (16 Banks and 9 insurance companies).[4]
The iTraxx is sensitive to perceived risk in the economic world. It expresses the credit risk related to the lending to bank and insurance companies. Then, an increase of the iTraxx suggests that lenders think that the risk of default on interbank loans is rising.

Credit market tightness exerts a profound influence on the market price of default risk. As the use of an index brings at least one more condition (or constraint), taking the iTraxx spread is appropriate and more robust in our context (it is based on the 25 banks and insurance companies).

A broad financial stock index could relate too strongly to a particular bank's own stock price. This is why even if we have independently selected in our study 16 of the

[4] The composition of each Markit 5-year iTraxx index is determined by the Index Rules. Market iTraxx indices roll every 6 months in March and September.

banks among this list (and 34 more to get 50), 9 insurance companies had been added to it by Markit in order to build the index.

As *McDonald (2011)* suggested using Contingent Capital with a dual price trigger, we are going to use two indicators.

Our decision rules state that these triggers be activated if and only if:

1. The CDS price is above an absolute number of 100 bps for at least 20 of the last 30 trading days. The corresponding date is termed T100.
2. The iTraxx SF is above an absolute number of 100 bps for at least 20 of the last 30 trading days. The corresponding date is termed T100. We would have termed it T200 or T300 if we had chosen an absolute number of 200 bps or 300 bps respectively.

The conditions 1 and 2 must be met in order that any relevant action should be taken. However, considering Large Financial Institutions (LFI) especially i.e. systemic banks, it is vital not to wait for the second condition to be realized. Otherwise, it could lead to multiple equilibria, as *McDonald (2011)* showed (in its 9th footnote in particular) about “Too Big To Fail” institutions and the use of an index trigger.

2.5 Conditions for Bank default or financial distress

A bank default consists of a bank failure that leads more often to a bank bailout which is “not so common” in Europe.

We examine the factors that lead to significant financial distress. A bank financial distress may become a bank failure that eventually requires a bailout i.e. a national rescue.

Financial distress means that at least one of the following credit events occurs, *Thorez (2017)*:

- Recapitalization / new injection of capital of more than €1.5bn
- Rise of capital by shareholders or rights issue of more than €1.5bn
- Partial nationalization or total nationalization
- Takeover by another bank or transfer in a group of banks that merge together or forced mergers
- Failure to stress tests leading to the first and second bullet points above
- Important credit downgrade
- Run on the bank
- Substantial Guarantee issued by a state or approved by the EC
- Restructuring plan approved by the EC (EBA capital plan)
- “Restructuring”: a change in the terms of debt which are unfavorable to the creditor

- “Failure to pay”: Reference entity fails to make payments when they become due after expiration of any applicable grace period
- “Bankruptcy”: Reference entity is either dissolved or becomes insolvent or is otherwise unable to pay its debts

Credit events are different from that used by the ISDA for the “Big Bang” and “Small Bang” changes *(see ISDA supplements, 2009 and Markit study, 2009)*.

Our criteria are less restrictive and more numerous than the ISDA ones. We want to illustrate sufficient financial distress cases since there were less bank collapses in Europe than in USA.

A “Bankruptcy” credit event, for a bank, comes from the ISDA repository *(Source: Barclays Capital).* We refer to the same source for the two previous bullet points concerning a “Failure to pay” credit event and “Restructuring” credit event. They are both defined by the Reference entity’s obligations.

Financial distress have to occur not too far from our prediction date; otherwise the connection is less significant.

2.6 Description of iTraxx indices

<u>Illustration 1</u>: Markit 5-year iTraxx indices from Bloomberg (bps)

Between the 01/01/07 and the 17/05/10, the iTraxx SF and the iTraxx Europe indexes moved closely together. But not from the beginning of October 2008 to the end of March 2009, when the iTraxx SF curve was lower than the iTraxx Europe curve (showing the impact of the financial crisis on big corporates as a whole).

The 5-year Markit iTraxx HIVOL index consists of 30 equally weighted CDS on the widest spread of non-financial European corporate entities.

The 5-year Markit iTraxx Europe index consists of 125 equally weighted CDS on investment grade European corporate entities, distributed among 4 sub-indices: Financials (Senior & Subordinated), Non-Financials and HIVOL. Note that the 25 companies included in the iTraxx SF and the 30 companies included into the iTraxx HIVOL are also part of the 125 companies figuring in the iTraxx Europe. Therefore, this last index is really a global one for European companies in comparison to the two others which are much more specialized. *Hull (2009)* also used the iTraxx Europe by dealing with Credit Indices.[5]

We write T100 (BIS) for the second time the trigger is activated and T100 (Ter) for the third calculated T100 during the period of study.

2.7 Our initial approach and its limitations

A quick test on our sample of banks shows that nearly all of them had their T100 activated during the second year of the period of study (2008). In addition, we have been able to calculate other T100 for many banks such as T100 (BIS) or T100 (Ter).

Our results reveal that our second indicator (iTraxx SF) is not as efficient in predicting a default when using the second decision rule in complement to the first one.
So, we intend to tackle the subject differently as this initial approach does not appear to be sufficiently efficient and robust.

We could also have addressed our potential issue with the level of the trigger in the following theoretical part.

Hart and Zingales (2011) have suggested this procedure: “trigger intervention whenever the CDS price is above 100 bps for at least 20 of the last 30 trading days”.

It is now appropriate to discuss whether it is relevant to use a trigger value of 100 bps as we have done so far. Basically, their model suggests an intervention every time the CDS price is above 0, which is not really adequate, hence the need to select a value above 0 such that the given spread may be traded.

