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## Alarm System for Credit Losses Impairment under IFRS 9

Yahia Salhi · Pierre-E. Thérond

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**Abstract** The recent financial crisis has led the IASB to settle new reporting standards for financial instruments. The extended ability to measure some debt instruments at amortized cost is associated with a new impairment losses mechanism: Expected Credit Losses. The standards set out some disposals based on so-called three-stage provision measures. To implement this insurers are invited to use forward-looking measures of creditworthiness in order to anticipate and provision future deterioration. To do so, the norms explicitly invoke the use of available market information. In this paper, after a brief description of the principles elaborated by IASB for IFRS 9, we investigate a simple yet interesting procedure using credit default swaps (CDS for short) market prices in order to monitor significant changes in credit quality of financial instruments and subsequent credit losses impairment. This methodology is implemented in detail to a real world dataset. Numerical tests are drawn to assess the effectiveness of the procedure especially compared to changes of notation from credit rating agencies.

**Keywords** Financial Reporting · IFRS · Impairment · Credit Risk · Expected Credit Losses · Detection · Default · CDS

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## 1 Introduction

The financial crisis shed light on the need to strengthen, among others, accounting recognition of credit loss provisions. It highlighted the need of incorporating a broader range of credit information than the current practice under IAS 39 and IFRS statements suggest, see [Barth and Landsman, 2010]. Recently, the International Accounting Standards Board (IASB) together with the Financial Accounting Standards Board (FASB) also highlighted the need to recognize credit losses related to loans commitments and financial guarantee contracts. In IFRS 9: *Financial Instruments* (published by IASB on July 24, 2014, see [IASB, 2014]), preparers are invited to incorporate expected credit losses before they have been incurred. This is motivated by the fact that the delayed recognition of credit losses was identified by the Financial Crisis Advisory Group (FCAG) as a weakness in existing accounting standards (IAS 39) during the last financial crisis.

The current practice in the IAS 39 uses incurred losses that arise from past events and actual conditions. Thus, variations in expected future credit loss events are generally not considered. Moreover, such an approach is subject to much criticism due to the significant divergence that occurs in practical applications, which harden the task for stakeholders and users of financial statements to make comparison among entities, see [Magnan and Markarian, 2011]. From a more global view, this mechanism (like the principle for impairment losses on equity securities, see [Azzaz et al., 2015]) has been judged pro-cyclical and lead to a *snowball effect* among financial institutions (banking establishments through their loans and insurance companies which mainly invest in bonds) and, then, to the so-called “real economy”.

Therefore, the new standards set out some disposals that are based on a so-called *three-stage* model for impairment of provisions related to credit risk deterioration. This is intended to provide information about changes in the credit quality of financial instruments. This three-stage procedure requires an entity to firstly distinguish between

- *financial instruments that have not deteriorated significantly in credit quality since initial recognition.* For those instruments, 12-months expected credit losses are recognised in profit or loss ; and
- *financial instruments that have increased significantly in credit risk since they have been originated or purchased.* For those instruments, lifetime expected credit losses are recognised in profit or loss.

In the second case, interest revenue are modified whether the instrument is considered credit-impaired or not. More details are given in Section 2.

Based on this new accounting standards one should be able to early detect any deterioration of the borrower’s creditworthiness. One can imagine that the outlooks given by credit-rating agencies will remain a standard for this purpose. Nevertheless these assessments are generally pro-cyclical and may lack of accuracy. So we believe that they should not be the single reference for impairment losses purposes. The same view is expressed Within the Basel

Committee’s guidance (see [BIS, 2015]): “The Committee expects banks to rely primarily on their own credit risk assessments in order to evaluate the credit risk of a lending exposure, and not to rely solely or mechanistically on ratings provided by credit rating agencies (where the latter are available)”.

It thus seems important for bonds holders to rely on alternative or complementary market indicators to assess the credit quality up to maturity in order to fill IFRS 9 requirements. To this end a monitoring strategy could be useful and one can rely on the current market conditions in order to track the credit quality of bonds. In this case, one need a representative quantity that assesses the credit quality during the period of interest. Therefore, we build an indicator assessing quantitatively the credit quality evolution allowing the monitoring of any deterioration and sounding an alarm once the latter is detected. More formally, we construct default probabilities based on the market available information. These market-implied default probabilities will determine the credit risk level inherent in all securities depending on the same borrower.

If there is no precise definition of *default* in IFRS 9 (§B5.5.37 of [IASB, 2014]) invites the entities to consider *a default definition that is consistent with the definition used for internal credit risk management purposes*), we rely, in this paper, on the celebrating approach proposed in [Lando, 1998]. This is the so-called reduced-form model of default, which provides a natural framework for establishing a robust proxy for credit risk through the intensity of default. This approach is used to derive prices of most liquid product in the credit derivatives market, see Section 3. Therefore, we use the latter to extract the information flow on the creditworthiness of a given entity. To do so, we use a closed-form formula based on an adequate specification of the intensity dynamics to recover the intensity of default from market quotes. This implied intensity incorporates the market forward-looking appreciation of the underlying entity own credit risk. This will be used to assess the need for an impairment as suggested by the financial reporting standard.

**Table 1:** *Figures from consolidated financial reports 2013. Debt instruments measured at fair value through other comprehensive incomes (FVOCI), at amortized cost and at fair value through profit or loss (FVPL) are reported. The bottom panel depicts the percentage of debt instruments over the total financial investments detained by the considered companies.*

	Allianz	Axa	CNP Assurances	Generali
<b>Total financial investments</b>	<b>411.02</b>	<b>450.04</b>	<b>339.56</b>	<b>342.04</b>
<b>Debt instruments</b>				
FVOCI	359.73	319.62	209.52	212.679
Amortized Cost	4.65	6.52	0.60	59.003
FVPL	2.37	34.24	30.32	8.691
<b>Total</b>	<b>366.74</b>	<b>360.37</b>	<b>240.44</b>	<b>280.37</b>
	89%	80%	71%	82%

To do so, we set up an appropriate surveillance strategy aiming at sounding an alarm as soon as the market implied intensities suggest a change of regime. In other words, the sequential estimated default intensities are monitored in order to detect any deviation from a given initial credit quality at the recognition date to a more riskiest level. Formally, the monitoring strategy relies on the specification of a critical regime, which corresponds to the case where the credit worthiness of the considered entity belongs to the non-investment grades. This critical regime is characterized using the *average implied intensity* for entities within the non-investment grades category. Hence, the sequential surveillance is operated using the well-known *cusum* procedure which measures sequentially the *distance* between the actual regime and the critical one. The alarm for credit deterioration is sounded as soon as the entity enters into the rating category of interest. By doing so, we aim at anticipating the change of grade as we may see in Section 4 and advocated by the accounting standards discussed in Section 2.

The remainder is organized as follows. In Section 2, we recall the principles introduced in the IASB's IFRS 9 regarding the impairment of financial instruments measured at amortized cost of *Fair Value through Other Comprehensive Income* (FVOCI). We present the main challenges and key issues when it comes to recognize *significant* credit risk deterioration. We also discuss the use of market information to recognize creditworthiness. In Section 3, we recall financial concepts related credit risk and discuss the representative credit information embedded in each product. Hence, we explain how default intensities used as a proxy of credit deterioration can be recovered from market quotations. Next, we use these quantities as to assess and monitor the creditworthiness. The latter is handled using a detection procedure introduced in Subsection 3.3. Finally, in Section 4, we carry out an empirical analysis on real-world data.

## 2 Credit Losses Impairment

The aim of this section is to present the principles for recognizing credit losses impairment as required in IFRS 9.

