CDS and the forecasting of bank default[*]

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Abstract

The last financial crisis hit worldwide economies with an unprecedented magnitude. In order to predict bank default or banking crises, some empirical papers have been written ever using sophisticated tools that can use models from operational research. Based on a short analysis of the forecasting power of several types of financial products, we conclude that CDS characteristics are the best measure to forecast and thus ideally prevent the potential default of a bank. Thanks to the economics of CDS and the results of other empirical studies, we show that CDS spreads are undoubtedly a good, though not a perfect proxy for bank risk, even though they are more sensitive to information changes than other products.

So, by creating and using a specific trigger based on CDS and the appropriate response, in the case of the trigger being activated, we examine if we could prevent the default of a bank. But as CDS spread cannot be taken as a perfect proxy for the true probability of default of the underlying corporate entity, we had to investigate further to try to find another benchmark. Initially, a good candidate appeared to be the Markit 5-year iTraxx Senior Financial index. So, using the CDS of each bank and this index, we first applied the following procedure: an intervention should be triggered whenever the CDS price is above 100 bps for at least 20 of the last 30 trading days.

We studied 50 among the TOP 100 European banks from a 63 European bank sample for the period from 2007 to 2013 and examined a few in detail results. We found that one or even two triggers at 100 bps gave disappointing results, as most of the banks went over this limit during the second year of our period of study. Subsequently, we were better able to see how to manage some properties that we had identified by using 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 gave more reliable results for forecasting bank default than our less sophisticated first approach and could be useful to regulators.

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1. Introduction

At the end of the 90's, a few researchers have addressed the question of the prediction of bank default and banking crises. Indeed, the two last decades of the past century ended with a substantial amount of different types of banking crisis everywhere in the world i.e. situations where banks can no longer perform their role as intermediates because they become insolvent i.e. their liability value is larger than their asset value.

Three-quarters of IMF countries experienced such 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 because of the computerization and internationalization of financial markets. Hence, the major changes to the American Glass-Steagall Act adopted in 1999 under the Gramm-Leach-Bliley Act allowed commercial banks, investments banks and insurance companies to consolidate and then to become universal which permits these new whole entities to fully diversify their investments with negative and positive effects on risk-taking as a results.

The financial crisis that peaked between 2008 and 2009 began in the US in 2007 with the collapse of subprime mortgages. *Demyanyk and Hasan (2011)* 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 to the total of the US securitized mortgage debt of $6.8 trillion. We now know that the strong impact on economy was because of the grouping together of individual securities that were later repackage to create even more sophisticated products. 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 during the preceding decade with regards to financial policies, major conflicts of interests appeared among Credit Rating Agencies and banks 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 (not to mention the lack of transparency within OTC markets). This regulatory decision had a terrible impact on the banks which then reallocated capital to higher-risk assets, 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)* inside a market of credit derivatives of $600 trillion where more than 80% are OTC traded.

Obviously, other factors or determinants must be taken into account as *Taylor (2008)* shows that due to lenient monetary policy, interest rates fell from 2002 to 2004 and this resulted in a monetary excess in turn that 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)* and they also 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 own financial crisis. 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 and also, that the related effects are reduced by a strong institutional environment. Their study during the period 1980 to 1994 is based on a multivariate logit model in which they link the likelihood of a crisis to a vector of explanatory variables.
They find that if the macroeconomic context is not strong enough then low GDP growth, high real interest rates and high inflation as well as an explicit deposit insurance system can lead to banking crisis.

However, in theory, an explicit deposit insurance system should mitigate against the fragility of banks as a self-fulfilling panic as described by *Diamond and Dybvig (1983)*, but this implies some more risk-taking by bank decision makers (i.e. a moral hazard), all the more as we are considering the years after 1999 i.e. post the Gramm-Leach-Bliley Act.
As they focus mainly on macroeconomic determinants they examine this weakness in their conclusion and assert that this is partly because of a lack of data among the potential choice of candidates for 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)* who found that financial liberalization often results in a banking crisis and subsequently a currency crisis, which in turn fuels the banking crisis, thereby creating a vicious circle.
Their sample consists of 20 countries for a period from 1970 to 1995 and included 76 currency crises and 26 banking crises. They find 26 currency crises and 3 banking crises for the period from 1970 to 1979 and 50 currency crises and 23 banking crises for the period 1980-1995. This major increase of the banking crises is linked to the post-liberalization era, whereas that of the 70's may be attributed to a very regulated decade. They use a non-parametric approach based on a signal extraction model to come to their conclusions (*).
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 eventually 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 and show 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)*.

(*) 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.

Using their model, the monitor select the probability threshold that would minimize a loss function that characterizes 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 one 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 countries out of the six the results are too optimistic and the authors explain this by the novelty of their econometric evaluation of systemic banking crises, in particular with the use of their forecasting and monitoring tools. Furthermore, as a new 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 take into account 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 last financial crisis.

By comparison between the multivariate Logit models in *Demirgüç-Kunt and Detragiache (2005)* and the signal extraction in *Kaminsky and Reinhart (1999)*, *Davis and Karim (2008 a)* 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. Besides, the results show that the multinomial logit model is more able to cope with global Early Warning Systems and signal extraction methodology for country specific Early Warning Systems and find that changes in terms of trade and real GDP growth are the best predictors for banking crises for their sample.

Binary Recursive Trees (BRT) or decision tree techniques are used in research on machine learning and often feature in medical research. Based on a recursive partitioning algorithm using “If-Then” rules to undertake solving prediction questions implemented in Early Warning Systems, these rules can classify banks as in *Davis and Karim (2008 b)* or later, in *Davis, Karim and Liadze (2011),* using a proprietary software package (“CART”, Salford Systems Inc.).
Instead of addressing the question of the likelihood of a banking crisis in n years as in a multivariate logit model, BRT partitioning endeavours to guess what non-linear variable interactions more likely weaken an economy with regards to banking crises. Moreover, the BRT non-parametric approach requires no specific statistical distribution which is a substantial advantage, especially as there is no need that all variables follow the same distribution as each variable takes the same distribution across cross-sections.
However, the results for OECD countries (including emerging market countries) in *Davis and Karim (2008 b)* with both BRT and logit models give no robust results regarding a potential

increase of crisis probability before the subprime crisis (i.e. for the preceding two years). Specifically, the logit model gives better performances for the UK and the US.
In addition, *Davis, Karim and Liadze (2011)* show that because global samples are irrelevant when they pool data it was more efficient to use both models to assess regions separately (such as Asia, or Latin America) in order to deal with policy objectives.

The movements of Distant to Default (DD) which is a classical market-based measure of corporate default risk has been found to be a tool with predictive power for major Japanese banks, *Harada, Ito and Takahashi (2013).* Indeed, by investigating specifically three major failed banks they find that the DD is a reliable measure of bank failure prediction, as well as the DD spread (DD of a failed bank minus the DD of sound banks i.e. a benchmark defined by the average of the five largest regional banks' DD). However, this sample is not very large and what is more, one of the three failed banks did not produce the expected results because its financial statements were window-dressed, even though *Harada et al. (2013)* tried to control results in an econometric probit model using panel data of three failed plus eight former banks.

Another non-European study partly confirms the forecasting power of Distant to Default (DD), *Miller, Olson and Yeager (2015)*. Between 2006 and 2012, they estimate the quality of prediction (accuracy) of market signals i.e. Expected Default Frequency (EDF) and Subordinated Note and Debenture (SND) yield spreads against accounting-based signals which would turn out to indicate distress.

In particular, they show that if EDF signals from 2007 to 2008 succeeded in identifying Bank Holding Companies (using 473 BHCs) in the USA that became distressed within two following years, their economical impact concerning reducing missed distress events is not significant.

Wilson (1998) and McKinsey company proposed a model, CreditPortfolioView, which 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 variable is assumed to follow an autoregressive model of order 2 (AR(2)). Then, the main idea of CreditPortfolioView 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 *Crouhy et al. (2000),* and 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 really difficult to cover several credit cycles and test the inherent model robustness in case of a crisis.

Another strategy used to improve results consists of improving an existing methodology. Thus, *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 i.e. a distress event from macroeconomic and banking oriented microeconomic explanatory variables.
Indeed, they show that their regressions are of better quality than those which are based on logistic models with an important reduction of the false negatives that correspond to bank failures that are classified as correct (or type I errors) especially as this is important for Early Warning System criteria.

In fact an asymmetric link function such as the GEV mitigates against the problem of the symmetry around the value 0.5 for the logistic link function by more appropriately taking account of information that exists in the default distribution tail when approaching the value of one.