They use the following credit triangle relation to estimate the one year default probability for a CDS price of 100 bps given an expected recovery rate set at 80% (100% - 20% = 80% where 20% is the Loss Upon Default).

[5] The composition of each Markit iTraxx index is determined by the Index Rules and Markit iTraxx indices roll out every six months in March and September.

Using:

1YearCDS_Spread = 1YearDefault probability x (1 - Expected Recovery Rate),

they obtained a risk neutral probability of default of 5% provided that their rule had been designed to include the probability of regulatory mistakes. However, following the CDS standardization in 2009, the recovery rate is fixed by convention at 40% or 20% for contract referencing sub debt. As we use Bloomberg 5-year Senior CDS spread for our selected banks, we are obliged to use this 40% recovery rate.

Then, using the same rational in reverse, it implies a default probability of 1.66% (5/3) which is three times inferior to theirs, hence leading to a huge value of CDS price at 300 bps if we want to keep the same error ratio at 5%.

Given the imposed 40% recovery rate, a default probability of 5% is more consistent with the chart from Barclays capital (see the next sub-section).

At the beginning of our period of study i.e. 01/01/2007 and during the first half year, CDS daily spreads were below 25 bps for our selected banks and this is also indicated either by the iTraxx SF or the iTraxx Europe indices for the first half year.

So, apparently, there is no need to use a trigger at 300 bps when 100 bps seems sufficient as a barrier and in addition this provides us with a shorter and more sensitive risk neutral probability of default at 1.66% rather than 5%.

Now, a CDS spread below 25 bps for our banks is definitely connected to low levels of risk which is not the reality in the long term for bank CDS spreads (even if a trigger at 100 bps worked quite well with the 6 American banks used during 2007 / 2008 in the *Hart and Zingales* paper).

As mentioned previously, nearly all of our selected banks had their T100 activated during the second year (2008) of our period of study suggesting that a 100 bps level may not be the best choice for our European banks, because it is too low.

Thus, we need to consider a larger level for our trigger, but what number exactly and can we determine it theoretically, if possible?

So returning to our theoretical approach that produced a larger trigger at 300 bps when we decided to maintain the default probability at a maximum of 5%, why not conclude that under these circumstances that we consider both a high “upper bound” of 300 bps and a low “upper bound” of 100 bps for our triggers?

Consequently, this possibility implies implementation of two levels of trigger, one for the period where the CDS spread are low and one for the period where the CDS spreads are high.

But, in doing so we would perhaps be moving from the fundamental idea of our initial rule based on two conditions using two different indicators with the same trigger at 100 bps (or 300 bps now).

In the next section some more detailed explanations strengthens that previous discussion.

2.8 CDS exposures and quantification

From a CDS position, the main related risks or exposures consist of a credit event risk and its “spread delta” (the same concept as that used by the Greeks indicators for options) that can be calculated from the credit triangle relation, as well as the interest rate sensitivity, the recovery rate sensitivity and exposure to the passage of time.

Based on the credit triangle relation that we have mentioned above it follows that the CDS spread is not really sensitive to recovery rate. In effect, the implied probabilities of default are roughly commensurate to 1/(1-Expected Recovery Rate) and the CDS payoffs are proportional to 1- Expected Recovery Rate.

Consistent with that, we notice that on the default probability on the following page, when the recovery rate increases from 20% to 60%, it produces a rise of less than 5% for the default probability. So, if we raise the recovery rate, then we implicitly raise the default probability, but not significantly until a recovery rate of 80% (and conversely).

This explains why with a recovery rate that falls from 80% to the 40% rule, the probability of default diminishes more than for a fall of the recovery rate from 60% to 20%.

For instance, with a recovery rate of 40%, the corresponding spread of 200 bps i.e. the mid-point between 100 bps (our low “upper bound”) and 300 bps (our high “upper bound”) gives an implied probability of default of 3.33%.

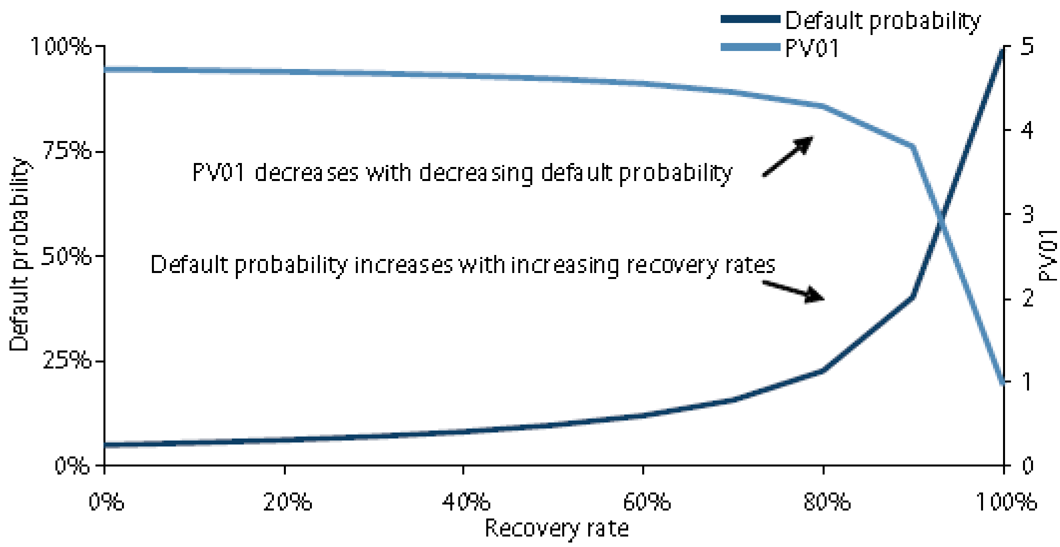
CDS-based estimates of default probabilities assume a 40% recovery rate, which is the average recovery rate estimated for North America by the Moody’s rating agency (1985-2005). In 2009, CDS standardization also fixed recovery rate at 40% by convention, as previously mentioned.