### 2.1 Principles

The present IAS 39 states that *an impairment loss is recognised only when it has been incurred*. More precisely §58 in [IASB, 2014] specifies that *an entity shall assess at the end of each reporting period whether there is any objective evidence that a financial asset or group of financial assets is impaired*. If some quantitative principles have been given in order to deal with equity securities objective evidence of depreciation (the *significant* and *prolonged* criteria studied in [Azzaz et al., 2015]), there are no such criteria with regard to the

debt instruments. Until recently, impairment losses are recognized in the financial statements whenever there is an objective evidence of depreciation. In other words, only incurred (or almost sure) losses are recognized for debt instruments. This mechanism has been criticized by the FCAG which recommended to explore some more forward-looking alternatives. This is the topic of impairment requirements of the recent [IASB, 2014] norms.

The main requirements consist in setting an *expected credit loss model* (ECL) in order to overcome the weaknesses identified by the FCAG. This approach advocates recognizing expected credit losses as a loss allowance. Three stages of credit deterioration are defined:

- *Stage 1 (performing)*: Financial instruments that have not deteriorated significantly in credit quality since initial recognition (or have a low credit risk at the reporting date).
- *Stage 2 (underperforming)*: Financial instruments that have deteriorated significantly since initial recognition (unless they have a low credit risk at the reporting date) but do not have objective evidence of a credit loss event.
- *Stage 3 (non-performing)*: Financial instruments for which credit risk has increased to the point that they are considered credit-impaired.

At initial recognition, a financial debt instrument is supposed to be in Stage 1 (unless for *purchased or originated credit-impaired financial assets*). At each reporting date, the entity holding such an instrument will have to assess whether credit risk has increased significantly since initial recognition (Stage 2) and if there is any objective evidence of impairment (Stage 3) in order to maintain it at Stage 1 or downgrade it at Stage 2 or Stage 3. Considerations about assessment of credit risk significant increasing are given in Subsection 2.3.

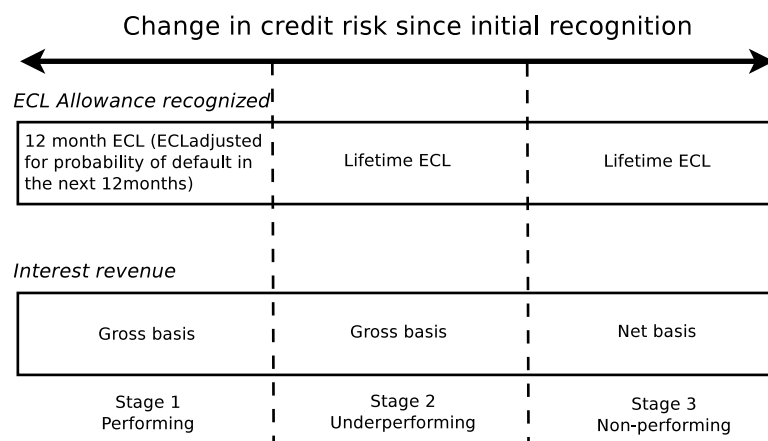
**Table 2:** *IFRS 9 impairment requirements synthesis*

Stage	Definition	Measurement
1	No significant increase in credit risk since initial recognition or 'low credit risk' at reporting date	12-month ECL
2	Significant increase in credit risk since initial recognition (and not 'low credit risk' at reporting date)	Residual lifetime ECL
3	Objective evidence of impairment	Residual lifetime ECL

The level of loss allowance has to be determined with regard to the stage in which the financial instrument stands. When the credit risk on that financial instrument has not increased significantly since initial recognition, an entity shall measure the expected credit losses for that financial instrument at an amount equal to the 12-month expected credit losses. Otherwise this measurement shall be equal to the lifetime expected credit losses. In terms of financial reporting, the entity should recognize in profit or loss the amount of expected

credit losses (or reversal) needed to adjust the loss allowance or provision to the balance-sheet (at the reporting date) under this standard.

These rules can be summarized as in Table 2 and figure Figure 1.



**Fig. 1:** Overview of the general impairment model

## 2.2 Presentation and Disclosures

As a consequence of expected credit losses presented in Subsection 2.1, an entity should present in the statement of profit or loss :

- interest revenue (effective interest rate applied to the gross carrying amount);
- and
- gains or losses resulting from changes in ECL.

As an exception, when there is objective evidence of impairment resulting from events that occurred after the initial recognition or if the asset was already credit-impaired at initial recognition (i.e. for Stage 3 assets), interest revenue has to be calculated using the effective interest method on the net (of loss allowance) carrying amount.

Beyond the financial statements, disclosures are required in order to identify and explain the amounts of ECL that arises in the financial statements, i.e. the effect of changes in credit risk. These disclosures consist mainly in :

- reconciliation of gross carrying amounts and allowance balances;
- disclosures on credit risk grading;
- disclosures on techniques, assumptions and policies underlying the assessment of credit risk.

### 2.3 Assessment of Significant Increases in Credit Risk

In order to assess credit risk, the entity should consider *the likelihood of not collecting some or all of the contractual cash-flows over the remaining maturity of the financial instrument*, i.e. to assess the evolution of the probability of default (and not of the loss-given default for example). The standard did not advocate a particular method for this assessment but included the two following operational simplifications:

- For financial instruments with 'low-credit risk' at the reporting date, the entity should continue to recognize 12-month ECL;
- there is a rebuttable presumption of significant increase in credit risk when contractual payments are more than 30 days past due.

In practice, most credit risk watchers rely on ratings and outlooks released by major rating agencies, e.g. Moody's, Standard & Poors and Fitch among others. These ratings evaluate the creditworthiness of institutional and governmental debtors and assign a grade class for each depending on their default likelihood. Different tranches of creditworthiness are available ranging from Aaa to Baa3 for investment grades and Ba1 to C for speculative grades<sup>1</sup>. For each entity the rating may evolve over time when relative fundamental creditworthiness changes.

Thus, credit ratings could be a valuable source of information for investors assessing the riskiness of their exposures. However, it turns out that credit rating agencies base their ratings on backward-looking accounting information which may not be useful to for impairing credit losses, especially when it comes to predict future losses. Indeed, IFRS 9 advocates the use of *information that is more forward-looking than past-due information*, see [IASB, 2014, §9]. Moreover, aside the accuracy of the ratings, the lack of timeliness was the most criticized and highly visible rating drawback, see [Cheng and Neamtiu, 2009] and [Bolton et al., 2012] for a discussion. For example, rating agencies have repeatedly not only received critics for downgrading too slowly, see e.g. [Morgenson, 2008] among others, but also for being unable to predict some high-profile bankruptcies as noted by [Buchanan, 2009]. This together with the IFRS 9 recommendations make the ratings less valuable for determining credit quality deterioration. As noted earlier, the latter encourages considering changes in market indicators of credit risk which include, but are not limited to: the credit spread, the credit default swap prices for the borrower and other market information related to the borrower, such as changes in the price of a borrower's debt and equity instruments, see [IASB, 2014, §5.5.11].

Therefore, it is relevant to develop market-based measures of default risk to give a point-in-time indication of creditworthiness of an entity of interest. In the following, we search to assess credit risk (and its eventual deterioration

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<sup>1</sup> These ratings classes are those used by Moody's. Different classifications and terminologies are also in use by the other major credit rating agencies.



since the acquisition date) using market information delivered by the price of credit derivatives.

## 2.4 An Illustrative Example

In order to motivate the proposed approach, let us first start with an example that accompanies the new standard, see [IASB, 2014, §IE2]. This is a hypothetical situation which illustrates the use of some credit proxies in order to ease the judgment for depreciation. To this end, let us consider an entity that originated a loan of 1,000,000\$. This entity using the most relevant information available, estimates that the loan has a 12-month default probability of 0.5% and the estimated amount of loss when the default occurs is 25%. In this case, the entity decided that the loan has a low credit loss since the initial recognition and thus recognise the 12-month ECL, being equal to 1,250\$<sup>2</sup>. In the following reporting date, suppose the default probability increased to 20% given the most relevant information available. In this case the lifetime ECL recognition applies. The main difference between the two reporting periods relies on the difference between the default probabilities.

Therefore, some natural questions arise: At which level of default probability the lifetime ECL should be recognised and vice versa? But above all, how can we choose a good estimate of the default probability? The present paper suggests a methodology to (partially) answer these questions.

