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# Alarm System for Credit Losses Impairment \*

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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. In this paper, after a brief description of the principles elaborated by IASB for IFRS 9, we propose a methodology using CDS market prices in order to monitor significant changes in creditworthiness 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.

**Keywords:** Credit Risk, Default, Detection, Monitoring, Impairment, Accounting, IFRS, Insurance, CDS

## 1 Introduction

The financial crisis put a spotlight 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 would 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

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recognize credit losses related to loans commitments and financial guarantee contracts. In an exposure draft, hereafter referred to as the ED, released by the IASB (2013), practitioners are invited to incorporate 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), among others, as a weakness in existing accounting standards during financial crisis.

The current practice in the IAS 39 uses incurred losses that arise from past events and current conditions. Thus, future credit loss events are not considered, even when they are expected. As mentioned, this 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).

The ED set out some proposals being based on a so-called *three-stage* model for impairment of provisions related to credit risk deterioration, which provides 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 or that have low credit risk at the reporting date*. In this case, 12-month expected credit losses (ECL) are recognized. Secondly, there are *financial instruments that have deteriorated significantly in credit quality since initial recognition (unless they have low credit risk at the reporting date) for these items, lifetime expected credit losses are recognized*. Finally, when the credit quality of a financial asset deteriorates to the point that credit losses are incurred or the asset is credit-impaired. Interest revenue is then calculated based on the net amortized cost carrying amount. When the recognition of expected credit losses is unchanged, lifetime expected credit losses are still recognized.

Based on this new accounting standards one should be able to early detect any deterioration of the borrower's creditworthiness. It thus seems important for bonds holders to assess the credit quality during up to maturity in order to fill the ED's proposals. To this end a monitoring strategy is needed and one can rely the current market conditions in order to track the credit quality of bonds. In this case, one needs 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 conditions. These market-implied default probabilities will determine the credit risk inherent in all securities depending on the same borrower.

As the ED does not propose a precise definition of default (see §BC97 in IASB (2013)) we rely on the celebrating approach proposed in Lando (1998). So-called reduced-form models of default provide a natural setting 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](#). We then use the closed form formula based on an adequate specification of the intensity dynamics to recover the intensity of default from market quotes, which will be used later to monitor the creditworthiness of corresponding company.

The remainder is organized as follows. In [Section 2](#), we recall the principles introduced in the IASB's ED regarding the impairment of financial instruments. We present the main challenges and key issues when it comes to recognise *significant* credit risk deterioration. We also discuss the use of market information to recognise 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 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 such as proposed in the march 2013 IASB's ED.

**2.1 Principles.** The present standard IAS 39 stated that *an impairment loss is recognised only when it has been incurred*. More precisely §58 states 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. \(2014\)](#)), no such criteria stands for considering a debt instrument. Also this model has been called *incurred loss model* since no impairment losses are recognized in the financial statements until 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 misjudged by the FCAG which recommended to explore some more forward-looking alternatives. This is the topic of the march 2013 IASB's Exposure Draft.

The main ED's proposals consist in setting an *expected credit loss model* in order to overcome the weaknesses identified by the FCAG. This approach mainly consists in recognizing expected credit losses as a loss allowance. Three stages of credit deterioration are defined:

- *Stage 1*: Financial instruments that have not deteriorated significantly since initial recognition or that have a low credit risk at the reporting date.
- *Stage 2*: 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*: Financial instruments have objective evidence of impairment at the reporting date.

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 (case 2) and if there is any objective evidence of impairment (case 3) in order to maintain it at stage 1 or downgrade it at stage 2 (case 2) or 3 (case 3). Considerations about assessment of credit risk significant increasing are given in [Subsection 2.3](#).

The level of loss allowance has to be determined in reference with 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 shall recognise in profit or loss the amount of expected credit losses (or reversal) that is required to adjust the loss allowance or provision to the balance-sheet (at the reporting date) that is required with this standard.

These rules can be resumed as in table [Table 1](#).

**Table 1:** *IASB's ED 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

**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 of 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, the ED proposed disclosures in order to identify and explain the amounts of ECL that arises in the financial statements, the effect of changes in credit risk. These disclosures mainly consist 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.** 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 ED did not impose a particular method for this assessment but it 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 released by major 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 valuable source of information for investors assessing the riskiness of their loans 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, the ED advocates the use of *information that is more forward-looking than past-due information*, see §9. Moreover, aside the accuracy of the ratings the lack of timeliness was the most criticized and highly visible rating property, see [Cheng and Neamtiu \(2009\)](#) and [Bolton et al. \(2012\)](#). For example, rating agencies have repeatedly not only received critics for downgrading too slowly, [Morgenson \(2008\)](#), but also for being unable to predict some high-profile bankruptcies [Buchanan \(2009\)](#). This together with the recommendation of the ED makes the ratings less

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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.

valuable for determining credit quality deterioration. The latter encourages to consider 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 §B20.

Therefore, it is of high relevance to develop market-based measures of default 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 increasing 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 ED, see §IE2. This is a hypothetical situation which illustrates the use of some credit proxies in order to ease the judgement 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 following proposes a methodology to answer these questions.

## 3 Credit Risk Monitoring

The aim of this section is to give an overview of credit-sensitive products which we will use in order to assess credit risk of an individual debt financial asset issuer.