In the following figure, we show the default probability and PV01 against expected recovery rate (keeping the CDS spread constant) and we observe that:

A rise of the recovery rate => a “small” rise of the default probability on [0, 60] %

=> a “small” fall of PV01 on [0, 70] %

<u>Illustration 2</u>: default probability and PV01



(Source: Barclays Capital; note that PV01 decreases with ***in****creasing probability)*

Note that the PV01 (or duration), sometimes referred as the risky PV01 or the CDS duration mentioned above is defined by:

PV01 = PV (Present Value) of a stream of 1bp payments at each CDS coupon date

Thus citing *Jarrow (2010)* concerning spread decomposition, it is commonly accepted to suggest that the credit risk applied to the reference entity and consists of three parts which are:

- The default
- The spread signature variation
- The variation of the underlying asset rating

This provides good evidence that there is a strong link between the probability of default and the CDS price in the credit triangle, although the initial 5% ratio of errors introduced by *Hart & Zingales (2011)* cannot appear as an absolute number which is not an issue because we should primarily consider it just as a target.

3. Empirical study

Banks are selected using the ranking of the Top 100 European banks on their total assets in 2008 (Fitch Ratings companies' data-base) that included 31 countries: EU and European Free Trade Association i.e. EFTA including Iceland, Norway, Switzerland and Liechtenstein.

3.1 Data sample

Analysts had to reprocess accounting data using consolidated accounts. This explains why the data are not always those communicated by the financial department of the related banks.

Our sample encompasses the data for more than 63 European banks (the maximum of banks found in the Bloomberg data-base for our European study). We decided to choose 51 banks.

In our European study, more than half i.e. 32 of these banks are considered to be systemic or LFI. If we had strictly decided to take into account their total assets in Europe (over US$ 1 trillion, for instance), then in 2008, the top ten systemic banks would have been only: RBS, Barclays PLC, Deutsche Bank, BNPPARIBAS SA, HSBC Holdings PLC, Credit Agricole SA, ING Group, UBS AG, Société Générale SA, Banco Santander SA.

We also decided to take into account the contribution of any bank to its country which increases the total number of selected banks.

We were not able to use all the 100 European banks for our regression analysis because some of them disappeared during this period.

For more than 80% of the retained 50 banks in our empirical part we have succeeded in obtaining their 5-year Senior CDS spread for each of the trading days from 1/01/07 to 12/03/13 (from Bloomberg). 50 and not 51 because we did not keep Bankia as its Bloomberg data covered a too short period.

It covers the financial crisis because we can consider the years 2014 and 2015 as a return to normal times. In appendix, we provide the CDS curves of a few banks from Bloomberg (2005-2017) just to illustrate this point.

When data were not available for the whole period (for less than 20% of our banks), we were in a position to get the evolution of their CDS and potential activation of our relevant indicators and triggers.

We also obtained daily 5-year CDS spread curves (in bps) directly from Bloomberg for our studied period (1/01/07 to 12/03/13).[6]

[6] Mid-spread (mid-point) was studied.

We use the 5-year Markit iTraxx Senior Financial index which comprises 25 equally weighted CDS for investment grade European entities (16 Banks and 9 Insurance companies). We selected the same period as for the banks and insurance companies.

We collected information on credit events for the 51 different banks with regard to the rise of capital, capital injection, and nationalization, rescue, run on bank, recapitalization, failure or default.

In order to gather the maximum amount of information, we extensively used the Factiva database and direct article extracts from classical newspapers (Les Echos, l'Express, le Monde, The Financial Times, etc.). We used them to determine bank credit events for this essay.

3.2 Descriptive statistics (indices)

Table 1 (in bps) gives the results for our three iTraxx indices covering the period of study from 01/01/07 to 12/03/13:

	iTraxx Europe	iTraxx HIVOL	iTraxx Sr Financial
Mean	107,67	179,16	131,40
Median	105,61	169,42	125,88
StDev	45,29	90,87	76,37
High	216,87	552,52	355,31
Low	20,16	38,78	6,95
High(date)	05/12/2008	05/12/2008	25/11/2011

If we focus on the iTraxx Europe statistics, we see that its curve fluctuates between 20.16 and 216.87 bps i.e. [0,200].

The median is very close to 100 (and also very close to its mean), which can mimic a practical barrier (low "upper bound") at 100 bps, consistent with our 1st and 2nd conditions. It gives a complementary explanation to the *Hart and Zingales (2011)* trigger at 100 bps and to our previous discussion. However, we showed that with the same rational and a new condition due to ISDA standardization of 2009, it should lead to a trigger at 300 bps (with a probability of default at 5%).

Before July 2007, the trend for the low values is weak (under 25 bps) and around the low numbers. We observe in our chart a low at 20.16 bps for the iTraxx Europe index, all the more that we are aware that the subprime crisis started in July.

To simplify, it shows that European CDS for any big company during the period of our study are within a tunnel approximately between 0 and 200 bps i.e. [0, 200].