## 3 Credit Risk Monitoring

The aim of this section is to give an overview of credit-sensitive products used within the scope of assessing credit risk of debt issuers.

### 3.1 Credit Risk in Bond and CDS Market

In the financial market, there are various contracts in which credit risk is a significant factor. Some particular instruments aim at providing investors with flexible tools to create synthetic credit risk exposures tailored to their needs. The most popular credit derivative is a credit default swap (CDS). On the other hand, there are instruments that are not directly linked to credit risk but remains very sensitive to the latter. Among others, a corporate bond is an appealing example. Like all investments, corporate bonds carry risks. These include the risk that the issuing company fail to make timely payments of interest or principal. In that case, company will default on its bonds, which makes the creditworthiness of the issuer an important factor contributing to

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<sup>2</sup> This does not account for the discounting effect.

her bond premia. In the credit derivatives universe, the CDS are the most liquid contracts accounting for nearly half the total transactions' notional worldwide.

Although the IASB highlights the use of *market indicators of credit risk for a particular financial instrument*, i.e. [IASB, 2014, §B20], measuring credit from the market price of corporate bonds, for example, is not an easy task. There are some debates currently about how much information, if it exists, one would extract from quoted prices of bonds and to which extent we can rely on this information to establish a robust proxy for assessing credit risk. Meanwhile, it is shown that yield spreads are far larger so that it cannot be justified by the sole historical default losses. Several explanations for this phenomena have been explored, such as tax effects, market risk and liquidity premia, see [Feldhütter and Lando, 2008] among others. On the other hand, an analysis of the factors affecting the CDS provides an understanding on why the latter reacts more strongly than bond spreads to deteriorations of the credit quality of the issuer. Indeed, as they are widely and deeply traded, CDS do reflect market information about the credit risk of the underlying financial obligations. Also, various studies have shown that CDS markets generally features valuable information and thus should convey credit quality about counterparties. [Acharya and Johnson, 2007] find that the CDS markets are transmitting non-public information into publicly traded securities such as stocks. They showed that the information flow in such markets can succeed to anticipate certain negative credit news, and thus infers for entities that experience or are more likely to experience adverse credit events. Similar findings are supported in [Norden and Weber, 2004] showing that CDS markets anticipate rating downgrades and reviews for downgrade by three major credit rating agencies. In the same line, recent evidences on CDSs usefulness for regulatory purposes and private investors are presented in [Flannery et al., 2010]. In [Blanco et al., 2005], the authors show that the CDS prices lead in price discovery process making them a useful indicator to measure credit risk. However, IFRS 9 also suggests using some economic information which may reflect the conditions that are likely to *cause significant change in the borrower's ability to its debt obligation*, see [IASB, 2014, §B20(f)]. Although the latter may be of a great interest we choose to only focus on the CDS spreads and do not encompass any economic information. This is motivated by [Greatrex, 2009] showing that the CDS spreads reflect credit conditions better than either macroeconomic interest rates or other economic or aggregate equity returns.

Therefore, in the light of the above discussion, we extract credit specific information on market expectations of default from the CDS quotes. This will be in line with the scope of our analysis as we aim at isolating the credit component.

### 3.2 Credit Default Swap

A CDS contract is an agreement between two parties, called the protection buyer and the protection seller, to transfer to the seller the financial loss that the protection buyer would suffer if a particular credit event happened to a third party, called the reference entity. The protection buyer pays a fixed fee or premium to the seller (fixed leg) for a period of time (the maturity of the CDS) and if certain pre-specified credit event occurs, the protection seller pays a compensation to the protection buyer (floating leg). A credit event can be a bankruptcy of the reference entity, or a default of a bond or other debt issued by this reference entity. It also refers to any restructuring, obligation acceleration and payment failure of the reference entity (see Ch. VII in [Brigo and Mercurio, 2006]). Moreover, as IFRS 9 has not precisely defined the credit event leading a recognition of the credit deterioration, the events triggering the CDS floating leg fill into the broader definition of a default event. Therefore, judgments on specific events to account for are necessary in this particular credit sensitive instrument.

In the precise definition of a CDS contract, there is a predefined collection of settlement dates,  $[\mathbf{T}] = [T_1, \dots, T_n]$  and a starting time  $T_0 < T_1$ . Here,  $T_n = T > T_0$  is the maturity of contract. The year fraction between any two consecutive dates is denoted  $\alpha_j = T_j - T_{j-1}$  and is in general constant and equal to three months. The fixed leg payment at each period  $T_j$  is denoted  $S_0$ . This is a constant rate paid until default or maturity, whichever is first. Thus, letting  $\tau$  be the random time of the default event, the present value of the CDS fixed leg, denoted  $\text{FIL}(T_0, [\mathbf{T}], T, S_0)$ , is given by

$$\text{FIL}(T_0, [\mathbf{T}], T, S_0) = S_0 \sum_{j=0}^n B(T_0, T_j) \alpha_j 1_{\{\tau > T_j\}}, \quad (3.1)$$

where  $B(t, T)$  is the price at time  $t$  of a default-free zero-coupon bond maturing at  $T$ , i.e.  $B(t, T) = \exp\left(-\int_t^T r_s ds\right)$  and  $r_s$  is the risk-free interest rate. Similarly, the present value of the floating leg  $\text{FLL}(T_0, [\mathbf{T}], T, L)$ , that is the payment of the protection seller contingent upon default, equals

$$\text{FLL}(T_0, [\mathbf{T}], T, L) = L_{\text{GD}} \sum_{i=0}^n B(T_0, T_j) 1_{\{\tau \in [T_{j-1}, T_j]\}}, \quad (3.2)$$

where  $L_{\text{GD}}$  is the loss given default being the fraction of loss over the all exposure upon the occurrence of a credit event of the reference company.

We denote by  $\text{CDS}(T_0, [\mathbf{T}], T, S_t, L_{\text{GD}})$  the price at time  $T_0$  of the above CDS. The pricing mechanism for this product relies on the risk-neutral probability measure  $\mathbb{Q}$ , the assumptions on interest-rate dynamics and the default time  $\tau$ . Accordingly, the price is given as follows

$$\begin{aligned} \text{CDS}(T_0, [\mathbf{T}], T, S_t, L_{\text{GD}}) = & \mathbb{E} \left[ S_0 \sum_{j=0}^n B(T_0, T_j) \alpha_j 1_{\{\tau > T_j\}} \right. \\ & \left. - L_{\text{GD}} \sum_{j=0}^n B(T_0, T_j) 1_{\{\tau \in [T_{j-1}, T_j]\}} \right], \end{aligned}$$

where  $\mathbb{E}$  denotes the risk neutral expectation (under probability measure  $\mathbb{Q}$ )<sup>3</sup>. For a given maturity, the market quote convention consists in the rate  $S_0$  being set so that the fixed and floating legs match at inception. Precisely, the price of the CDS is obtained as the fair rate  $S_0$  such that

$$\text{CDS}(T_0, [\mathbf{T}], T, S_0, L_{\text{GD}}) = 0,$$

which yields to the following formulation of the premium

$$S_0 = L_{\text{GD}} \frac{\sum_{j=0}^n B(T_0, T_j) \mathbb{E} [1_{\{\tau \in [T_{j-1}, T_j]\}}]}{\sum_{j=0}^n B(T_0, T_j) \alpha_j \mathbb{E} [1_{\{\tau > T_j\}}]}. \quad (3.3)$$

Note that the two expectations in the above equation can be expressed using the risk-neutral probability  $\mathbb{Q}$  as follows:

$$\mathbb{E} [1_{\{\tau \in [T_{j-1}, T_j]\}}] = \mathbb{Q}(T_{j-1} \leq \tau \leq T_j) \quad \text{and} \quad \mathbb{E} [1_{\{\tau > T_j\}}] = \mathbb{Q}(\tau \geq T_j). \quad (3.4)$$

In what follows we characterize these probabilities using the well-known reduced form framework.