In order to compute the probability of failure, a discrete-time survival model can also be used, *Fiordelisi and Mare (2013)* following *Männasoo and Mayes (2009)*. Working on one of the largest cooperative banking markets (Italy) that is mainly composed of small credit institutions between 1997 and 2009 they show that the more efficient banks are, then the higher is their probability of survival. In their paper, efficiency determines three funding hypotheses that are related to cost minimization, revenue maximization and profit maximization.
If cooperative banks are more fragile than commercial banks with regards to failure in a period of financial stability then they also find that a higher capital adequacy capacity decreases the probability of default, hence giving credence to the European banking regulation enforcement with the Basel III agreement (addressing moral hazard mitigation and increased capability of loss absorbency). We note that this study mainly focuses on small credit institutions that constitute the group of cooperative banks in Italy which is far different from the bigger banks in Europe that we have studied.

Other very technical and sophisticated tools have been developed in the empirical literature using operational research models such as Case-based reasoning, Neural Networks, Trait Recognition, Multicriteria decision aid, etc. as described in *Demyanyk and Hasan (2011)*.

Amazingly, none of these sources appear to be substantially better than another, if we compare their results. This is why it may be more efficient to combine at least two of them e.g. *Davis and Karim (2008 a)* or *Davis, Karim and Liadze (2011)*, depending on either the global or country / region specific Early Warning Systems we want to focus on.

2. A well-balanced approach for CDS forecasting power: justifications

2.1 Why use CDS in our approach?

Our main purpose is to focus on empirical ways to examine how CDS should be used to forecast and prevent the potential default of a bank. So, this research could be useful to the regulator which could make an intervention in due time before a bank defaults provided that an ad hoc procedure is conceived.

We define "bank default" in terms of "financial distress" (see sub-section 2.6).

CDS or Credit Default Swaps are part of the credit derivative group of financial products. They provide a type of insurance against credit risk. In 1994, these CDS credit derivatives were developed by Blythe Masters of JP Morgan. Initially, banks used them to hedge credit exposures on their balance sheets.
We could pose the question why use CDS instead of other financial products?
Portfolio strategy became more efficient and more sophisticated in the early 90's when credit derivatives first appeared. Basically, one can now separate credit risk management 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 and 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 for risk management, we can now regard markets as complete because of credit derivatives.

One of the main reason 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, 2009, Chiaramonte and Casu, 2011, Flannery et al, 2010).*

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

We could also use equity prices, but these are not a good measure of financial distress, despite their related liquid markets and market prices which are hard to manipulate. 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.

This is why it is important to have a more detailed view of exactly what approach to default risk we need exactly. 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.

But are we sure that CDS spreads are a good indicator of a bank default or the best one *(Chiaramonte and Casu, 2011, Sundaresan and Wang, 2011, Flannery et al, 2010)*?
These empirical studies and others have attempted to answer this question as well as the specific CDS type of trigger to choose. Exactly what spread and what level of spread is required to activate the trigger is definitely important to investigate.
It remains to evaluate if CDS could become a relevant product and what are the triggers for that and what precisely CDS are and how they operate, especially in order to predict and avoid bank default.

Hart and Zingales (2009) have found that the following condition would make sense in order to detect the right time to intervene, based on an indicator and a trigger that are both relevant:
"Trigger intervention whenever the CDS price is above 100 bps for at least 20 of the last 30 trading days"**.** Moreover, 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 on several banks. It may also be interesting to mention cases where CDS did not react as we would have expected and to understand why.

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

Thus, as *Hart and Zingales (2009)* specifically illustrated that we could use CDS contracts to monitor banks' solvency, we would like to show that the observation of CDS (combined this time 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.

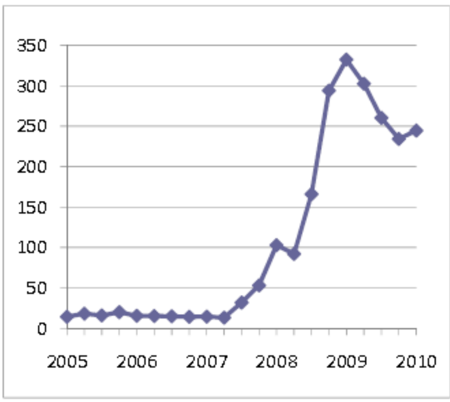
Based on evidence from the financial crisis, *Chiaramonte and Casu (2011)* focus on the field of bank CDS spreads on a true international level in comparison to other less specialized studies.
Their approach is original in that they focus specifically on balance sheet ratios, because these provide brief 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>Trend of average CDS spread values (in bp i.e. basis points) for the 57 sample banks chosen world-wide</u>



(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 Aspects of the forecasting potential of CDS

The prediction capacity is precisely what we would like to investigate further.

Unfortunately, according to for *Anderson (2009),* changes in CDS tend to reflect mainly the market's trend to bear default risk of a company rather than changes in the solvency of that company. Indeed, he has found that the volatility of the price of default risk was ten times larger than the physical default intensity.
Thus, things are certainly more complex than *Hart and Zingales (2009)* claimed. The reliance upon CDS spreads for the purpose of macro-prudential regulation is likely to be misguided or else an adapted control for the change in spread (absolutely resulting from changes in the markets' pricing of credit risk) is needed.
It is of paramount importance to note that there is a convergence of the relevance of some proxies used in the *Anderson (2009) and the Chiaramonte and Casu (2011)* papers.
One of the main results of the *Anderson's (2009)* paper is that credit market tightness exerts a profound influence on the market price of default risk (the proxy used is a measure of non-performing commercial loan).
From a conceptual point of view, it comes very close to the ratio "loan loss reserve" to "gross loans" (Asset quality determinant) used by *Chiaramonte and Casu (2011)* and both of those proxies have been shown to be the best ones for the regressions in each study.

Of course, this implies that considering CDS spreads, there is a market consensus on the creditworthiness of the underlying corporate (and also for a bank). However, according to *Rama Cont (2010),* the market practice of computing the implied default probability of a company from its CDS spreads incorporates this characteristic by using default probabilities for the pricing of credit derivatives.

As implied volatilities are derived from option prices, we suggest that such implied default probabilities do not necessarily provide any information of a potential default or even the actual likelihood of a default of the reference entity. They may simply be the result of the market consensus on the CDS premium for default protection at different maturities.
In this context, it is important to remember that hazard rates and implied default probabilities are dependent on the hypothesis set for recovery rates.
Now, the use of the CDS spreads as sign of credit quality have been appropriate in the CitiGroup and Washington Mutual case with a trigger intervention mechanism as described by *Hart and Zingales (2009),* hence the relevance for an earlier potential intervention of the regulator.

2.3 Choice of a possible second indicator to complement CDS spreads

The major contribution in the article by *Huang, Zhou and Zhu (2009)* was the design of a new indicator to assess the systemic risk of the banking sector (examining a group of 12 major US banks for their sample period 2001-2008) using the price of insurance against financial distress for those banks in the following 12 weeks.

They proposed a regularly capital surcharge that could be estimated on these major US banks based on information from the CDS market.

Thus, this capital charge is based on ex ante measures of the large individual banks' CDS spreads to obtain their probability of default (PD) and an estimation of asset return correlations was undertaken using high-frequency equity information.
In particular, their results suggest that *"the systemic risk indicator, the theoretical insurance premium required to protect against insurance default losses that equal or exceed 15% of total liabilities of the 12 US banks, stood at $ 110 billion in March 2008 and had a projected upper bound of $ 250 billion in July 2008".*
Thus, this indicator is higher when the average failure rate increases or when the exposure to common factor rises.

In the introduction, we have noted that CDS spread cannot really be taken as a perfect proxy of the true probability of default (PD) of the underlying corporate. In fact, the market price of a CDS is based on the risk-neutral distribution of the underlying risk. And one of the 10 major conclusions of *Jarrow (2010) about CDS* is the following:
"*CDS spreads can be decomposed into: (a) the expected loss, plus (b) a default risk premium (reflecting the market price of default risk), plus (c) asymmetric information monitoring costs, plus (d) a liquidity risk premium due to a quantity impact of trades on the price. Of course, these components are interrelated*".
Note: 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.

So, any of these four factors could have an impact on changes over time observed in CDS spreads. Then, there is little possibility that factors b to d 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.

As we have already stated using the assertion by *Hart and Zingales (2009)*, 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.

Hence, we are strongly suggesting that only monitoring CDS spreads on banks might not provide a complete explanation for bank solvency and a potential default.
This is why we would like to produce a combined approach to monitor banks' solvency based on both observations of CDS and another indicator (which could be an index of CDS) as well as their interrelation.

It is also worth knowing that 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)

where 1-Expected Recovery Rate = Loss Upon Default (or Loss Given default).

Note that expected recovery rates and default probabilities are both often unobservable but the CDS spread is observable and it can be used to calculate default probabilities given a recovery rate assumption.

2.4 Factors that create conditions for a trigger

As stated by *Hart and Zingales (2009)* concerning indicators and especially a trigger we do not want to get a static barrier such as 100 bps, because it could lead to the same sort of bias obtained using triggers based on market price, for example, or induce potential market price manipulation.