(PCS=Pricing source: CBIN i.e. BBG CDS Intra NY)

3.3 First analysis of our results

What if our rule has been set off for a given bank and that for example, we now are more than 6 months in front of its initial T100?

We find a T100 on 14/03/08, a T100 (BIS) on 20/10/08 and a T100 (Ter) on 17/05/10 for the iTraxx SF. It certainly may be of interest after a period of decrease which was not at all the case. So, what if the curve keeps on rising after the first T100 is exceeded?

What is more, the goal we really try to achieve, deals with the capability to monitor the bank spreads in our tunnel [0,200] bps than to issue “perfect” forecasts of bank defaults.

In short, staying within [0, 100] appears safe and logical for a given bank. But, going over
100 bps within [100, 200] should require most of the time an intervention under conditions 1 (and 2). Thus, staying within [100, 200] has not to be considered as a normal situation. If nothing happens for a given bank after its two conditions gave a first T100, this bank needs to be maintained under a very careful ongoing scrutiny and probably recapitalized one way or another.
If we are for example more than 6 months ahead of that initial T100 and if the curve keeps on rising and goes over 200 bps, then crossing this high upper barrier of T200 means an intervention has to be made (substantial recapitalization or even rescue).

Extreme economic conditions may cause this situation such as the Greek crisis in 2011 which resulted in a profound impact on European banks spreads.

4. Applied study: methodology and empirical results

One way to find a correct trigger level requires not just one trigger, but two. This produces a more dynamic approach by including the time for which a given bank spread goes from the first trigger to the second.

4.1 Optimization of our rule

We are not going to calculate a growth rate for the differences between our two selected triggers i.e. 100 bps and 200 bps.

It is far more convenient to calculate the number of days between the obtained T200 minus the obtained T100 for a given bank (using the 30/360 convention): the shorter this period, the more risky is the bank!

A significant financial distress (requiring massive recapitalization, nationalization, rescue, etc.) occurs most of the time pretty close to a given bank T200 trigger. Hopefully, intervention follows very soon afterwards. Thus, we can design a meta-rule that would add a very strong dynamic third condition.

This third decision rule requires that we should:

3. trigger a "real intervention" when the number of days between the T200 and the T100 is under or equal to 180 days i.e. **T200 – T100 ≤ 180 days**

The second decision rule is no more taken into account. Thus, we show that it works well for any substantial financial distress for our sample. The length of time such as 180 days must be neither too short nor too long. In fact, if it is too short, this may not be sufficient time to observe a financial distress and if it is too long, this might be too much.

When the first trigger at 100 bps is activated, the concerned bank should raise equity. Its Management should commit itself to take all necessary decisions in order to make the bank spread go down (under 100 bps). Regarding LFI that are systemic banks, the regulator could also undertake a stress test to determine if the LFI debt is at risk.

After a careful observation of the CDS price for a bank, the regulator should decide to intervene if the Management of the bank has not succeeded in reversing a dangerous trend.

We consider that 6 months is a classic period of time to turn around a company or at least, to notice the first positive profits made by that company. Hence, the necessary intervention of the regulator if the number of days between the T200 and the T100 is inferior to 180 days i.e. 6 months.

This is consistent with *Hart and Zingales (2011)* by developing this dynamic approach within our regulation procedure. Their selected banks, Washington Mutual and especially Bear Stearns, showed that the difference between their T200 and their T100 is inferior to 6 months (cf. the CDS curve of these banks in their paper).

4.2 Detailed applied study methodology

We choose to use a Probit model

- P($\boldsymbol{y_i}$=1 $|\boldsymbol{x_i}$) = F($\boldsymbol{x'_i}$ β) in the general case, where $\boldsymbol{x_i}$ is a vector of bank characteristics and β a vector of parameters to be estimated.
- F is the standardized normal cumulative distribution function (Probit model).

In our particular case, one of the regressor will be a dummy, x_i (the others are control variables).

- where x_i can be a dummy for the bank i such that x_i=1, if T200 – T100 ≤ 180 days ⬄ 180 - (T200 – T100) ≥ 0
- and $\boldsymbol{y_i}$=1, for a financial distress (bank i)

We could have tried a smaller period than the 6 month classical lapse of time i.e. 180 days. However, if 180 days is relatively close to 160 days, this last period of time created issues with our regression because of specification problems (the issues are even worse if we chose 150 days or less). Indeed, a short period means that all financial distress that is correctly predicted based on our meta-rule is automatically linked to a true financial distress. If we choose 150 or 160 days, there is not a single bank with one prediction given an activated trigger of 1 when in fact, no financial distress has been reported.

Basically, our model gives quite reasonable results with a number of days spanning from 180 to 220 as 160 days is absolutely too short and 240 days too large.

However, in comparison with other periods, 220 days produces better balanced results (see in appendix TABLE 2 "Global results per bank" for a number of 220 days and the related regression).

Incidentally, it is important to note that for a few banks some trading days are missing, so if we consider the expected number of trading days we find that:

- A period of 200 days implies a maximum of 146 trading days
- A period of 220 days implies a maximum of 160 trading days

This is why we consider that even if a few trading days are missing we should get at least 150 trading days using a period of 220 days. Moreover, this is a better way of reducing the risk of a specification model than using the option of 180 or 200 days.

It is also consistent with what we obtain from our data for each bank. We find that the maximum number of trading days for one of the banks on our total period of study from 01/01/2007 to 12/03/2013 is equal to 1611 days. The relevant Excel function gives a result of 1617 theoretical trading days between those two dates for a total number of days amounting to 2231.