### 3.2.1 Cox Model

In the reduced-form framework, the default time  $\tau$  is modelled as the jump of a Cox process with a given intensity  $\lambda = (\lambda_t)_{t \geq 0}$ , see [Lando, 1998]. A way of representing  $\tau$  given the intensity  $\lambda$  is to set  $\tau = A_\xi^{-1}$ , where  $A$  is the stochastic hazard function defined as the time-integral of the intensity from 0 to  $t$ , i.e.  $A_t = \int_0^t \lambda_s ds$ . Here,  $\xi$  is a standard uniform random variable. With this in mind and assuming a deterministic intensity  $\lambda$  we have  $\mathbb{Q}(s \leq \tau \leq t) = \exp(-A_s) - \exp(-A_t)$ . This amounts to modelling  $\tau$  as the first jump time of a Poisson process with intensity  $\lambda$ . In view of our purpose, we further assume that the intensity  $\lambda$  is constant over maturities. This is to translate that the market stakeholders credit risk appreciation remains stable. Indeed, this assumes a fixed creditworthiness during the lifetime of the entity's specific CDS at time  $T_0$ .

In order to fully characterize the CDS spread, we should substitute the probability of the default event into Equation (3.3). Under the constant intensity assumption, this probability is simply given by  $\exp(-A_s) = \exp(-\lambda s)$ , which yield the following closed form formula for  $S_0$

$$S_0 = L_{\text{GD}} \frac{\sum_{j=1}^n B(T_0, T_j) (e^{-\lambda T_{j-1}} - e^{-\lambda T_j})}{\sum_{j=1}^n B(T_0, T_j) \alpha_j e^{-\lambda T_j}}. \quad (3.5)$$

It should be mentioned that the constant intensity assumption would not be suited to best fit the CDS prices. Nevertheless, the objective of our analysis which aims at extracting the instantaneous information from the market should not be disturbed by such an assumption.

<sup>3</sup> Here, we deliberately omit to mention that the expectation is taken with respect to the filtration  $\mathcal{F}_{T_0}$ , which is the filtration gathering information on non-default quantities, e.g. information flow of interest rates and other relevant market quantities up to time  $T_0$ .

In what follows, we introduce the mechanism of market quotations for CDS contracts. Hence, we describe a methodology to extract the default intensities implied by the market from CDS premia.

### 3.2.2 Market-Implied Default Intensities

The formulation in Subsection 3.2 is known as the postponed CDS contract which is well suited to derive market implied intensities from CDS rates, see [Brigo and Mercurio, 2006]. This implicitly assumes that exchanges between the buyer and seller are moved to  $T_j$  when it arrives in the interval  $[T_{j-1}, T_j]$  and thus the payments in case of default events, i.e.  $L_{GD}$ , are postponed and made at the end of each period  $T_j$ . Similarly the spread is paid until  $T_j$  and not until the default when it happens during the period  $[T_{j-1}, T_j]$ . This will not affect our analysis as we are focusing on the credit events timing but on the market perception of the latter. Back to the CDS market rates, those are quoted, in practice, at a fixed set of maturities, e.g.  $T \in \{1, 3, 5, 7, 10\}$  in a year basis, and the typical year fraction between any two different settlement dates is constant,  $T_j - T_{j-1} = \alpha$  and is equal to three months. Consider a CDS with maturity  $T$  then at each date  $t$  the market quotes the CDS spread starting at  $T_0 = t$  at a price  $S_t$ , with maturity  $T + t$ .

### 3.2.3 Recovering Market Intensities

As mentioned, it is possible to recover default intensities from CDS quotes. To this end, we will need the bond prices  $B(t, t + T_j)$  for each maturity  $t + T_j$  available also from the market. Thus, the only remaining quantities in Equation (3.5) is the loss given default  $L_{GD}$  and the intensity  $\lambda$ . Following common practice, we consider a constant  $L_{GD}$  which would correspond, for example, to the mean recovery rate computed in the market for rate-equivalent CDS contracts. Aside from being in line with existing credit risk management assumptions, the constant  $L_{GD}$  is not recognized as proxy for assessing the lifetime expected losses under IFRS norms, see [IASB, 2014, §53]. Moreover, assuming a constant  $L_{GD}$  will ease the estimation the default intensities, which may not require the full require of the expected credit losses.

Finally, it only suffices to equate the closed form formula in Equation (3.5) to the CDS quotes.

## 3.3 Monitoring Credit Risk

Let us now introduce the monitoring scheme that aims at detecting some specific change in the default intensities.

### 3.3.1 Quickest Detection Problem

We assume that the time varying intensity  $\lambda_t$  obeys to the following dynamics

$$\log \lambda_t = \underline{\mu} + \sigma \epsilon_t, \quad (3.6)$$

where,  $\epsilon_t$  is a zero-mean homoscedastic white noise and  $\underline{\mu}$  and  $\sigma$  are some constant parameters. The trend  $\underline{\mu}$  is assumed to be deterministic and known. With credit quality deterioration in mind, the intensity  $\lambda_t$  (in logarithmic scale) may change its drift  $\underline{\mu}$  in the future at an unknown time  $\theta$  referred to, henceforth, as a change-point. We assume that the change-point  $\theta$  is fully inaccessible knowing the pattern of  $\lambda_t$ . It can be either  $\infty$  (in case of absence of change) or any value in the positive integers.

After the occurrence time  $\theta$  the  $\lambda_t$ 's evolve as follows:

$$\log \lambda_t = \bar{\mu} + \sigma \epsilon_t, \quad (3.7)$$

where  $\bar{\mu}$  is the new drift, which is assumed to be deterministic and known.

As the credit quality of the firm changes over time, this model describes the migration between two rating classes. As such, a straightforward interpretation of the latter relies on the expected stability of the mean intensity between two credit events. We can implicitly assume that the pre-change drift  $\underline{\mu}$  corresponds to the average (implied) intensity - in logarithmic scale - for a given credit grade class. Hence,  $\bar{\mu}$  is the average intensity when the entity undergoes a rating change and thus corresponds to the next rating class implied intensity. The error part  $\sigma \epsilon_t$  captures the fluctuation of the credit quality induced by market speculation rather than an effective change of market perception of credit quality of the debtor.

Consequently, the task is to locate the change-point  $\theta$  as early as possible, while keeping the rate of false alarm under a given level. In the quickest detection framework, the solution this problem can be seen as the result of optimizing the tradeoff between two performance criteria. First, there is the detection delay, which is the time between the occurrence and the detection time. This measures the ability of the detection scheme to sound an alarm after a change actually happens. Secondly, there is the rate of a false alarm, which is related to the detection accuracy. In fact, we wanted to raise an alarm when an actual change happens and avoid temporary effects that may originate from momentary market speculation.

As a set of detection strategies, we consider the set of all stopping times  $t_d^c$  with respect to the information generated up to time  $t$ . The quickest detection objective imposes that  $t_d^c$  be as close as possible to  $\theta$ . Meanwhile, we balance the latter with a desire to minimize false alarms, see [Lorden, 1971]. For this detection objective, it is shown that the cumulative sums (cusum for short) is optimal. More formally, if one fixes a given false alarm to  $\pi$ , which stands for the time until a false alarm (when the change never occurs), the stopping time  $t_d^c = \inf\{t \geq 0; V_t \geq m\}$  is optimal for triggering an alarm. Here,  $V_t$  is

the process given by

$$V_t = \max_{1 \leq s \leq t} \left( \prod_{k=s}^t L(\log \lambda_k) \right), \quad S_0 = 0,$$

where  $x \rightarrow L(x)$  is the likelihood ratio function. In view of our model in Equations (3.6)-(3.7) the likelihood function  $L(x)$  is the one linking the two marginals  $Q_0 = \mathcal{N}(\underline{\mu}, \sigma)$  and  $Q_1 = \mathcal{N}(\bar{\mu}, \sigma)$ , which is given as follows

$$L(x) = \frac{\bar{\mu} - \underline{\mu}}{\sigma} \left( x - \frac{\bar{\mu} - \underline{\mu}}{2\sigma} \right). \quad (3.8)$$

The behavior of the process  $V$  is of paramount importance. First, note that the log-likelihood process  $L$  works as a measure of the adequacy of the observations to the underlying model in Equation (3.6). The process  $V$  can be interpreted as a sequential cumulative log-likelihood. The latter is equal to 0 when the incoming information of the log-intensity does not suggest any deviation from the model in (3.6). In other words, the credit quality did not change since the last recognition. When  $V$  becomes greater than 0, we can interpret this as a deviation from the model in (3.6). This means that the 'real' model stands in between (3.6) and (3.7). In order to declare that the intensity is evolving with respect to the model in (3.7), i.e. credit risk quality deterioration, we need a constraint in order to characterize the barrier  $m$ . This is typically achieved by imposing that the optimal time to raise a false alarm when no change occurs should be postponed as long as possible. We deliberately omit the technical details on such a procedure which stand beyond the scope of this paper. However, further insights on the quickest detection problem can be found in [Basseville and Nikiforov, 1993] and the reference therein.