It may be better to look for a dynamic trigger. *Prescott (2012)* proposes four properties of Contingent Capital and concludes *"the trigger is the weak point of contingent capital and, more specifically, a trigger based on market price".*
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. It is worth examining why and seeing if there are some conditions or a path which could sufficiently be useful without condemning or rejecting this approach totally.
They assert that "*a contingent capital with market equity trigger does not in general lead to a unique equilibrium in the prices of the bank's equity and contingent capital".*
Depending on the design of the contingent capital and the underlying dynamics assets, unique, multiple or even no equilibrium may result: if conversion strongly dilutes equity, then there are multiple equilibria and if conversion increases the equity value, then there are no equilibria.
Indeed, this is contradictory to the definition of this type of equilibrium which requires that a unique price should be consistent with the chosen rule of conversion.
In addition, no agent is authorized to select a policy conversion for their best interest. So, conversion rules should make sure that it does not change the security value (on which the trigger is set).
In conclusion concerning equity triggers, they showed that no value transfer should be created by the conversion ratio which gives a unique equilibrium. And, dilutive ratio especially shaped to punish bank management or to promote coercive issuance will lead to multiple equilibria.

Similarly with the accounting ratios consequences, whether multiple or no equilibrium, contingent capital of this kind not only leads to price manipulation, but also to capital allocation of poor quality, market uncertainty and no reliable conversion. If contingent capital cannot evolve into loss-absorbing equity when necessary, then contingent capital will not be a true substitute for common equity as a capital buffer.

This still occurs even if banks have the capacity to issue new equity in order to avoid conversion.

Naturally, it is even more problematic if there are bankruptcy costs and sudden jumps in bank assets; then, we must not transfer value between equity holders and contingent capital investors, in order to obtain a unique equilibrium, at the trigger price. However, this unique equilibrium will deprive contingent capital from its incentive component that prevents management from taking excessive risks (hence, no punitive conversion can be expected!).

As a 1st short set of conclusions using the research above, we would like to 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 and 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.

This is why we are attempting to establish conditions for a dynamic trigger used with CDS as indicators. Of course, if we could find a trigger that prevents Capital Contingent with a market equity trigger from not leading to a unique equilibrium or that gives minor inefficiencies, this would be perfect.
Unfortunately, we have just shown that this is not realistic and these results may apply to all triggers if they depend on market value of equity (directly or indirectly).

Now, *Sundaresan and Wang (2011)* (quoting *Pennachi (2010), McDonald (2011), Glasserman and Nouri (2010)*), came to the conclusion that under the conditions that the trigger's variables should not be affected by the capital conversion or in other words they are exogenous, thus we obtain a unique equilibrium and hence get a price for Contingent Capital.

As a 2nd set of conclusions, we come to three additional fundamental points:

3. Any trigger that depends on market value of equity (directly or indirectly) is not appropriate; hence, the relevance of CDS. The same effect applies to the intervention of a regulator. *Bond, Goldstein and Prescott (2010)* find that interventions in the operations of a bank by regulators do not produce robust solutions.

4. The variables upon which the trigger is based for the conversion should be as much exogenous as possible.

5. Considering the four previous fundamental points, we should not use a single indicator based only on the CDS of the concerned bank.

Market manipulation is another issue we must also address. *McDonald (2011)* showed that a reduction of the potential impact of manipulation could be considered provided that we implement the following 3rd set of conclusions:

6. If we look for a second indicator as an index as in the dual price trigger approach used by *McDonald (2011)*, then the index conversion should be based on an average price over time, or see also the point 7. These two processes are indeed suggested to prevent traders from manipulating the index when the bond is close to maturity.

7. The main drawback of the point 6 lies in the delay that may be induced by a multi-day average. So, by randomly and gradually withdrawing the bond as maturity approaches, one can mitigate against the big gains that may happen at maturity.

8. A rather direct consequence based in part on the point 7 requires that conversion must occur transparently, automatically and above all, promptly (as soon as the trigger is released, see *Flannery, 2009*).

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

In order to build our trigger mechanism, we are going to use the Markit 5-year iTraxx Senior Financial index given by the Bloomberg company (by default we call it iTraxx or iTraxx SF). It comprises 25 equally weighted CDS on investment grade European entities (16 Banks and 9 insurance companies).
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.
It is important to understand that 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.

And, this is exactly what we want to look at. Indeed, 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 really appropriate and more robust in our context, as it is based on the 25 banks and insurance companies shown in the following page.

Bank and Insurance companies that are used by the iTraxx

Company name (1/2)	Company name (2/2)
Aegon NV	Hannover Rueckversicherung AG
Allianz SE	HSBC Bank PLC
Assicurazioni Generali SpA	ING Bank NV
Aviva PLC	Intesa Sanpaolo SpA
AXA SA	Lloyds TSB Bank PLC
Banco Santander SA	Muenchener Rueckversicherungs AG
Barclays Bank PLC	Societe Generale SA
BNP Paribas SA	Standard Chartered Bank
Commerzbank AG	Swiss Reinsurance Co Ltd
Credit Agricole SA	Royal Bank of Scotland PLC/The
Credit Suisse Group AG	UBS AG
Deutsche Bank AG	UniCredit SpA
	Zurich Insurance Co Ltd

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 banks among this list (and 34 more to get 50), 9 insurance companies had been added to it in order to build the index.
Consequently, as *McDonald (2011)* suggested using Contingent Capital with a dual price trigger, we are going to use two indicators.

Then, 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 and 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 institution and the use of an index trigger.

Now, if the first trigger is set off with a non-LFI, we also suggest that this bank should immediately be placed under careful scrutiny. An equivalent rationale leads us to suggest that the calculated T100 for the iTraxx Senior Financial index produces an important starting date to put all the declared systemic banks under careful scrutiny, even if their own trigger has not been reached yet.

However, in this case, it would not be such a big problem if in normal times we let a non-LFI performing badly go bankrupt. So, this process permits a non LFI to collapse in good times which is in accordance with classical liberal views, by giving a strong signal to too many risk takers.

Basically, giving the Too Big To Fail institutions a false feeling of security in that they believe that they will always be saved at the expense of the states, it makes them increase their risks. This is the reason why we must clearly distinguish between the systemic banks and non-systemic ones.

Indeed, we definitely require fixed triggers that are activated if absolute barriers are breached.

Note that the 1st condition was introduced by *Hart and Zingales (2009)*, but no combination with another trigger to build a more sophisticated process was used.

2.6 Conditions for Bank default or financial distress

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

This is why we are going to examine the factors that lead to significant financial distress. Of course, it sometimes happens that a bank financial distress becomes a bank failure that may require a big bank bailout i.e. a national rescue.

Then, a financial distress means that at least one of the following credit events occurs:

- 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

Note that these credit events are quite different from the one used by the ISDA (International Swaps and Derivatives Association) for the Big Bang and Small Bang changes *(ISDA supplements, 2009 and see also Markit study, 2009)*. Indeed, our criteria are less restrictive and more numerous than the ISDA ones, especially because we want to be sure to illustrate sufficient financial distress cases and also because there were far less bank collapses in Europe than in USA.

The last bullet point above that concerns a “Bankruptcy” credit even, for the Reference entity (a bank in our case), 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, both defined by the Reference entity’s obligations.

It is also essential to check that a financial distress when it exists occurs not too far from our prediction date; otherwise the connection is less significant.

2.7 Description of iTraxx indices

Markit 5-year iTraxx indices (from Bloomberg)

Between the 01/01/07 and the 17/05/10, the iTraxx SF and the iTraxx Europe indexes moved closely together, except 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 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. It is also interesting to 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.

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.

Note: we use T100 (BIS) for the second time the trigger is activated and T100 (Ter) for the third calculated T100 during the period of study.

2.8 Our initial approach and its limitations

In our list of European Bank Credit Events (see appendix), we list for each bank our calculated T100 trigger that is activated by the decision rule n°1, based on the simple mechanism of *Hart and Zingales (2009)*. As the T100 for the iTraxx Senior Financial gives the 14/03/08 date, we just have to evaluate if each bank is considered as systemic in order to follow our decision rules.

Should we opt for a systemic LFI, then the relevant trigger is necessarily the T100 found for that specific LFI, whatever the iTraxx date may be (14/03/08) in the decision rule n°2 i.e. condition n°2. In our list of bank credit events (see appendix), the 16 banks out of 25 financial companies that include 9 insurance companies used in the iTraxx SF index are named in quotes and (S) means that we consider that they are systemic in Europe which is not ideal, though it adds more stability.

For a non-systemic bank, the relevant trigger should be the bank trigger if its date is after the T100 of the iTraxx. On the contrary, the resulting T is going to be the T100 for the iTraxx Senior Financial and we show this in our list of bank credit events (see appendix) using "T= iTraxx SF".