Nevertheless, we had better consider that waiting 40 days more (220 minus 180) may be more risky and that an earlier intervention would normally be less costly. The sooner, the better hence our theoretical choice of a 180-day period i.e. 6 months.

We have proposed some assumptions for the types of our credit events, but we should not forget to check that a financial distress when it exists does not occur too far from our prediction date; otherwise the connection is less significant.

For the regressions, we consider only 39 European banks among the 50 for which we have obtained detailed financial data on Bloomberg year by year between 2007 to 2013 (this is definitely a subset of the 50 described earlier).

We collected from the Bloomberg data-base, a few more financial variables such as Return On Assets, Tier 1 Capital Ratio and Price to Book Ratio which are used as control variables. Consequently, we had to reduce here our study from 50 banks to 39 because of a lack of data at some points for these financial variables (307 observations for our panel data: Cf. table 2 in appendix).
The subset of 39 banks maintains the same properties as the set with 50 banks when we only regress the Financial Distress on the dummy variable (FD_Predicted). However, this very specific univariate regression is as robust as the previous case from an econometrical point of view. Hence we do not show these results in this study.

4.3 Practical insights

We can now be absolutely confident and suggest that once the T100 calculated for the iTraxx SF is achieved, not only the systemic banks need to be under a careful scrutiny, but also the non-systemic ones. However, all of our European banks had their T100 activated during the second year of our period of study (2008), but that does not mean that nothing as to be done.

The same rationale applied to the T200 calculated for the iTraxx SF. When the 200 bps level is reached, the economic environment parameters happen to be fundamentally much worse for the banking field, implying extreme ongoing conditions. However, the T200 was activated very late on 31/08/11 revealing abnormal conditions that led lots of banks outside our [0, 200] tunnel.

Above all, our main approach consists of examining very carefully the difference between a given T100 for a bank and the following T200 (if there is one).

5. Conclusion

This empirical paper studies CDS and the forecasting of bank default for the European Market (50 among the TOP 100 European banks for the period from 2007 to 2013). To our best knowledge, this is the first study using a large European sample to forecast bank default with such a methodology.

Firstly, we explain why CDSs were sufficiently reliable to lead other markets in terms of information and price discovery. This was done after having undertaken a short review on different Early Warning System models that gave various results.

Secondly, we observe that CDS may be of interest as an indicator to predict bank default, provided that the relevant trigger point has been activated. This is our initial proposal which is in line with the work of *Hart and Zingales (2011)*: "trigger intervention whenever the CDS price is above 100 bps for at least 20 of the last 30 trading days".

Since the CDS forecasting power is not "optimal" in this case, we show that a second indicator was necessary to optimize the procedure giving a second condition. A good candidate appeared to be the Markit 5-year iTraxx Senior Financial index that comprises 25 equally weighted CDS on investment grade European entities (Banks and insurance companies). But the results were still not "optimal" using two indicators.

Thirdly, considering a theoretical approach and with the help of the iTraxx Europe index (125 corporate entities), we identified a tunnel for their spread curves that fluctuate within [0, 200] during our period of study which spans more than six years. In fact, we had had first to address the question: what if the curve keeps on rising after the first trigger (T100) is exceeded?

We changed our approach: it is appropriate to monitor the bank CDS spread in the [0, 200] tunnel with two practical barriers for triggers at 100 and 200 bps called T100 and T200. So, we design a meta-rule that added a strong dynamic 3rd decision rule/condition: trigger a "real intervention" when the number of days between the triggers T200 and the T100 is under or equal to 180 days i.e. T200 – T100 ≤ 180 days.

As this approach was clearly more powerful, the second decision rule is no more taken into account.

It still remains to understand completely why the use of CDS spread for the forecasting of bank default is not more efficient. And, should this rule be activated, what to do and when exactly, so that bankers take urgent financial decisions. Hence, regulators can exert an early intervention before a bank default occurs.

Our methodology can be extended to other samples in Europe or other countries. Regulators may also use it for a more global regulation follow-up on banking systems.

6. Appendix

Tables of the applied study for the 50 banks

TABLE 2 – Global results per bank (Nb of days = 220)