### 3.3.2 Alarm System for Credit Impairment

To adapt the above methodology to our study, we broadly follow the considerations of the IFRS standard. In [IASB, 2014, §5.5.9], it suggests that an entity shall compare the creditworthiness of a financial instrument at the reporting date taking into consideration its initial credit risk. This requires an entity to recognize at the reporting date a *significant increase* in credit risk based on an increase in the default intensity of the issuer or the borrower [IASB, 2014, §B5.5.17]. The IFRS standards do not specify how significant should be the increase when assessing the change in credit risk nor the amount of change in probability of a default that would require the recognition of a creditworthiness deterioration. However, to ease the application, IFRS 9 requires that financial instruments with low credit risk at the reporting date would not meet the lifetime expected credit losses criterion. For example, a financial asset rated 'investment grade' at the reporting date is regarded as not having suffered significant credit deterioration and will remain as such until leaving this investment grade. To draw a connection with the monitoring procedure in

the above subsection, let us consider an instrument with a rating above Baa in Moody's credit ratings scale which corresponds to an investment grade. In Table 3, we show estimates of the average seven-year risk-neutral and real-world (actual) default intensities (DI) per annum for different credit ratings, see [Hull et al., 2005]. The real-world DI are estimated from statistics on average cumulative default rates published by Moody's between 1970 and 2003. The implied DI are estimated from market prices of the CDS in the US market. In order to achieve this monitoring scheme, we need various inputs. First,

**Table 3:** *Average real world and market-implied default intensities based on 5-year CDS*

Rating	Actual DI	Implied DI
<b>Aaa</b>	0.04%	0.67%
<b>Aa</b>	0.06%	0.78%
<b>A</b>	0.13%	1.28%
<b>Baa</b>	0.47%	2.38%
<b>Ba</b>	2.40%	5.07%
<b>B</b>	7.49%	9.02%
<b>Below B</b>	16.90%	21.30%

the average DI  $\underline{\mu}$  should be specified and must match the market DI of the instrument since initial recognition or the last reporting date. Next, the average  $\bar{\mu}$  should provide a level of market DI beyond which the instrument would belong to non-investment grades. For example, if the instrument has a A1 rating with a market DI, i.e.  $\underline{\mu}$ , in  $[0.78\%, 1.28\%]$  should be monitored by setting  $\bar{\mu} \geq 5.07\%$ , see Table 3.

Finally, we should specify an average rate of false alarm, which specifies the frequency of sounding an alarm when nothing happens. A part being as large as possible no further requirement are needed. For example, one could set the latter to 100 years. This means that a false alarm would go off once each hundred years of observations. This being set, we then recover the threshold level  $m$  by resolving the following equation (see [Poor and Hadjiliadis, 2009])

$$\exp(m) - m - 1 = \frac{1}{2} \left( \frac{\bar{\mu} - \underline{\mu}}{\sigma} \right)^2 100, \quad (3.9)$$

where  $\sigma$  is estimated based on the historical observations. The latter sets the threshold  $m$  at a level that allows to recover the targeted average time until the false alarm. Indeed, the theoretic false alarm is given by  $2(\exp(m) - m - 1)(\sigma/(\bar{\mu} - \underline{\mu}))^2$  as in Equation (3.9), see [Poor and Hadjiliadis, 2009] for further details.



## 4 Empirical Analysis

We apply the alarm sounding procedure to AIG, which witnessed a critical period of successive downgrades during the financial crisis of 2007-2008. We go through details for this particular example and explain how one can apply the procedure.

### 4.1 Data

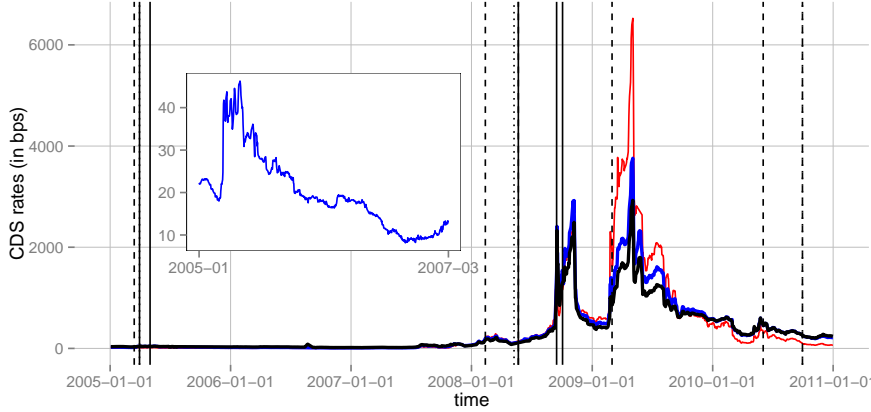
The CDS data in this section consists of bid and ask quotations for 1-year, 5-year and 10-year CDS on AIG credit risk during the period ranging from January 1, 2005 to December 31, 2010. It goes without recalling that quotations are obtained on days when there is some level of participation in the market. Following common practices we use the midpoint of bid and ask quotations as a point estimate of CDS premium, see [Longstaff et al., 2005].

#### 4.1.1 Spreads and Credit Events

Figure 2 plots the daily CDS spreads for the three maturities over the considered period. When looking more closely at these spreads, we notice that they exhibit similar behaviour. More precisely, we can distinguish two periods fundamentally different from each other. Indeed, over the first half of our sample (roughly from early 2005 to early 2007, see the zoomed period in Figure 2), CDS spreads declined reflecting a period of calm. Then, beginning in March 2007, spreads increased and became more volatile, which corresponds to important early events in the financial crisis, which we will discuss later on this section. Despite this negative information, the AIG rating remained unchanged at Aa2 level until the US government announced in, September 16<sup>th</sup> 2008, it would make an emergency intervention in an attempt to rescue AIG. Not surprisingly, the CDS spreads increased significantly before the downgrade announcement. They rose to more than 250 basis points in mid-March 2008 and then fell to below 100 basis points in mid-May. From that point forward, its spread steadily increased. Two weeks before the government rescue, its spread was at 375 basis points. Over the next two weeks, the spread increased dramatically, exceeding 2500 basis points on the day of the announced rescue.

Based on these facts we will build our detection procedure on two distinct periods. We thus divide the sample into two parts: The first will run from January 2006 until the end of 2008 and the second is starting on 2009 until the end of the sample. As mentioned above, the first period is characterized by quiet calm credit risk events period followed by a near collapse of the underlying entity. During this period, various credit events have emerged in the market, which did not affect the rating of AIG. In the next period, although

the spread has declined by the end of 2008 at around 500 basis points, it suddenly increased and was one more time above 2500 basis points in May 2009. It then declined thus until the end of our sample. These different periods are explored in details in the following when it comes to detecting the change of the credit quality.