Only 8 banks belong to this category and most of the time, their calculated T100 in March or even February 2008 is very close to the final calculated T=iTraxx SF, excepted for Bancaja with a T100=03/12/07.
44 out of 50 banks had their T100 trigger activated in 2008 and for the 6 remaining banks it was activated in 2007 and 2009, so does a trigger at 100 bps also makes sense for our period of study?

Highlighting some interesting results using our initial approach with four banks

(See in appendix our graphed data for these four systemic banks).

From Bloomberg Business week (07/01/13): *"since 2008, the EC has approved more than $6.6 trillion in state aid to banks. So far only a quarter of that has been used, with the UK, Germany and Ireland receiving the bulk of the funds" (John Glover)*. L'Express on 3/07/13 mentions a recapitalization plan of €1.7 trillion to rescue banks and that is consistent with the Bloomberg figure.

Thus, we could directly observe the advantages of our rule using the selected banks such as the following four.

Banca Monte dei Paschi di Siena S.p.A. (MPS): T100=30/12/08 (S). The third largest bank in Italy (Information from 12/04/13). From our research, it appears that the first capital injection was on 27/03/09. If our model had been used intervention could have happened 3 months earlier, but we should bear in mind that ideally, all the declared systemic banks should have been under rigorous scrutiny from 14/03/08, consistent with the condition n°2 (iTraxx SF).

After a year of hesitation and rumours about recapitalization in 2011, in July 2012, a final bailout request of €3.9bn on 26/01/13 was approved by Banca d'Italia (CDS spread at 459.22 bps).

Conclusion for this initial approach: ideally a state intervention should have occurred on 30/12/08, but it is hard to understand why no serious action had been taken in 2011, especially because our second condition for the T100 had then been activated 3 times (the last time being 17/05/10) and also because the second 2011 half year was so difficult for the European banks, because of the Greek crisis.

So, more than one year of time could have been saved for this bank using our model!

Note that "Le monde" (10/08/13) reported that the bank did some window-dressing of its accounts before their near collapse at the beginning of the year 2013.

Allied Irish Bank (AIB): T100=26/02/08 (S). Allied Irish Bank is one of the "Big Four" financial institutions in that country along with Bank of Ireland, Ulster and National Irish banks (Information from 21/02/13).

Being considered as systemic, our rule predicts a trigger activation on 26/02/08, even if our iTraxx SF=14/03/08. According to our research, it appears that the first planned bailed out of €3.5bn arranged by the Irish government commenced on 12/02/09. By March 2011, the total sum of the required bailout was expected to climb up to €13.3bn.

The ISDA Determination Committee, consisting on 15 USA and European banks, decided that a restructuring credit event ONLY occurred on 9/06/11 (spread at 1193.65 bps)! No more Bloomberg data was available after 01/08/2011.

Conclusion for this initial approach: using our rule, intervention could have taken place a year earlier and even more, if we rather take into account the late date of the ISDA decision.

Banco Commercial Portugues SA (BCP): T100=13/03/08 (S). According to our research, it appears that the first available information for BCP, but also for Caixa Geral de Depositos SA (T100=14/03/08) and Banco Espirito Santo SA (BES) (T100=11/03/08) starts on of 5/05/10 with a status "on review" by Moody's for a possible downgrade.

BCP was actually downgraded on 2/06/10 by Moody's which also downgraded 7 other Portuguese banks (including the two previously mentioned) on 15/07/10, following the downgrading of the Portuguese government to A1.

The fact that Moody's has chosen this period of time appears all the more relevant as there were three bank CDS spreads over 500 bps in May 2010 (with a peak at 562.09 bps on 07/05/10 and at 1739.05 bps on 25/11/11, for BCP).

Conclusion for this initial approach: in April 2012, there was a Portuguese Government commitment for a €3.5bn recapitalization that led to a €3bn rescue on 7/06/12 with a CDS spread at 1162.91 bps!

Being a systemic bank, a state intervention should have occurred on 13/03/08, but it is hard to understand why no serious action had been done at least in 2011, because our second condition for the T100 had then been activated 3 times (the last time being on 17/05/10) and also because the second half year of 2011 was so difficult for the European banks (see at the iTraxx Financial CDS curve and the BCP one), because of the Greek crisis.

Dexia Credit Local SA: T100=16/07/08 (S). Unfortunately in this case, our data does not start at the beginning of our period of study i.e. 1/01/07, but only 16/06/08 with a huge slope. However, given the spread curve for many of banks before this date, we consider that our T100=16/07/08 is correctly calculated.

So, being considered as systemic, our rule would have required the bank to raise capital especially as the second condition had already been triggered with an iTraxx SF on 14/03/08. Using our rule, intervention could have occurred more than 2 months earlier as French, Belgian and Luxembourg states injected €6.4bn capital in Dexia on 30/09/08 and later the Belgian part was rescued by the Belgian Federal Government for €4bn on 10/10/11 (CDS at 956.7 bps on 25/11/11).

It is also interesting to note that the Belgian Government undertook a rescue near the 9/05/11 date when the iTraxx SF and the iTraxx HIVOL began to converge. Indeed the European banking value dropped during the second half year of 2011, mainly because of the Greek crisis.

Conclusion for this initial approach: since 2008, the global cost for the French state has amounted to a €5.5bn pure loss and to €2.5bn loss for the Belgian state *(Isabelle Rey-Lefebvre, Le Monde 6/06/13)* and this would have been undoubtedly been smaller if the rescue had happened sooner, with careful scrutiny of this systemic bank starting from 14/03/08, when the second condition of our rule was triggered.

Limits

We could continue to do this for many banks, as nearly all of them had their T100 activated during the second year of our period of study. In addition, we have been able to calculate other T100 for many banks such as T100 (BIS) or T100 (Ter).

Our results also reveal that our second indicator is not as efficient in predicting a default.
So, we intend to tackle the subject differently as our initial approach does not appear to be sufficiently efficient and robust.

3. Theoretical approach

3.1 Issue with the level of the trigger

Hart and Zingales (2009) have suggested the following 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).
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 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).

3.2 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.

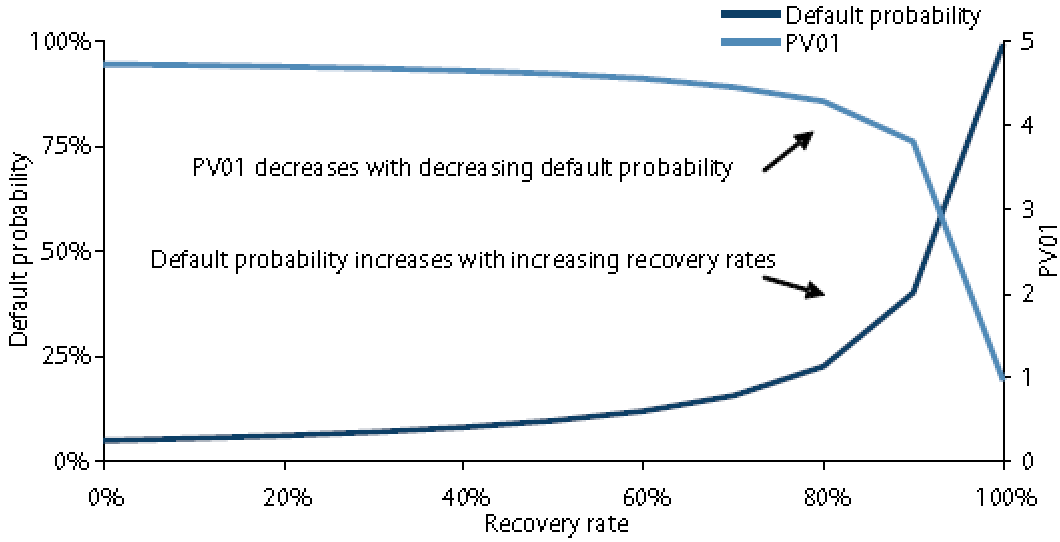
Consistent with that, we notice that on the default probability on the following page, when the recovery rate increases from 20% to 60%, it produces a rise of less than 5% for the default probability. So, if we raise the recovery rate, then we implicitly raise the default probability, but not significantly 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 300bps (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] %



(Source: Barclays Capital)

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* cannot appear as an absolute number which is not an issue because we should primarily consider it just as a target.

4. Empirical study

4.1 Data sample

We have selected our banks 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). It is necessary to use consolidated accounts and this explains why the data are not always those communicated by the financial department of the related banks, because analysts had to reprocess accounting data.

Specifically, our sample encompasses the data for more than 63 European banks (the maximum of banks we found in the Bloomberg data-base for our European study), but we decided to choose 51 banks from these.

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

Other reasons explaining why we have not been able to use all the 100 European banks for our regression analysis is because many of them disappeared during this period. Hence, "caja" banks from Spain do not figure in our sample because many of them went bankrupt or were taken over (e.g. with the creation of Bankia on 3/12/10 for some of them). Or simply because we could not obtain relevant data about them from our chosen databases, because the banks are just too small or not listed because of their "caja" status as for example "caisses d'épargne" and "mutual banks" in France (Savings-Banks).