Company Name	FD	FD_Predicted	Systemic	T100	T200	Nb of days (T200-T100)	Nb of days (threshold)
Allied Irish Bank	1	0	1	26/02/2008	05/01/2009	309	220
Anglo Irish Bank (Irish Bank Resolution)	1	1	1	21/11/2007	17/03/2008	116	
Bancaja	1	1	0	03/12/2007	26/02/2008	83	
Banca Monte dei Paschi di Siena S.p.A (MPS)	1	1	1	18/05/2010	29/09/2010	131	
Banco Comercial Portuges SA (BCP)	1	1	1	11/02/2010	12/05/2010	91	
Banco Esperito santo SA (BES)	0	0	1	11/03/2008	12/05/2010	781	
Banco Popular Espanol SA	0	1	0	14/03/2008	27/08/2008	163	
Banco de Sabadell SA	0	1	1	13/02/2008	05/09/2008	202	
Banco Popolare	1	0	0	14/03/2008	16/03/2009	362	
Banco Popolare di Milano Scarl (BPM)	0	0	0	25/05/2010	05/07/2011	400	
Banco Santander SA	1	0	1	16/02/2010	21/12/2010	305	
Bank of Ireland	1	1	1	15/02/2008	22/09/2008	217	
Bankinter SA	0	0	1	18/03/2008	28/11/2008	250	
Barclays Bank PLC	0	0	1	23/07/2008	20/03/2009	237	
Bayerische Landesbank (Bayern LB)	0	0	0	14/03/2008	05/09/2011	1251	
BBVA	1	1	0	16/02/2010	14/06/2010	118	
BNP Paribas SA	0	0	1	01/06/2010	06/09/2011	455	
Credit Suisse Group	0	0	1	16/10/2008		0	
Caja Madrid	0	1	0	14/03/2008	02/10/2008	198	
Caixa Geral de Depositos	1	1	0	23/02/2010	20/05/2010	87	
Commerzbank AG	1	0	1	25/05/2010	30/08/2011	455	
Credit Agricole SA	1	0	1	19/05/2010	01/09/2011	462	
DNB Bank ASA	0	0	1	07/11/2008		0	
Dankse Bank A/S	1	0	1	10/12/2010	09/09/2011	269	
Deutsche Bank AG	0	0	1	19/05/2010	01/12/2011	552	
Dexia Credit Local SA	1	1	1	16/07/2008	16/09/2008	60	
Esrte Group Bank AG	1	1	1	23/07/2008	02/03/2009	219	
Fortis	1	0	0	28/05/2010	08/09/2011	460	
HBOS	1	1	0	14/03/2008	29/09/2008	195	
HSBC Holdings PLC	0	0	1	16/12/2008		0	
ING Bank NV	1	0	1	31/05/2010	08/12/2011	548	
Intesa Sanpaolo SpA	1	0	1	20/05/2010	04/08/2011	434	
Kaupthing Bank Hf	1	1	0	13/09/2007	03/12/2007	80	
KBC Bank NV	1	1	0	16/10/2008	30/12/2008	74	
Lloyds TSB Bank PLC	1	0	1	26/12/2008	16/06/2010	530	
Mediobanca	0	0	1	27/05/2010	05/08/2011	428	
Nordea Bank Ab	0	0	1	29/10/2008		0	
Norddeutsche Landesbank Girozentrale	1	0	0	13/11/2008	19/09/2011	1026	
Rabobank	0	0	1	15/12/2008		0	
Raiffensen	1	1	1	24/07/2008	16/12/2008	142	
Santander UK	0	0	0	19/05/2010	31/08/2011	461	
SEB	0	0	0	05/08/2008	26/03/2009	231	
SNS Bank NV	1	1	0	14/03/2008	16/10/2008	212	
Societe Generale SA	1	0	1	19/05/2010	30/08/2011	461	
Standard Chartered Bank	1	1	1	18/11/2008	10/03/2009	112	
Svenska Handelsbanken AB	0	0	0	31/12/2008		0	
Royal Bank of Scotland PLC/The	1	0	1	11/03/2008	16/06/2010	815	
Ubi Banca	0	0	0	15/10/2008	20/01/2011	815	
UBS AG	1	0	1	13/03/2008	13/01/2009	300	
UniCredit SpA	1	1	1	30/10/2008	16/03/2009	136	
Sum of 1 / Average nb of days (T200-T100)	**30**	**19**	**32**			**304,66**	

"FD" = the Financial Distress or Event is the dependent variable.
"FD_Predicted" = explanatory variable sets to 1 if our model truly predicts a financial distress.

TABLES 3 and 4 – Probit regressions and related statistical results

The first table shows the regressions for our 39 banks with our variables taken from Bloomberg data that span the period 01/01/2007 to 12/03/2013 (307 observations for our whole panel data of 50 banks: Cf. table 2). The Financial Distress or Event is the dependent variable. Standard errors (based on Hessian) are reported in parentheses below coefficient values. Significance levels: *** for 1%, ** for 5%, and * for 10%.

TABLE 3: Probit regressions

VARIABLES	(1) nDays=180	(2) nDays=200	(3) nDays=220	(4) nDays=240	(5) nDays=260
TIER1_CAP_RATIO	0.205*	0.205*	0.270**	0.175	0.184
	(0.119)	(0.119)	(0.131)	(0.111)	(0.113)
PX_TO_BOOK_RATIO	-2.018**	-2.018**	-2.371**	-1.303*	-1.404*
	(0.964)	(0.964)	(1.038)	(0.745)	(0.739)
RETURN_ON_ASSET	-0.805	-0.805	-0.905	-0.566	-0.548
	(0.587)	(0.587)	(0.592)	(0.494)	(0.491)
FD_Predicted	2.188***	2.188***	2.335***	0.896*	0.825
	(0.849)	(0.849)	(0.853)	(0.501)	(0.502)
Constant	-0.482	-0.482	-0.973	-0.670	-0.679
	(1.130)	(1.130)	(1.196)	(1.111)	(1.121)
Observations	39	39	39	39	39

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 4: statistical results for each regression

STATISTICAL RESULTS	(1) nDays=180	(2) nDays=200	(3) nDays=220	(4) nDays=240	(5) nDays=260
McFadden R-squared	0,299893	0,299893	0.332365	0.170564	0.160167
Log-likelihood	-18.48360	-18.48360	-17.62632	-21.89804	-22.17254
Schwarz criterion	55.28501	55.28501	53.57044	62.11388	62.66289
Likelihood ratio test:Chi-square (4)	15.835***	15.835***	17.5496***	9.00616*	8.45715*
and its p-value	(0.0032)	(0.0032)	(0.0015)	(0.0609)	(0.0762)
Nb cases correctly predicted	76.9%	76.9%	79.5%	82.1%	76.9%
Observations	39	39	39	39	39

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

CDS curves of a few banks from Bloomberg (2005-2017)