**Fig. 2:** CDS spreads between January 1<sup>st</sup>, 2005 and December 31<sup>st</sup>, 2010 on AIG for different maturities: 1-year (red), 5-year (blue) and 10-year (black). The zoomed period ranges from early 2005 to early 2007. During this period, CDS spreads on AIG declined then, beginning in March 2007, spreads increased and became more volatile, which corresponds to important early events in the financial crisis.

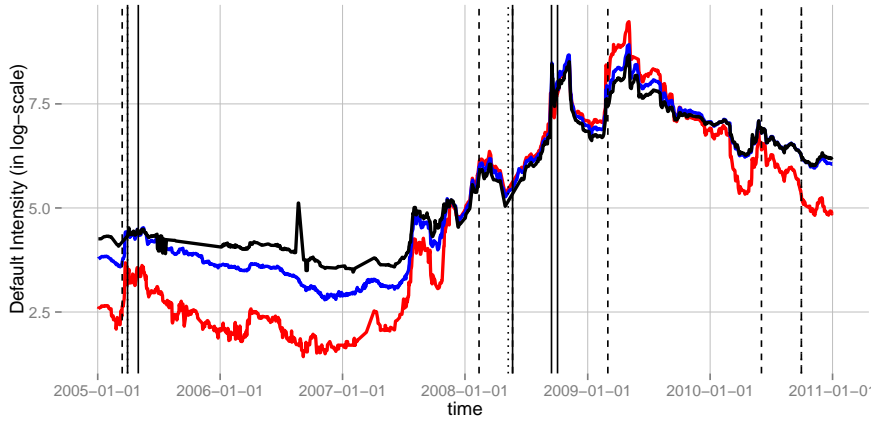
#### 4.1.2 Implied Intensities

Before proceeding to the estimation of the default intensity, we shall specify a discounting factor  $B(t, T)$  covering both the observation dates  $t$  and the maturities  $T$  involved in Equation (3.5). To this end, we collect data from US treasury yield curve covering the desired period. The use of such a curve is line with the definition of the risk-free discount factor<sup>4</sup>. We use data for constant maturity  $\{1/12; 3/12; 6/12; 1; 2; 3; 5; 7; 10\}$  years from the Federal Reserve. Hence, we use a standard four-parameter model of [Nelson, 1987] to interpolate these par rates and obtain the value of the discount function at other maturities  $T_j$ , needed to fully span the CDS settlement dates in Equation (3.5).

As mentioned before, the spreads  $S_t$  only depends on the loss given default  $L_{GD}$ , the intensity  $\lambda_t$  and the discount factors  $B(t, T_j)$ . The loss given default

<sup>4</sup> Although the US Treasury bonds may embed some liquidity or *specialness* risk, it is the standard curve used in practice but also in empirical finance.

is assumed to be constant and is fixed at 40%, which is the rate commonly used in empirical studies as well as in major rating agencies. We then substitute the fitted curve of  $B(t, T_j)$  for the CDS spreads in Equation (3.5). To derive the implied intensities for each observation date  $t$  we equate Equation (3.5) to the market quotes. Figure 3 depicts the implied default intensities in logarithmic scale for the AIG's CDS with maturities at 1-year, 5-year and 10-year. In this figure, we also show various credit events based on Moody's announcements. The vertical lines correspond to a 'Rating Action': The solid lines represent a 'Grade Review' and correspond to downgrades, the dashed lines show the announcement of a 'Negative Outlook' and the dotted are the 'Under Revision' status of the grade<sup>5</sup>. The downgrades dates are displayed in Table 4 from five periods of stable rating. For example, during the period P1, the AIG rating was at Aa1 level.



**Fig. 3:** Time-series plot of AIG's market implied intensity process for different CDS maturities: 1-year (red), 5-year (blue) and 10-year (black)

In Figure 3, we depicted the implied intensities in logarithmic scale, which ease the observation of the intensities evolution. We can distinguish similar behaviours as those already mentioned with regard to the spread evolution. We see in particular that the intensity has increased steadily since mid-2007 to reach a first record level of about -1.185716 (in logarithmic scale). In other words, if we consider the intensity in September 15, 2008, just before the governmental rescue of AIG, the 1-year default probability of the latter is around 30%. In the previous period, i.e. P3, this probability was approximately at 5%, and in the period P2 it was averaging 0.46%.

<sup>5</sup> These credit events are collected from Moody's and are available in <https://www.moody.com/credit-ratings/AIG-Financial-Products-Corp-credit-rating-782350>

Looking more closely at the average default intensities for each period, we can remark that those are in adequacy with the calculations of [Hull et al., 2005]. From Table 4, we see that during the period P1, when AIG had a Aa1 rating, the average DI was at 0.79% and the calculation of this same DI over the US market was around 0.78% for the grade Aa. Another statistic of paramount importance is the D-test, reported in the third row of each panel in Table 4. It provides information on the p-value of normality test of the intensity during each period. In other words, we test whether the model (3.6) is valid during the period: larger the p-value, smaller is the significance meaning that the model (3.6) may not adequately explain the observation. We see that the p-value is significant only during the period P1 (almost for each CDS). We thus may conclude that there has not been a change of the average DI during P1. During the period P4 ranging from September 15, 2008 to March 10, 2008 the p-values are relatively large, which invokes a stable period in terms of the average DI. Apart from these two periods, however, the p-values are very small indicating that the model (3.6) is not valid and possible change in the trend of the intensity have occurred during these periods. This implicitly comforts our intuition that changes in the credit quality are not accounted for by the rating agencies as the market implied intensities would suggest.

**Table 4:** *Descriptive statistics for different risk grade periods. The last row of each panel expresses p-value of the normality test of the log-intensity.*

Period		P1	P2	P3	P4	P5
Starting date		3/31/05	5/2/05	5/22/08	9/15/08	10/3/08
Rating		Aa1	Aa2	Aa3	A2	A3
1Y	mean	-5.89	-6.51	-2.78	-1.73	-2.32
	sd	0.06	0.80	0.34	0.28	0.73
	DI	0.28%	0.15%	6.02%	16.21%	9.39%
	D-test	0.1348	2.20E-16	4.81E-05	0.1059	4.70E-09
5Y	mean	-4.84	-5.38	-2.91	-1.30	-2.09
	sd	0.06	0.80	0.34	0.28	0.73
	DI	0.79%	0.46%	5.29%	23.88%	11.68%
	D-test	0.498	2.20E-16	0.001893	0.2629	1.19E-11
10Y	mean	-4.81	-4.91	-2.99	-1.40	-2.17
	sd	0.05	0.58	0.33	0.31	0.64
	DI	0.81%	0.74%	4.90%	21.82%	10.79%
	D-test	0.2567	2.82E-15	0.007826	0.2412	8.89E-11

## 4.2 Alarm Sounding

The above preliminary analyses suggest that changes on the trend may have been occurred on the DI's dynamics. Here and subsequently, we focus on the detection procedure of these different changes over the sample and in order to

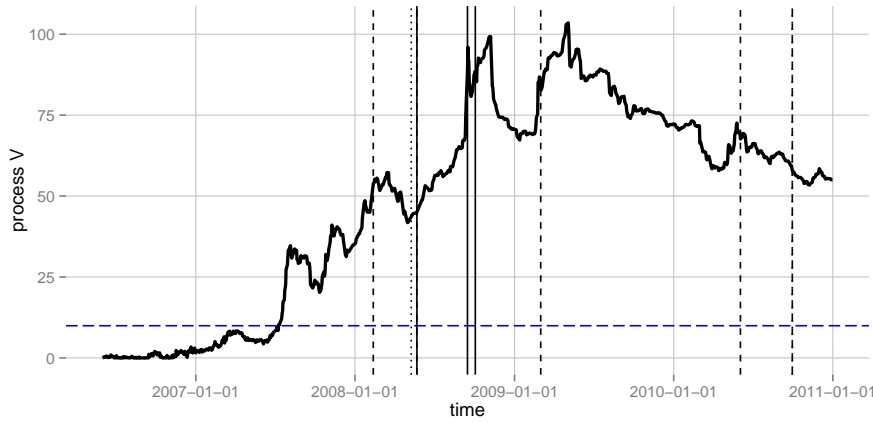
assess the effectiveness of the procedure to anticipate credit quality deterioration and hence be able to trigger an alarm to depreciate the asset of interest. Before proceeding, let us recall the main inputs of our approach:

- The historical DI average  $\underline{\mu}$ : It must match the average intensity during the observation period or since the last recognition as stipulated by the accounting norm. However, note that the calculation of the latter shall be made on a stable period. By stable we mean a period when the financial instrument of interest has not experienced any major credit events. We must acknowledge that this is not an easy task because most of the periods in our sample are far from being stable (see the D-test results in Table 4). For this, we choose to consider the average intensity observed on the market for the same rating class. For example, if the monitoring procedure is carried out during the period P1, the average intensity  $\underline{\mu}$  is set to 0.78% (for the 5-year CDS), which is the average intensity for Aa level in the US market, see Table 3. The same reasoning should be applied to the other periods.
- The critical DI average  $\bar{\mu}$ : This quantity should reflect the critical level of the average intensity beyond which the underlying entity falls into the speculative grade class. A suitable candidate is the market average intensity for such a class. According to Table 3, average DI greater than 5.07% corresponds to a rating of under Baa (speculative grade). To circumvent possible misestimation for the latter we fix  $\bar{\mu}$  to 6.05%.
- The alarm threshold  $m$ : This level is derived as a solution of Equation (3.9). The only assumption is the false alarm level set equal to 100. Generally, the threshold level  $m$  is not as much sensitive to such an assumption.

This being put in place, we can now implement our detection procedure. For this, we need to construct the trajectory of our process  $V$ , given in formula 1. Nevertheless, to facilitate this step it is easily to show that the process  $V$  can also be built using the following simple recursive formula:

$$V_t = \max(V_{t-1} + L(\log \lambda_t), 0), \quad (4.1)$$

with  $V_0 = 0$  and  $L$  is the log-likelihood functional given in Equation (3.8). Then, it suffices to raise an alarm once  $V$  goes beyond  $m$ . Figure 4 illustrates the evolution of the process  $V$  since the beginning of the monitoring in September 1, 2006. This date corresponds to the origination of the financial instrument. It is assumed that an observer follows the deterioration of the credit risk of AIG based on the above procedure. The rating of AIG during the preceding period (and even at the date of origination) was Aa1, see Table 4. We thus consider  $\underline{\mu} = 0.78\%$ ,  $\bar{\mu} = 6.05\%$  and the level triggering the alarm is equal to  $m = 10.81$ . We see that the process  $V$  exceeds this threshold in July 10, 2007, meaning that the level of credit risk of AIG has changed before this date (from the market point of view). The rating agencies have downgraded AIG by September 2008. Notice that before the alarm, the process  $V$  remains below the threshold and close to zero meaning that the initial model does correspond to the incoming observations.



**Fig. 4:** *The evolution of the process  $V$  since the initial recognition in September 1, 2006.*

In order to understand this credit event alarm, we can refer to the major events announced during 2007 and particularly two important early events in the financial crisis. First, we recall that various measures of subprime mortgage risk, including the ABX indices, CDS prices of the mortgage-backed securities, had begun to increase in early 2007. Second, New Century Financial, a prominent subprime mortgage broker, filed for bankruptcy on April 2, 2007. Although the extent of AIG exposure to subprime mortgages was not yet known, the alarm could be associated with a market anticipation of its implication. It is also difficult to isolate any further information associated with this alarm from news articles and analyst reports during this period. However, we can implicitly deduce that this could be related with the late announcement of a negative outlook of Moody's in February 12, 2008, followed by a downgrade to Aa3 level in May 2, 2008.

Besides being able to detect real breaks we will focus on the sensitivity of the detection procedure with regards to some particular setting: the maturity of the CDS and the granularity of the data.

#### 4.2.1 Spread Maturities

We look at the detection results according to the maturity of the CDS spread. Each CDS with a maturity of 1-year, 5-year or 10-year gives different intensity streams. These are shown in Figure 3. Note that the behaviour of these intensities is substantially similar. Nevertheless, we can see that the default probabilities increase with the maturity of the underlying CDS. This is due to the fact that the entity is more likely to default in the long-term at least from the market participants point of view than if one looks at very short

dated maturities. This difference, however, tends to shrink in times of crisis, see Table 4. Table 5 shows the results for different maturities for a monitoring

**Table 5:** *Comparative results for the detection with different sets of assumptions on the data periodicity (daily, weekly and a monthly average) and the CDS maturity (1-year, 5-year and 10-year)*

Initial Recognition	Periodicity	1Y	5Y	10Y
<b>1/1/06</b>	<b>Daily</b>	3/27/06	7/10/07	3/31/06
	<b>Weekly</b>	4/5/06	7/12/07	4/12/06
	<b>Average</b>	4/7/06	7/10/07	3/31/06
<b>6/1/06</b>	<b>Daily</b>	10/5/06	7/10/07	8/22/06
	<b>Weekly</b>	5/11/07	7/12/07	8/23/06
	<b>Average</b>	5/6/07	7/11/07	8/23/06
<b>1/1/07</b>	<b>Daily</b>	5/5/07	7/16/07	4/5/07
	<b>Weekly</b>	5/11/07	7/18/07	7/11/07
	<b>Average</b>	5/6/07	7/20/07	7/13/07
<b>6/1/07</b>	<b>Daily</b>	7/2/07	7/20/07	7/16/07
	<b>Weekly</b>	7/18/07	7/25/07	7/25/07
	<b>Average</b>	7/13/07	7/27/07	7/20/07
<b>1/1/08</b>	<b>Daily</b>	8/19/08	2/12/08	1/23/08
	<b>Weekly</b>	8/27/08	2/20/08	2/13/08
	<b>Average</b>	9/5/08	3/14/08	2/15/08
<b>8/1/08</b>	<b>Daily</b>	11/11/08	9/4/08	9/4/08
	<b>Weekly</b>	11/26/08	9/17/08	9/17/08
	<b>Average</b>	11/21/08	9/12/08	9/12/08

procedure based on daily observations (first row of each panel). The method used is that described previously, except that the input parameters are estimated on the historical data. In order to better compare the results we chose to fix  $\mu$  equal to the average DI over the period ranging from the origination (first column) until to the last change of the rating. The critical value is set  $1.4 \times \mu$ .

For an origination date lying in the calmer period in our sample (the first two panels), we note that the procedure based on the CDS with 1-year and 10-year maturities sound an alarm in March-April 2006. On the other hand, the one based on the 5-year CDS triggers an alarm in July 2007. The first two alarms are difficult to explain since the period concerned has experienced a decline in spreads and no information from the market can given any further explanation. We can see that even with an origination date in June 2006 the two alarms are triggered in the same year, i.e. 2006. It must be said that the data's quality used is mostly responsible for this alarm. On the other hand, the 1-year CDS are much volatile and may bias the detection. Together with the 10-year CDS maturities, the 1-year CDS is less liquid and no much trades are available in the market. This has to impact on the stability of the latter

and thus on the detection effectiveness. We must acknowledge that starting from the mid-2007 these contracts gains on attractivity, which is observable from the detection times. In fact, the difference between the detection times for origination dates starting on early 2007 are smaller.

Finally, if we consider an origination date just before the near-collapse of AIG (August 2008), the 5-year CDS based intensities outperform on detecting the downgrade in September 2008. Overall, we should highlight that the latter is effective on detecting credit events much earlier than the rating agencies would downgrade.

#### 4.2.2 Data Periodicity

In Table 5, we show the detection times when using different data. First, we consider weekly data which are the CDS prices of each Wednesday of the week during our sample period. Next, we also average out the intensity over weeks and consider the resulting quantity.