In addition, Northern Rock had already been nationalized on 17/02/2008 in the UK as it was too dependent on market refinancing after a bank run during the summer 2007, Nationwide was partially nationalized, Bradford & Bingley was nationalised in the UK on 29/09/08, Alliance & Leicester was definitely acquired by Santander UK on 13/10/08.

Outside the UK, ABN Amro was taken over by Fortis, RBS and BNPPARIBAS (offer on 8/10/07), Sachsen LB was taken over by Landesbank Baden-Württemberg (LBBW), IKB was saved by its shareholders, Dresdner merged with Commerzbank on 11/05/09 after this last bank announced this future acquisition on 31/08/2008 and WestLB incurred embezzlement with its prop-trading department.

Furthermore, even if Banques Populaires Group and Caisses d'Epargne Group appear in the ranking of the Top 100 European banks, we have not been able to integrate them into our sample as they later merged creating the BPCE Group. Nor was using Natixis a possibility as their Corporate and Investment Banking branch depends a lot on this new BPCE Group and its business is quite specialized in comparison to most of the banks in our sample.

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

When we did not obtain the data for the whole period for less than 20% of our bank, it was not an issue as we were in a position to get what we needed concerning the evolution of their CDS and potential activation of our relevant indicators and triggers.

We also obtained CDS curves directly from Bloomberg for our studied period (1/01/07 to 12/03/13).

Note: this is more specifically the mid-spread (mid-point) that we studied. PCS=Pricing source: CBIN i.e. BBG CDS Intra NY.

As stated previously, we also use the 5-year Markit iTraxx Senior Financial index which comprises 25 equally weighted CDS for investment grade European entities (Bank and insurance companies). We selected exactly the same period as for the banks and insurance companies.

Also, we collected a lot of information on credit events for the 51 different banks with regards to the rise of capital, capital injection, nationalisation, 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.). See the list of bank credit events in appendix (restricted version in this paper that does not include tedious facts and figures on the credit events).

4.2 Descriptive statistics (indices)

Now, it is appropriate to specify the adapted trigger for our empirical approach, using the theoretical approach we have just developed.

As previously mentioned, between 01/01/07 and 17/05/10, the iTraxx SF and the iTraxx Europe tended to move closely together, except that from the beginning of October 2008 to the end of March 2009, the iTraxx SF curve was lower than the iTraxx Europe one (showing the impact of the financial crisis on big corporates as a whole).

Note that this is precisely on 17/05/10, when climbing again the 5-year iTraxx SF gets a third calculated T100 (Ter). Then, there was a transition period from 17/05/10 to 9/05/11, before the iTraxx SF and the iTraxx HIVOL started to move closely together from 9/05/11 until the

12/03/13. Indeed, as we noticed earlier, the 5-year iTraxx SF rose again and its curve went over the iTraxx HIVOL on 9/05/11.

This may also explain why the spreads of the European banks reached record levels from 13/09/11.

Now, we understand that the iTraxx Europe is definitely global, so it may be useful to consider that it consists of a kind of repository or reference which is very practical in order to shed light on our results.

The table below (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].

It is also of paramount importance to see that its median is very close to 100 (and also very close to its mean), which can then mimic a practical barrier (low "upper bound") at 100 bps, consistent with our 1st and 2nd conditions and give a complementary explanation to the *Hart and Zingales (2009)* trigger at 100 bps and to our previous theoretical 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%).

Of course, before July 2007 the trend for the low values is weak (under 25 bps) and around the low numbers we observe in our chart i.e. 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].

4.3 Analysis

From what we have just developed we might ask: 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, especially as this trigger at 100 bps is not optimum?

We have already calculated a T100 (BIS) on 20/10/08 and a T100 (Ter) on 17/05/10 for our iTraxx SF, that 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?

Going over 200 bps (rather than 300 bps which would be too high) shows that we exceed the natural tunnel set by the iTraxx Europe global index, meaning that the situation for a given bank is structurally abnormal and it is at risk.
It is important to consider this concept of a tunnel because it leads to subtle conclusions and we had to find an acceptable approach to monitor spreads on banks.

We now know that using a combined approach of a bank CDS and the iTraxx SF is not really efficient, especially once a still increasing spread exceeds the obtained T100.
So, a relevant response to that might now be designing our high "upper bound" at 200 bps, in the light of the conclusion of *Anderson (2009)* article, claiming that "spreads may be good proxies for differences in default probabilities in a cross section of firms".

Indeed, we can now understand why a T200 (200 bps giving an implied probability of default of 3.33% when the recovery rate amounts to 40%) is going to be a better choice than a T300.
What is more, the goal we had really tried to achieve, deals with the capability to monitor the bank spreads in our tunnel [0,200] bps with two practical barriers at 100 bps and 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), especially if the iTraxx SF is still deeply into [0, 100].
Thus, staying within [100, 200] has not to be considered as a normal situation and if nothing happens for a given bank after its two conditions gave a first T100, this bank need to be maintained under a very careful ongoing scrutiny and probably recapitalized one way or another.

Furthermore, if we are now 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).

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

However, lots of spreads were already comprised within [100, 200] before the mid-year 2011 and the Greek crisis new outbreak meant that most of the banks have not yet fully recovered from the subprime and financial crisis from 2007 to 2009.
This is why it is not at all surprising that our calculated T200 for our iTraxx SF index is released on 31/08/11, two weeks before European banking values fell on 12/09/11 and nearly two months before its peak on 25/11/11 within our whole period.

Obtaining a T200 for iTraxx SF means that the situation is more than preoccupying for the banking field, and luckily, this happened only once (31/08/11) within our period of study, even though we had found a first peak at 207 bps on 09/03/09 and 2 others before the 31/08/11.

5. Applied study

5.1 Optimization of our rule

As a result of the previous analysis, a way to tackle the issue of finding a correct trigger level requires not just one trigger, but two which produces a more dynamic approach by including the time for which a given bank spread goes from the first trigger to the second.

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

In effect, it is far more convenient and appropriate 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!

It also important to observe, for it produces some consistency, that a significant financial distress (requiring massive recapitalization, nationalization, rescue, etc.) occurs mainly most of the time pretty close to a given bank T200 trigger and 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**

Note that the second decision rule is no more taken into account. Thus, we can now show empirically in this applied study that it works well for any substantial financial distress for our sample of European banks. It remains to explain why we decided to use a period of 180 days.

Intuitively we might suggest that this chosen length of time of 180 days must be neither too short nor too long. In fact, if it is too short, that might not be sufficient time to observe a financial distress and if it is too long, there might be too many.

When the first trigger at 100 bps is activated, the concerned bank should raise equity and 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, for example, if the LFI debt is at risk.

However, no institution is perfect and regulators can make mistakes in classifying as adequately capitalized a bank which is not, hence our selection of a risk neutral probability of default equal to 3.66% (and not 1.66% or 5%).

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.

So, we consider that 6 months approximately is a classic period of time to turn around a company or at least, to notice the first positive profits made by decision makers of that company. Hence, the necessaire 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 (2009)* by developing this dynamic approach within our regulation procedure. Indeed, their selected Washington Mutual and especially Bear Stearns examples showed that the difference between the T200 and the T100 of these banks is inferior to 6 months (See the CDS curve of these banks in their paper).

5.2 Detailed applied study methodology

We choose to use a Probit model

- P($\boldsymbol{y_i}$=1 $\mid \boldsymbol{x_i}$) = 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, we just use one regressor, x_i

- where $\boldsymbol{x_i}$ is a dummy for the bank i such that $\boldsymbol{x_i}$=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 robustness check in the next sub-section with the help of TABLE A "Global results per bank" for a number of 220 days and the related regression, especially with regards to the statistical results that accompany it, in appendix).

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 these 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 i.e. the sooner, the better hence our theoretical choice of a 180-day period i.e. 6 months.

We have proposed some hypotheses 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.

If a sampled bank has no financial distress during the entire period of our study then, this is the simplest and reveals nothing. Furthermore, we need to draw attention to the fact that all of our 6 banks that did not get a T200 trigger automatically had no financial distress which reduces any doubts we might have had about the choice of this trigger at 200 bps. Now we consider what happened for more than half of our banks when we suggest that a financial distress did effectively occur.

If we have correctly defined a "financial distress" what part for the whole period of our study do we have the right to take into account when the 3rd condition has been activated?

Firstly, a given financial distress has to exist before our prediction using our 3rd condition (meta-rule), although we even took into consideration a few credit events that happened before, and even some weeks before the calculated first T100 (cf. Standard Chartered Bank). We take into account the financial distress for this approach, even when the trigger was not activated for example Fortis and Lloyds TSB banks.

Secondly, if during our period of study there was a first pair (T100, T200) that did not lead to trigger activation for our 3rd condition, then if another pair (T100, T200) that works this time or appears later, we would not take into account the trigger activation. This is why even if we retained a financial distress for UBS we decided that no 3rd condition had to be activated.