Illustration 3: Bloomberg 5-year CDS spread (bps)

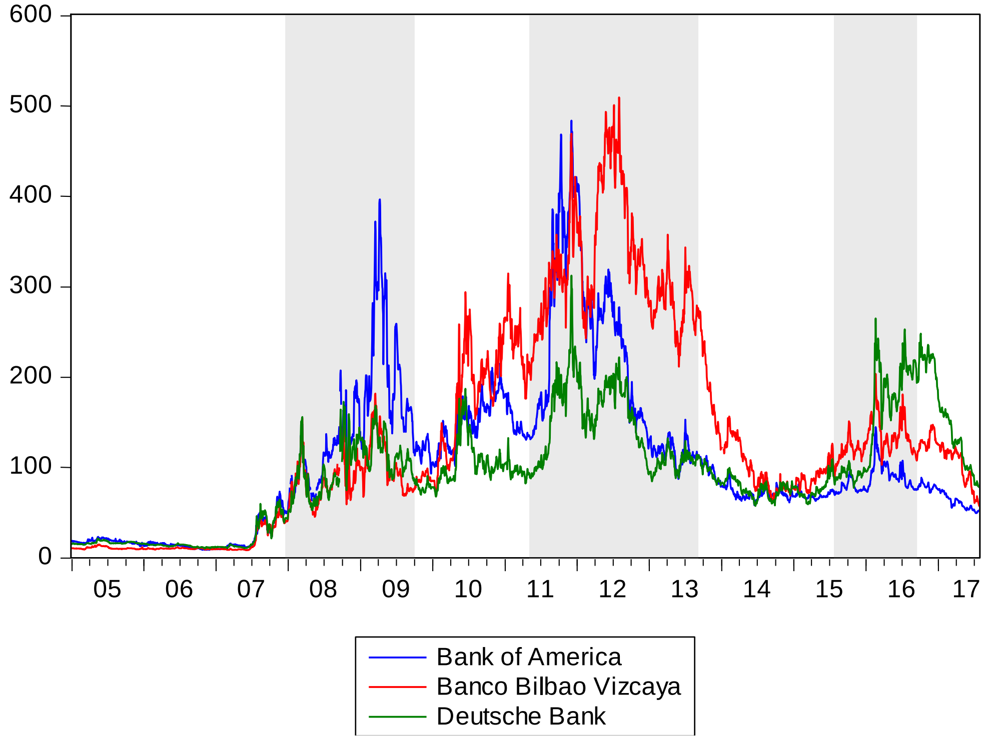
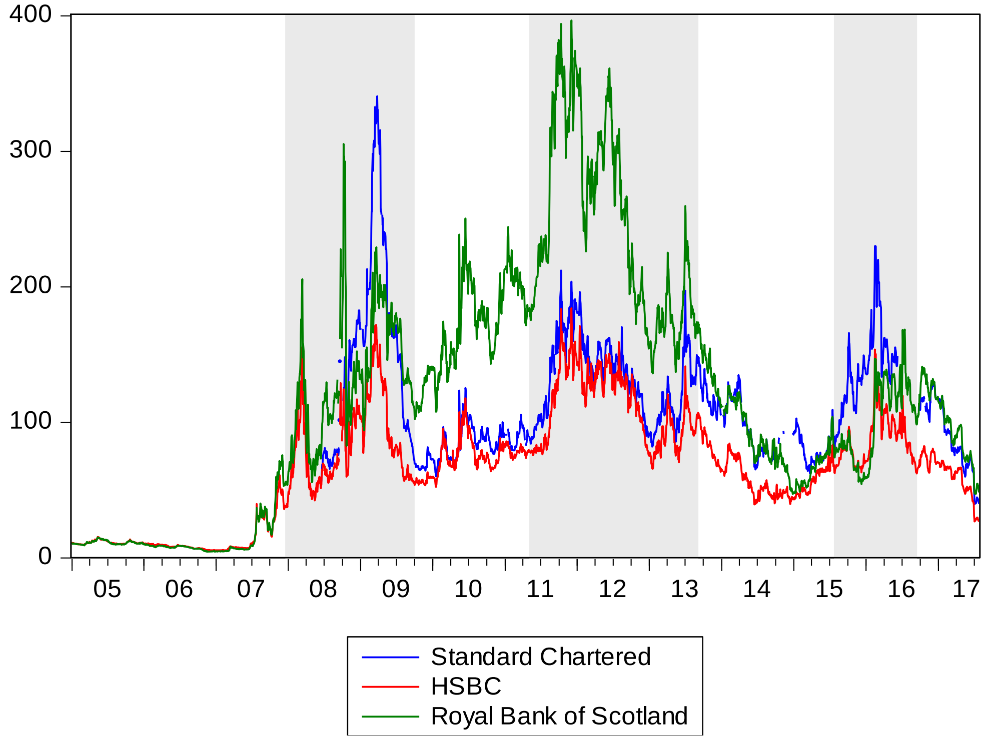


Illustration 4: Bloomberg 5-year CDS spread (bps)



7. References

- Barclays Capital (2010), “Standard Corporate CDS Handbook (ongoing evolution on the CDS market)”.

- Calabrese, R. and SA. Osmetti (2013),” Modelling small and medium enterprise loan defaults as rare events: the generalized extreme value regression model”, Journal of Applied Statistics, 40:6, 1172-1188.

- Calabrese, R. and and P. Giudici (2015), ”Estimating bank default with Generalised Extreme Value regression models”, Journal of the Operational Research Society 1–10.