We can see that this has practically no bearing on the performance of procedure based on 5-year maturity CDS. A discernible difference relies on the detection times compared to daily observations especially for the 5-year CDS: The detection is delayed by some few days. Nevertheless, we observe that taking average or weekly data improves the detection of 1-year CDS in particular during the calm period of 2006. The detection is thus triggered in mid-2007. Finally, the new range of data failed to blur the imperfections observed in 2006. Averaging over a longer period could possibly remedy this.

### 4.3 Global Analysis on Various Entities

Here, we emphasis our analysis by incorporating a wide range of entities whose 5-year maturity CDS are available. In Table 6, we reported the entities considered in this subsection classified their economic sectors. We focus our attention on financial entities that are more likely to exhibit credit weaknesses especially during the considered period. Indeed, as in the previous discussion on AIG creditworthiness we consider the period ranging from the beginning of 2005 till the end of 2013. For each entity we have collected the corresponding 5-year maturity CDS quotations and we extracted the implied intensities as detailed above. Hence, we consider the monitoring of each single 5-year CDS corresponding DI while keeping the same pre-change (deterioration) level objective. We then run the detection procedure using all the data at our disposal (frequent periodicity) and sound an alarm when the process  $V$  beyond the threshold determined by Equation (3.9) with level of false alarm set to 100.

In Table 6, we present the detection time (if it happens) for grade change. We see that most changes detected concern companies that belong the financial sector including banks and insurance companies. Most of these alarms are



triggered during the financial crisis period and corroborate the findings already observed for the AIG's DI. We can notice that some non-financial companies' CDS triggered an alarm during 2011 but also during the financial crisis. For the first French companies, this can be contingent to the turmoil witnessed during this period and linked to the downgrade of the French government. For the others, we can rely on the Moody's ratings to understand the alarms. Those are collected in the column "Grade Change" of Table 6 and present the time the entity entered to the speculative grade during the period of interest. This provides further support for the triggered alarms as the rating agency did issue at least negative outlooks for the concerned companies but with a certain delay.

#### 4.4 Appropriate and Accurate Measures of Creditworthiness

Different tests presented above show that the alarm system introduced in the previous section outperforms the rating agencies recognition of credit deterioration and especially during the last crisis. This lack of accuracy and timeliness of credit rating agencies gathers a broad consensus in numerous empirical studies, see for e.g. [Ashcraft, 2010], [Benmelech and Dlugosz, 2009] and [Bethel et al., 2008] among others. Even if the alarm system proposed here may fail at detecting some changes of the grade level, it has succeeded in sounding an alarm of the entities that have experienced a distress during the financial crisis. This was detected before any intervention of the regulator nor downgrading of the rating agencies, see for e.g. the case of AIG. However, we should outline that the timeliness of detection may be compromised by the need to accumulate enough observations for batching. Also, the methodology in this paper requires the sequential collection of the CDS information flow. This, generally, may be time consuming. However, as shown above a less frequent procedure based on weekly (averaged) observations should overcome this problem as the detection delay is slightly longer (in days) than a more frequent procedure.

### 5 Concluding Remarks

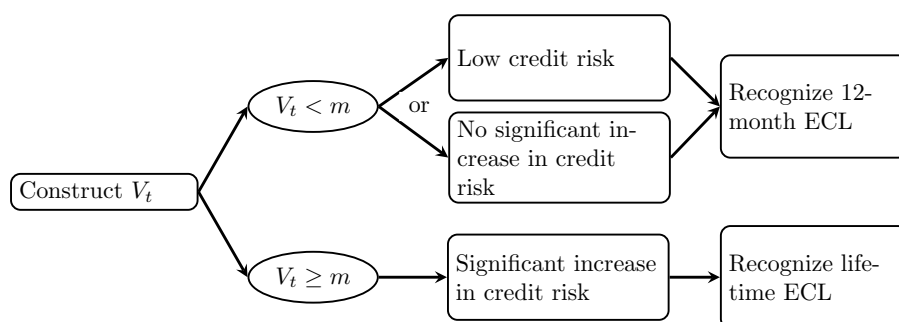
In this paper, we developed a monitoring procedure to address the recent principles of credit losses impairment introduced by the IASB. We proposed a credit risk indicator based on market quotes for some liquid CDS contracts. Thus, we extracted the implied intensity from these contracts and used it to set up a deterioration of credit risk quality of the underlying entity creditworthiness. The latter is shown to be a good proxy for anticipating credit events. It also falls into the standard requirement stated by the IASB's IFRS 9 and has the merit to anticipate changes in credit ratings especially for downgrades.

The monitoring scheme is based on the assumption that the logarithm of the market implied intensity has to be stable in average between two credit

**Table 6:** Various credit based entities from different economic sectors. The grade change column corresponds to the time the entity's grade witnessed the main downgrade during the period of interest. The alarm column gathers the time an alarm has triggered by the detection procedure.

	Main Change	Alarm		Grade Change	Alarm
<b>Industrials</b>			<b>Financials</b>		
Boeing co.	3/15/06 (A2)	—	HSBC	3/9/09 (A1)	1/21/08
Siemens		—	Allianz	8/26/04 (Aa3)	3/17/08
Alstom	5/7/08 (Baa1)	—	UBS	7/4/08 (B-)	7/27/07
<b>Technology</b>			AXA	3/19/03 (A2)	—
Google Inc.	7/5/10 (Aa2)	—	Dexia	10/01/08 (C-)	7/20/07
Cap Gemini	not rated	—	Merill Lynch	not rated	9/17/08
Alcatel-Lucent	11/7/07 (Baa3)	—	<b>Con. Goods</b>		
<b>Consumer Services</b>			Nestlé	8/15/07 (Aa1)	12/4/07
Pearson	12/2/98 (Baa1)	—	Coca Cola co.	8/21/92 (Aa3)	—
Carrefour	3/23/11 (Baa1)	8/9/11	Procter & Gamble	10/19/01 (Aa3)	—
Marks & Spencer	7/13/04 (Baa2)	—	L'Oréal	not rated	—
<b>Utilities</b>			<b>Energy</b>		
Iberdrola	6/15/12 (Baa1)	9/30/11	Total	2/2/11 (Aa1)	11/8/07
SUEZ	8/18/08 (Aa3)	—	Schlumberger	9/22/03 (A1)	—
<b>Healthcare</b>			Repsol	5/16/05 (Baa1)	—
Sanofi	2/18/11 (A2)	3/7/08	<b>Basic Materials</b>		
Pfizer inc.	3/11/09 (Aa2)	—	Arcelor	11/6/12 (Ba1)	—
			Solvay	9/5/11 (Baa1)	—

events. Any change in the latter may involve a change in the rating grade of the underlying entity. Thus assuming a critical level of average intensity beyond which the entity belong the speculative grade one may operate an on-line surveillance of the credit deterioration. It is based on the so-called cusum process which indicates somehow the adequacy of the model with the incoming observation from the market. The proposal is summarized in Figure 5.



**Fig. 5:** Summary of the main proposals. The time  $t$  refers to the current reporting date.

Even if the method turns out to be efficient for detecting changes in credit risk, nonetheless the practical implementation can be a delicate matter. Especially, when it comes to track several financial instruments, it would be appropriate to create an aggregate indicator of the creditworthiness of an entire class of instruments. Another possible choice of such an indicator is the so-called basket CDS, where a group of reference entities are specified in one contract. Also, we should stress out that this methodology could only serve as an alarm system and the effective impairment may rely on a closer investigation of financial statements of each entity when the alarm is triggered. Moreover, examinations of financial analyses and other non-quantitative information such as news articles and analyst reports can be very useful to explain the detected event.

As we have seen, the proposed method is mainly based on the availability of liquid CDS products allowing to extract the market appreciation of an entity credit risk. However, we must recognize that these are not generally available for each loan instrument especially for private equities and corporate debts from emerging markets. Nevertheless, as a consequence of prudential rules, most of insurance companies debt financial assets can be easily associated with a CDS contract since they are mainly issued from well referenced entities.

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