Finally, we state that counting a credit event occurring more than two years after the 3rd condition has been activated does not make much sense and so, though we find an activated trigger with Banco Popular Espanol SA, we did not keep it as a financial distress despite the fact that it had eventually to raise €2.5bn capital.

Indeed, this two-year period is consistent with *Miller, Olson and Yeager (2015)* as we mentioned in the introduction, because they used Expected Default Frequency (EDF) signals from 2007 to 2008 that succeeded in identifying Bank Holding Companies (using 473 BHCs) in the USA that became distressed within two following years (even if their economical impact concerning reducing missed distress events is not significant). They also examine signals based on the Federal Reserve SEER model that have directly a two-year failure probability for a Bank Holding Company (BHC) such as the Current Failure Probability (CFP) or the Dated Failure Probability (DFP).

<u>Highlighting on some interesting results: using our new approach and discussion using the same four banks</u>

(See in appendix our graphed data for these four systemic banks).

<u>Banca Monte dei Paschi di Siena S.p.A. (MPS)</u>: T100 (Ter)=18/05/10, **T200=29/09/10.**

<u>Revised Conclusion</u>: with our 3rd condition, it is now clear that a stronger intervention should have occurred on 29/09/10. In fact, our first condition for the T100 had then been activated the last time on 18/05/10 followed by a T200 on 29/09/10, and T200 – T00 = 131 (≤ 180 days).

So, using our revised model intervention could have been indicated nearly two years earlier for this bank (recapitalization in July 2012, followed by a bailout request of €3.9bn on 26/01/13).

<u>Allied Irish Bank (AIB)</u>: T100=26/02/08, **T200=05/01/09**.

<u>Revised Conclusion</u>: according to our research, we saw that the first plan (€3.5bn) arranged by the Irish government started on 12/02/09 which is hopefully after but quite close to the date of our calculated T200 giving this last trigger some meaningful properties!

However, although that an intervention should have certainly been made at least on 05/01/09, our 3rd rule did not predict what happened later in 9/06/11 (restructuring credit event issued by the ISDA), because T200 – T100 = 309 > 180 days.

<u>Banco Commercial Portugues SA (BCP)</u>: T100 (Ter)=11/02/10, **T200=12/05/10**.

<u>Revised Conclusion</u>: we mentioned previously that BCP was downgraded on 2/06/10 by Moody's, following the downgrading of the Portuguese government to A1.

The fact that Moody's chose this date is satisfying as it is consistent with our model as the 3rd rule was activated on 12/05/10 and we obtain a period of 91 days between the last T100 and the T200. Then, it is all the more remarkable to notice now that our bank CDS spread went for a peak at 562.09 bps on 07/05/10 confirming the rapid growth between our last T100 and the following T200 (only 91 days).

It is even harder to understand why no serious action had been undertaken at least in 2011, as we “simply” got a peak at 1739.05 bps on 25/11/11!

With our 3rd rule the intervention could have been implemented nearly two years earlier as all ended with a €3bn rescue on 7/06/12.

Dexia Credit Local SA: T100=16/07/08, T200=16/09/08 and T200 (BIS)=18/05/10.

Revised Conclusion: as French, Belgian and Luxembourg states injected €6.4bn capital into Dexia on 30/09/08, but our calculated T200 and the 3rd condition had already been activated and it produces a very short period of 60 days that does not add a strong added value. Indeed, it just confirms that the trends were not good at all for this bank as it indicated possible risks.

However, it is worth noting that Dexia announced a restructuring plan on 6/02/10 approximately 3 months before our T200 (BIS) date, even if this time the 3rd rule was not released.

Strictly speaking, our 3rd rule would have suggested an intervention only 2 weeks earlier for this bank.

5.3 Robustness check

The econometrics tests of robustness are linked to our theoretical discussion as well as the discussion on the methodology of the applied study. The dependent variable is the Financial Distress (FD).

Indeed, the z-statistic of the explanatory variable FD_Predicted which stands for a prediction sets to one issued by our model, is really significant, especially when the number of days is equal to 180, 200 and 220 with a p-value at the 1% level as shown in the regressions in Appendix. The Price to Book Ratio is significant at the 5% level for 180, 200 and 220 days and the Tier1 Capital Ratio has its best coefficient at the 5% level for 220 days and only at the 10% level for 180 and 200 days. The Return On Asset variable is never significant.

These correct results for the regression coefficients are also backed by the quality of the model when looking at the p-value of the Likelihood ratio test which is significant at the 1% level for the first three columns (180, 200 and 220 days).

The 180, 200 and 220-day columns also give the best Schwartz criterion i.e. the smallest numbers for our different simulations as well as the larger Log-likelihood when we look the related statistical results for each regression in the appendix.

But if the 220-day column gives the best result for the McFadden R-squared at 0.33 and the lowest p-value at the 1% level for the Likelihood ratio test indicating that the coefficients of the regression are really significant, the number of cases correctly predicted at 79.5% is the second best. Indeed, the 240-day column has the highest level at 82.1%. However, the FD_Predicted variable is only significant at the 10% level for 240 days (and not significant for 260 days).

We could add other explanatory variables in order to raise the value of the McFadden R-squared, but this could create interference or noise in our results. Primarily, we want to capture the best direct link between bank CDS spread thresholds that build the FD_Predicted variable and the potential related Financial Distress.

It is also important to mention that we eventually had to consider for the regressions 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).

Indeed, from the Bloomberg data-base, we collected some financial variables such as Return On Assets, Tier 1 Capital Ratio and Price to Book Ratio which are used as control variables (see in appendix the Table of the variable definitions given by Bloomberg).
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.

RETURN_ON_ASSET is an indicator of how profitable a company is relative to its total assets, expressed as a percentage. It gives an idea as to how efficient management is at using its assets to generate earnings.

TIER1_CAP_RATIO variable (Tier 1 Capital Ratio) is defined as the ratio of Tier 1 capital to risk-weighted assets.
The smaller it is, the riskier is the bank.

PX_TO_BOOK_RATIO is a classical ratio which is market oriented for being equal to the last price divided by the BOOK_VAL_PER_SH i.e. book value per share (book value of equity).

It is also interesting to note that the subset of the 39 banks maintain 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.

5.4 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, as mentioned earlier, all of our European banks had their T100 activated during the second year of our period of study, but that does not mean that nothing as to be done.

The same rationale applied to the T200 calculated for the iTraxx SF, especially because 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 next following T200 (if there is one). Then, when the number of days between the T200 and the T100 is under or equal to 180 days i.e. T200 –T100 ≤ 180 days, trigger a “real intervention”! As previously stated, all of our 6 banks that did not get a T200, automatically did not come under any financial distress.

Note that during the first quarter of 2009, the iTraxx SF unsurprisingly went over 200 bps at 207 bps on 09/03/09. It is also worth pointing out that in the graph of the trend of average CDS spread values we also find a peak during the first quarter of 2009, and that it nearly reached 350 bps. Now, this striking difference may be explained by the fact that these 57 banks are chosen from all over the world and are not necessarily systemic, like the sixteen European ones that are used in the iTraxx SF index.

Indeed, we have to consider that we have only studied European banks and that it would seem to be an asset that the iTraxx SF is based on systemic ones, for precisely being an index. Our rationale is all the more consistent in that the two more indices mentioned in our study belong to the iTraxx family and are complementary to the iTraxx SF.

A quite similar approach can give meaningful results when monitoring the iTraxx SF (with both other indices) in that, for example, on 9/05/11 the iTraxx SF climbs again and its curve goes over the iTraxx HIVOL on this day and then, they move closely together till the 12/03/13.

Consequently, we have reason to worry if we remember that between 01/01/07 and 17/05/10, the iTraxx SF and the iTraxx Europe moved closely together, except that from the beginning of October 2008 to the end of March 2009, where the iTraxx SF curve was higher than that of iTraxx Europe which indicated that bank and insurance companies incurred more risks during that period than the companies from other industries.

It is also worth noting that during our period of study, the 3rd decision rule / condition has been never activated for the iTraxx SF. Indeed, being an index, its curve fluctuations are smoother than a classic bank spread curve. This also shows that our 3rd condition is more adapted for a single name CDS spread which is consistent for each bank we studied.

6. Conclusion

In order to focus on our theme i.e. “CDS and the forecasting of bank default” for the European Market, we first tried to explain why CDS were sufficiently reliable to lead other markets in terms of information and price discovery, after having undertaken a short review on different Early Warning System models (for bank default or banking crises) that gave various results.

Though CDS spread cannot be taken as a perfect proxy of the true probability of a default (PD) of the underlying corporate, it still may be of interest to use them as an indicator for this purpose, provided that the relevant trigger has been activated. That was our initial proposal partly based on the article of *Hart and Zingales (2009)* using the following procedure: “trigger intervention whenever the CDS price is above 100 bps for at least 20 of the last 30 trading days”.