- Chabot, M., JL Bertrand and E. Thorez (2019), “Resilience of United Kingdom financial institutions to major uncertainty: A network analysis related to the Credit Default Swaps market”, Journal of Business Research, 101 70-82

- Chiaramonte, L. and B. Casu (2013), “The determinants of bank CDS spreads: evidence from the financial crisis”, The European Journal of Finance, Volume 19. Issue 9: 2nd Emerging Scholars in Banking & Finance. Conference: Further contemporary issues in financial institutions and markets.

- Crouhy, M., D. Galai and R. Mark (2000), “A comparative analysis of current credit risk models”, Journal of Banking & Finance 24 59-19.

- Davis, EP., and D. Karim (2008a), “Comparing early warning systems for banking crisis, Journal of Financial Stability, 4(2), 89-120.

- Davis, EP., D. Karim and I. Liadze (2011), “Should multivariate early warning systems for banking crises pool across regions?”, Review of World Economies / Weltwirtschafliches Archiv, Vol. 147. No. 4, pp. 693-716.

- Demirgüç-Kunt, A. and E. Detragiache (1998), “The determinants of banking crisis in developing and developed countries”, IMF staff papers, 45(1), 81-109.

- Demirgüç-Kunt, A. and E. Detragiache (2000) “Monitoring banking sector fragility: a multivariate logit approach”, The World Bank Economic Review, Vol. 14 No. 2 (May, 2000), pp. 287-307.

- Demirgüç-Kunt, A. and E. Detragiache (2005), “Cross-country empirical studies of systemic bank distress: a survey”, National Institute Economic Review, No. 192, pp. 68-83 published by Sage Publications, Ltd. Also in IMF Working paper (05/96), Washington, DC: International Monetary Fund.

- Demyanyk, Y. and I. Hasan (2010), “Financial crisis and bank failures: a review of prediction methods”, Omega 38 315-324.

- Diamond, D. and P. Dybvig (1983), “Banks runs, deposit insurance and liquidity”, Journal of Political Economy 91, 401-419.

- Flannery, MJ. (2016), "Stabilizing Large Financial Institutions with Contingent Capital", The Quarterly Journal of Finance, Vol. 06, No. 02, 1650006, DOI: 10.1142/S2010139216500063.
- Flannery, MJ., J. Houston and F. Partnoy (August 2010), "Credit Default Swap spreads as viable substitute for credit ratings", University of San Diego (School of Law), Legal Studies Research Paper Series (Research Paper N°. 10-31), also in University of Pennsylvania Law Review, Vol. 158, No. 7, Symposium: PROTECTIONOF INVESTORS IN THE WAKE OF THE 2008-2009 FINANCIAL CRISIS (June 2010), pp. 2085-2123.
- Glasserman, P. and B. Nouri (2012), "Contingent Capital with a Capital-Ratio Trigger", Management Science, Vol. 58, No. 10, pp. 1816-1833.
- Hart, O. and L. Zingales (2011), "A new capital regulation for Large Financial Institutions", American Law & Economics review 13, 453-490.
- Hull, JC. (2018), "Options, Futures and other Derivatives", 9th Edition, Pearson.
- Jarrow, R. (2010), "The economics of credit default swaps (CDS)", Johnson School Research Paper Series.
- Kaminsky, GL. and CM. Reinhart (1999), "The twin crisis: the causes of banking and balance-of-payments problems", American Economic Review, 89(3), 473-500.
- Kashyap, K., RG. Rajan and JC. Stein (2008), "Rethinking Capital Regulation", Federal Reserve Bank of Kansas City Symposium.
- Levine, R. (2010), "An autopsy of the US financial System", National Bureau of Economic Research (NBER Working paper series).
- Markit study (2009), "The CDS Big Bang: understanding the changes to the global CDS contract and North American Conventions".
- McDonald, R L. (2013), "Contingent Capital with a dual price trigger", Journal of Financial Stability 9 230– 241.
- Pennacchi, G. (2010), "A Structural Model of Contingent Bank Capital", University of Illinois, College of Business.
- Pirotte, A. (2011), "Econométrie des données de panel, théorie et applications", Economica.
- Prescott, ES. (2012), "Contingent Capital: the trigger problem", Economic Quarterly – Volume 98, Number 1 Pages 33-50.

- Raunig, B. (2011), "The credit risk of banks and non-banks during the crisis: evidence from the CDS market", presented at Midwest Finance Association 2012 Annual Meetings Paper.

- Reinhart CM. and KS. Rogoff (2008), "Is the US sub-prime crisis so different? An international historical comparison", American Economic Review 98, no. 2:339-344.

- Stulz, RM. (2010), "Credit Default Swap and the Credit Crisis", Journal of Economic Perspectives, Volume 24, No 1, 73-92.

- Sundaresan, S. and Z. Wang (2015), "On the design of contingent capital with market trigger", The Journal of Finance, Vol. 70, No. 2, pp. 881-920 (published by Wiley for the American Finance Association).

- Taylor, JB. (2008), "The Financial crisis and the policy responses: an empirical analysis of what went wrong", Bank of Canada. A Festshrift in honour of David Dodge. November 2008.

- Thorez, E. (2017), "CDS and the forecasting of bank default", Paper presentation for AFFI Conference 2017 at Valence (France) and for Conférence à l'Université de Rennes 2018 (CREM – UMR 6211). Chapter III of a Doctoral Thesis, Paris-Dauphine University.

- Wilson, T., (1998), "Portfolio Credit Risk", FRBNY Economic Policy Review.