However, as the CDS forecasting power is not optimal, we had to investigate further to show with our three short sets of conclusions (point one to eight) that a second indicator was necessary to optimize the procedure giving two conditions. Initially, 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).

We studied 50 (among the TOP 100 European banks) of our 63 European bank sample and selected a few to examine the reliability of both indicators with a trigger at a 100 bps threshold but the results were disappointing.

Considering a theoretical approach and with the help of the iTraxx Europe index (125 corporate entities), we identified a tunnel for their spread curve that fluctuates within [0, 200] during our period of study.

Our period of study spans more than six years and from our results we realised that we needed to add another trigger level at 200 bps. In fact, we had had first to address the question: what if the curve keeps on rising after the first T100 is exceeded?

Consequently, we changed our approach slightly in that we found that if the forecasting power of the banks’ spreads matters it was also appropriate to directly monitor the bank spreads in the [0, 200] tunnel.

It also led us to design a meta-rule that added a strong dynamic 3rd decision rule / condition: 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.

But 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, concerning the intervention of regulators as this could be really helpful to them.

7. Appendix

7.1 Tables of the applied study for the 50 banks

TABLE A – 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 1 and 2 – 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. 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%.

1. TABLE 1: 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

2. TABLE 2: 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

TABLES of events and predictions: number of events and number of correct predictions for each of the five probit regression

Regression (1): Nb of days = 180

	Nb of events	Nb correct predictions
Default=0	16	10
Default=1	23	20
Total	39	30

Regression (2): Nb of days = 200

	Nb of events	Nb correct predictions
Default=0	16	10
Default=1	23	20
Total	39	30

Regression (3): Nb of days = 220

	Nb of events	Nb correct predictions
Default=0	16	10
Default=1	23	21
Total	39	31

Regression (4): Nb of days = 240

	Nb of events	Nb correct predictions
Default=0	16	11
Default=1	23	21
Total	39	32

Regression (5): Nb of days = 260

	Nb of events	Nb correct predictions
Default=0	16	10
Default=1	23	20
Total	39	30

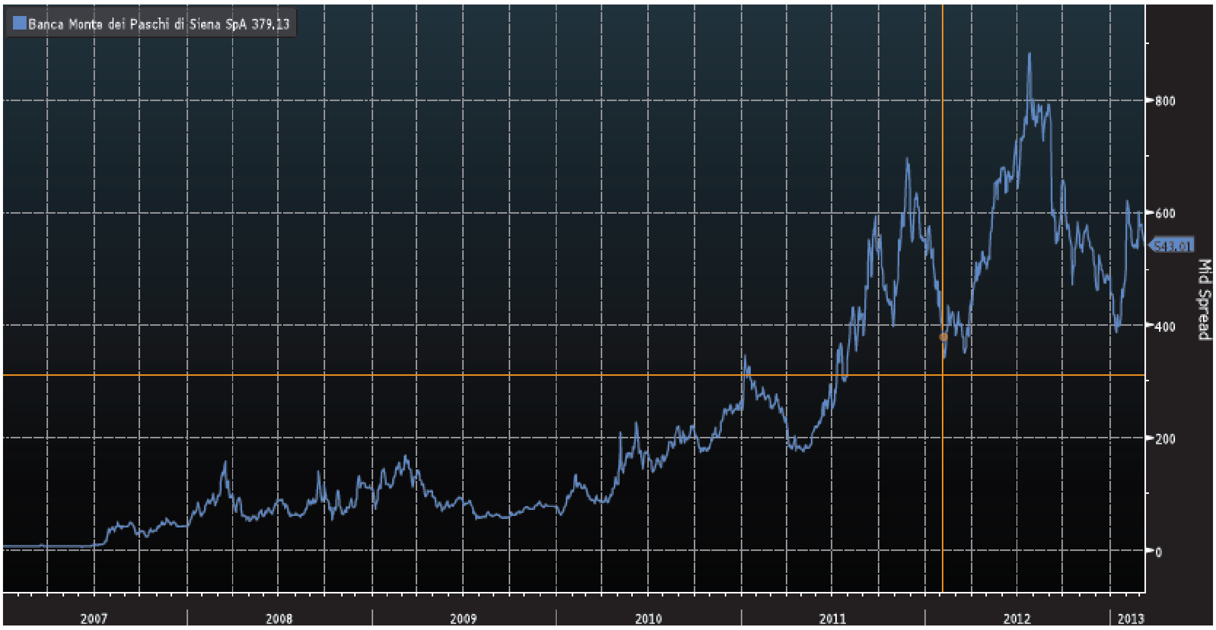
TABLE “Variables’ definition”

SELECTED BLOOMBERG VARIABLES	VARIABLES’ DEFINITION
TOT_ASSET	BANKS Total Assets: This is the sum of Cash & bank balances, Fed funds sold & resale agreements, Investments for Trade and Sale, Net loans, Investments held to maturity, Net fixed assets, Other assets, Customers' Acceptances and Liabilities.
RETURN_ON_ASSET	Indicator of how profitable a company is relative to its total assets, in percentage. Return on assets gives an idea as to how efficient management is at using its assets to generate earnings. INDUSTRIALS, BANKS, FINANCIALS, UTILITIES, & REITS Calculated as: (Trailing 12M Net Income / Average Total Assets) * 100 Where: Trailing 12M Net Income is RR813, TRAIL_12M_NET_INC Average Total Assets is the average of the beginning balance and ending balance of TOT_ASSET (Cf. above)
TIER1_CAP_RATIO	Banks Tier 1 Capital Ratio: Tier 1 or Core capital ratio. Tier 1 is used for commercial banks and core capital is used for savings and loans in the United States (U.S.). The ratio of Tier 1 capital to risk-weighted assets. For Core Tier 1 Capital Ratio see Core Tier 1 Capital Ratio (BS895, BS_CORE_TIER1_CAPITAL_RATIO). Common stockholders' equity: Qualifying perpetual preferred stock. Minority Interest in consolidated subsidiaries less Goodwill and other disallowed intangibles. Core capital for savings and loans: Common stockholders' equity. Noncumulative perpetual preferred and surplus. Minority interests less intangible assets (other than PMSR). The ratios are discussed in the Cooke Committee and adopted by each country. The information is provided in terms of absolute numbers and percentages. If the absolute amounts are disclosed, the percentages should be computed for this account. Slightly different ratios are defined for commercial banks and

	savings and loans. The minimum ratios set by the U.S. Federal Reserve and OTC are 4% for commercial banks and 3% for savings and loans, respectively. Europe: The Bank of International Settlements in Basel requires a Tier I ratio of 4.4%. In Europe it is referred to as the BIS ratio, the European Solvency ratio, or the Cooke ratio as the Cooke committee established it.
BOOK_VAL_PER_SH	Measure used by owners of common shares in a firm to determine the level of safety associated with each individual share after all debts are paid accordingly. Units: Actual Calculated as: Total Common Equity / Number of Shares Outstanding Where: Total Common Equity is RR010, TOT_COMMON_EQY Shares Outstanding is BS081, BS_SH_OUT
PX_TO_BOOK_RATIO	Ratio of the stock price to the book value per share. Calculated as: Price to Book Ratio = Last Price / Book Value Per Share Where: Last Price is PR005, PX_LAST Book Value Per Share is RR020, BOOK_VAL_PER_SH Data from the most recent reporting period (quarterly, semi-annual or annual) used in the calculation. Portfolio: Computed as the Total Market Value (IN089, INDX_MARKET_CAP) divided by the sum of Book Value from holdings. Contributions are computed as the value of Book Value Per Share (RR020, BOOK_VAL_PER_SH) of the security multiplied by the number of shares held.

7.2 CDS curves for our interesting results from Bloomberg

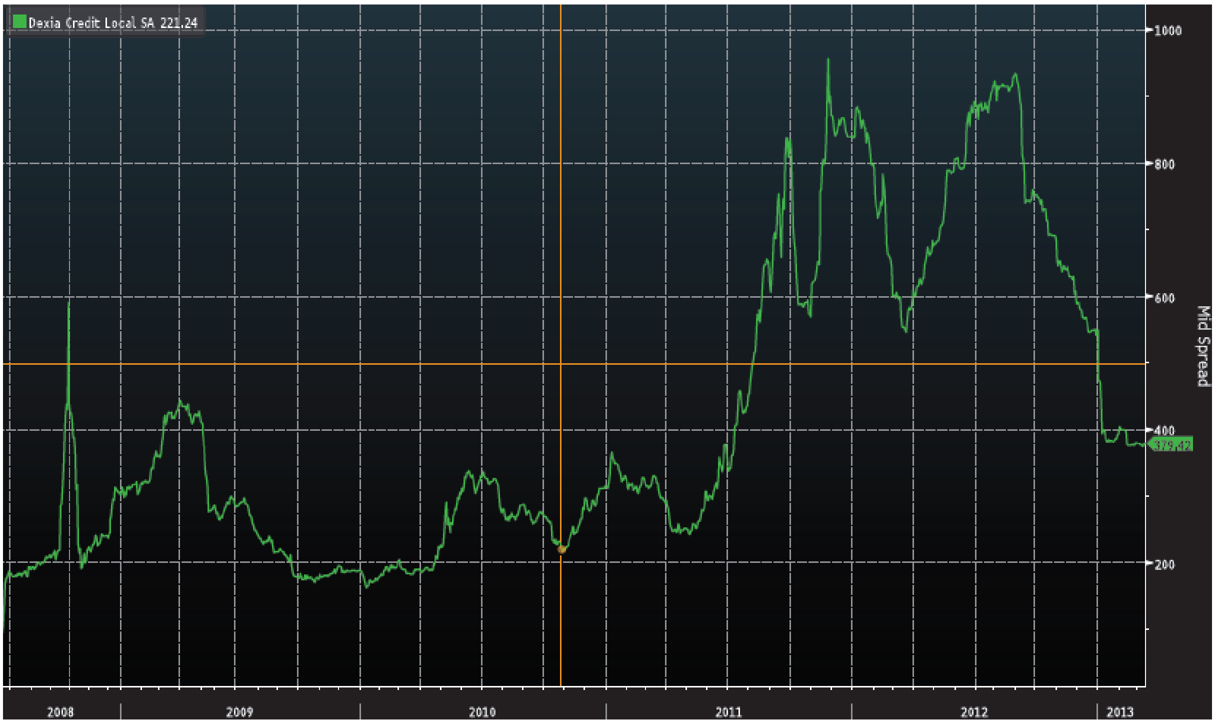
Banca Monte dei Paschi di Siena S.p.A. (MPS)



Allied Irish Bank (AIB)

Banco Commercial Portugues SA (BCP)

Dexia Credit Local SA



7.3 Timeline

A timeline of prominent events

- 8/02/07: HSBC plunges to its weakest level for 9 months, because of a rise of its provision for bad debts (real estate i.e. subprime mortgage) at $10bn.
- July 2007: because of the subprime mortgage the losses announced by HSBC, that make CDS spread rise sharply and this can be taken as a sign for the beginning of the crisis.
- 14/03/08: Bear Stearns is about to fail (it will be taken over on 16 March by JP Morgan). The 5-year iTraxx Senior Financial reaches the 20 out of 30 sessions above 100 bps on the same date i.e. our calculated T100 for this iTraxx SF index happens also on 14/03/08.
- 15/09/08: Lehman brothers file for bankruptcy.
- 20/10/08: after staying under 100 bps during 6 months, iTraxx SF gets a second calculated T100 (BIS) on 20/10/08.
- 11/01/10: weakest point since mid-2008 for the 5-year iTraxx SF during our period of study spanning from 1/01/07 to 12/03/13.
- 17/05/10: climbing again, the 5-year iTraxx SF gets a third calculated T100 (Ter) on 17/05/10.
- 9/05/11: the 5-year iTraxx SF climbs again and its curve goes over the iTraxx HIVOL on this day and they move closely together until 12/03/13.
- 31/08/11: The 5-year iTraxx Senior Financial reaches the 20 out of 30 sessions above 200 bps i.e. our calculated T200.

Note: we use T100 (BIS) for the second time the trigger is activated and T100 (Ter) for the third calculated T100 during the period of study.

7.4 List of European bank credit events (restricted version with no detail)

Company Name	Bank Credit events based on trigger activation
Allied Irish Bank	T100=26/02/08 (S). T200=05/01/09
Anglo Irish Bank (Irish Bank Resolution)	T100=21/11/07 (S). T200=17/03/08
Bancaja	T100=03/12/07. T200=26/02/08. T=iTraxx SF
Banca Monte dei Paschi di Siena S.p.A (MPS)	T100=30/12/08 (S). T100(Ter)=18/05/10. T200=29/09/10
Banco Comercial Portuges SA (BCP)	T100=13/03/08 (S). T100(Ter)=11/02/10. T200=12/05/10
Banco Esperito santo SA (BES)	T100=11/03/08 (S). T200=12/05/10
Banco Popular Espanol SA	T100=18/02/08. T=iTraxx SF. T200=27/08/08. T200 (BIS)=14/05/10
Banco de Sabadell SA	T100=13/02/08 (S). T200=05/09/08. T200(BIS)=03/03/10
Banco Popolare	T100=28/02/08. T=iTraxx SF. T200=16/03/09. T200(BIS)=16/06/10
Banco Popolare di Milano Scarl (BPM)	T100=02/12/08. T100(BIS)=25/05/10. T200=05/07/11
"Banco Santander SA"	T100=21/03/08 (S). T100(Ter)=16/02/10. T200=21/12/10
Bank of Ireland	T100=15/02/08 (S). T200=22/09/08
Bankinter SA	T100=18/03/08 (S). T200=28/11/08. T200 (BIS)=21/05/10
"Barclays Bank PLC"	T100=23/07/08 (S). T200=20/03/09
Bayerische Landesbank (Bayern LB)	T100=11/03/08. T=iTraxx SF. T200=05/09/11
BBVA	T100=16/02/09. T100(Ter)=16/02/10. T200=14/06/10
"BNP Paribas SA"	T100=31/03/09 (S).T100 (Ter)=01/06/10. T200=06/09/11
"Credit Suisse Group"	T100=16/10/08 (S). No T200
Caja Madrid	T100=18/02/08. T=iTraxx SF. T200=02/10/08
Caixa Geral de Depositos	T100=14/03/08. T100 (Ter)=23/02/10. T200=20/05/10
"Commerzbank AG"	T100=14/03/08 (S). T100(Ter)=25/05/10. T200=30/08/11
"Credit Agricole SA"	T100=19/03/08 (S). T100 (Ter)=19/05/10. T200=01/09/11
DNB Bank ASA	T100=07/11/08 (S). No T200
Dankse Bank A/S	T100=23/10/08 (S). T100(Ter)=10/12/10. T200=09/09/11
"Deutsche Bank AG"	T100=10/10/08 (S). T100(Ter)=19/05/10. T200=01/12/11
Dexia Credit Local SA	T100=16/07/08 (S). T200=16/09/08. T200 (BIS)=18/05/10
Esrte Group Bank AG	T100=06/03/08 (S). T100(BIS)=23/07/08. T200=02/03/09
Fortis	T100=11/03/08. T100(Ter)=28/05/10. T=iTraxx SF. T200=8/09/11
HBOS	T100=13/03/08. T=iTraxx SF. T200=29/09/08
"HSBC Holdings PLC"	T100=16/12/08 (S). No T200
"ING Bank NV"	T100=11/03/08 (S). T100(Ter)=31/05/10. T200=08/12/11
"Intesa Sanpaolo SpA"	T100=24/12/08 (S). T100(Ter)=20/05/10. T200=04/08/11
Kaupthing Bank Hf	T100=13/09/07. T200=03/12/07
KBC Bank NV	T100=16/10/08. T200=30/12/08. T200 (BIS)=04/02/11
"Lloyds TSB Bank PLC"	T100=10/10/08 (S). T100(Ter)=26/12/08. T200=16/06/10
Mediobanca	T100=13/10/08 (S). T100(Ter)=27/05/10. T200=05/08/11
Nordea Bank Ab	T100=29/10/08 (S). T100(BIS)=05/10/11. No T200
Norddeutsche Landesbank Girozentrale	T100=13/11/08. T200=19/09/11
Rabobank	T100=15/12/08 (S). No T200
Raiffensen	T100=24/07/08 (S). T200=16/12/08
Santander UK	T100=25/02/09. T100(Ter)=19/05/10. T200=31/08/11
SEB	T100=05/08/08. T200=26/03/09. T200(BIS)=07/10/11
SNS Bank NV	T100=04/03/08. T=iTraxx SF. T200=22/06/10. T200 (BIS)=16/10/08
"Societe Generale SA"	T100=16/12/08 (S). T100 (Ter)=19/05/10. T200=30/08/11
"Standard Chartered Bank"	T100=23/07/08 (S). T200=20/03/09
Svenska Handelsbanken AB	T100=31/12/08. T100(BIS)=21/10/11. No T200
"Royal Bank of Scotland PLC/The"	T100=11/03/08 (S). T200=16/06/10.
Ubi Banca	T100=15/10/08. T200=20/01/11
"UBS AG"	T100=13/03/08 (S). T100(Ter)=27/06/11. T200=13/01/09. T200 (BIS)=15/12/11
"UniCredit SpA"	T100=30/10/08 (S). T200=16/03/09. T200(BIS)=12/07/11

<u>Note</u>: we use T100 (BIS) for the second time the trigger is activated and T100 (Ter) for the third calculated T100 during the period of study. (S) is used for a systemic bank.

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