**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 instrument aim at providing investors with flexible tools to create synthetic credit risk exposure tailored to their needs. The most popular credit derivative is a credit default swap (CDS). On the other hand, there are instrument 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,

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

which makes the creditworthiness of the issuer an important factor contributing to 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 draft highlights the use of *market indicators of credit risk for a particular financial instrument* (§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 wider than is justified by 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 underlying financial obligations. Also, various studies have shown that CDS markets generally reflect valuable information and thus should convey credit quality about counterparties. [Acharya and Johnson \(2007\)](#) find that the CDS markets is transmitting non-public information into publicly traded securities such as stocks. They showed that the *information flow is concentrated on periods days with negative credit news, and 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 evidence that CDSs are potentially useful for regulatory purposes and private investors are presented in [Flannery et al. \(2010\)](#). In [Blanco et al. \(2005\)](#), the CDS spread has been considered as an upper bound on the price of credit risk. The authors show that the CDS prices lead in price discovery process making them a useful indicator to measure credit risk. However, the ED 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* (§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, it is straightforward to 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 credit default swap contract (CDS for short) 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. Formally, 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 the ED 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, judgements on specific events to account for are necessary in this particular credit sensitive instrument.

In the precise definition of a CDS contract, there are given collection of settlement dates,  $[\mathbf{T}] = [T_1, \dots, T_n]$  and a starting time  $T_0 < T_1$ . Here,  $T_0 < T_n = T$  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 quarterly 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

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

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

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

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

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

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  $S_t$  such that

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

which yields to the following formulation of the premium

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

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

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

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  $\tau = \Lambda_\xi^{-1}$ , where  $\Lambda$  is the stochastic hazard function defined as the time-integral of the intensity from 0 to  $t$ , i.e.  $\Lambda_t = \int_0^t \lambda_s ds$ . Here,  $\xi$  is a standard uniform random variable. With this in mind and assuming a deterministic intensity  $\lambda$  we have

$$\mathbb{Q}(s \leq \tau \leq t) = \exp(-\Lambda_s) - \exp(-\Lambda_t).$$

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 the market stakeholders credit risk appreciation remains stable. 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 in [Equation 3.3](#). Under the constant intensity, this probability is simply computed by noticing that  $\exp(-\Lambda_s) = \exp(\lambda s)$ , which yield the following closed form formula for  $S_0$

$$S_0 = L_{\text{GD}} \frac{\sum_{j=1}^n B(T_0, T_j) (e^{-\lambda T_{j-1}} - e^{-\lambda T_j})}{\sum_{j=1}^n B(T_0, T_j) \alpha_j e^{-\lambda T_j}}. \quad (3.4)$$

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<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  $T_0$ .

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.

In what follows, we introduce the mechanism of market quotation 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 well suited to derive market models of CDS rates, see [Brigo and Mercurio \(2006\)](#). This implicitly assumes that is 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  $T_j$ . 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  $T_0 = t$ , denoted  $S_t$ , with maturity  $T + t$ . Observations are available for each so we are able to extract the implied intensity at time  $t$ , i.e.  $\lambda_t$ .

**3.2.3 Recovering Market Intensities.** As mentioned, it is possible to strip default intensities from CDS quotes. To this end, we will need the bond prices  $B(t, t + T_j)$  for each maturity  $t + T_j$ . The only remaining quantities in [Equation 3.4](#) 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 a 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, see §53. Moreover, assuming a constant  $L_{GD}$  will ease the estimation the default intensities, which may not require the full require the full estimation of the expected credit losses.

Finally, it only suffices to equate the closed form formula in [Equation 3.4](#) 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

$$\log \lambda_t = \underline{\mu} + \sigma \epsilon_t, \tag{3.5}$$

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:

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

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  $\underline{\mu}$  should correspond 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.

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. 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  $t_d^c$  must 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 strategy, it is shown that the cumulative sums (cusum for short) is optimal. More formally, if one fix 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 (3.5)-(3.6) 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

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

It is worth looking more closely at the behaviour of the process  $V$ . First, note that the log-likelihood process  $L$  works as a measure of the adequacy of the observation with the underlying model in Equation 3.5. 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 (3.5). When  $V$  becomes greater than 0, we can interpret this as a deviation from the model in (3.5). This means that the 'real' model stands in between (3.5) and (3.6). In order to declare that the intensity is evolving with respect to the model in (3.6) 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 follow broadly the considerations of the ED. In §4-5, it suggests that an entity shall compare the creditworthiness of a financial instrument at the reporting date taking into consideration its initial credit risk (§BC67-BC75). 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 (§B12). The ED has not defined how significant should be the increase when assessing the change in credit risk nor specified the amount of change in probability of a default that would require the recognition of a creditworthiness deterioration. As to ease the application, the ED proposes 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 it is downgraded to below 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 which corresponds to an investment grade. In Table 2, 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 establish the monitoring scheme, we shall need various inputs. First, the average DI  $\underline{\mu}$  should be specified and must match the market DI of the instrument since initial recognition or the last reporting

**Table 2:** *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%

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  $\bar{\mu} \geq 5.07\%$ .

Finally, we should specify an average rate of false alarms, which specifies the frequency of sounding an alarm when nothing happens. A good candidate must reflect the aversion of the credit risk quality observe of a false alarm. 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 \(2009\)](#))

$$\exp(m) - m - 1 = \frac{1}{2} \left( \frac{\bar{\mu} - \underline{\mu}}{\sigma} \right)^2 100, \quad (3.7)$$

where  $\sigma$  is estimated based on the historical observations.

## 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 consist of bid and ask quotations for 1-year, 5-year and 10-year CDS on AIG credit risk during the period 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 1 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 1), 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. 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 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 375 basis points. Over the next two weeks, the spread increased dramatically, exceeding 2500 basis points on the day of the announced rescue.

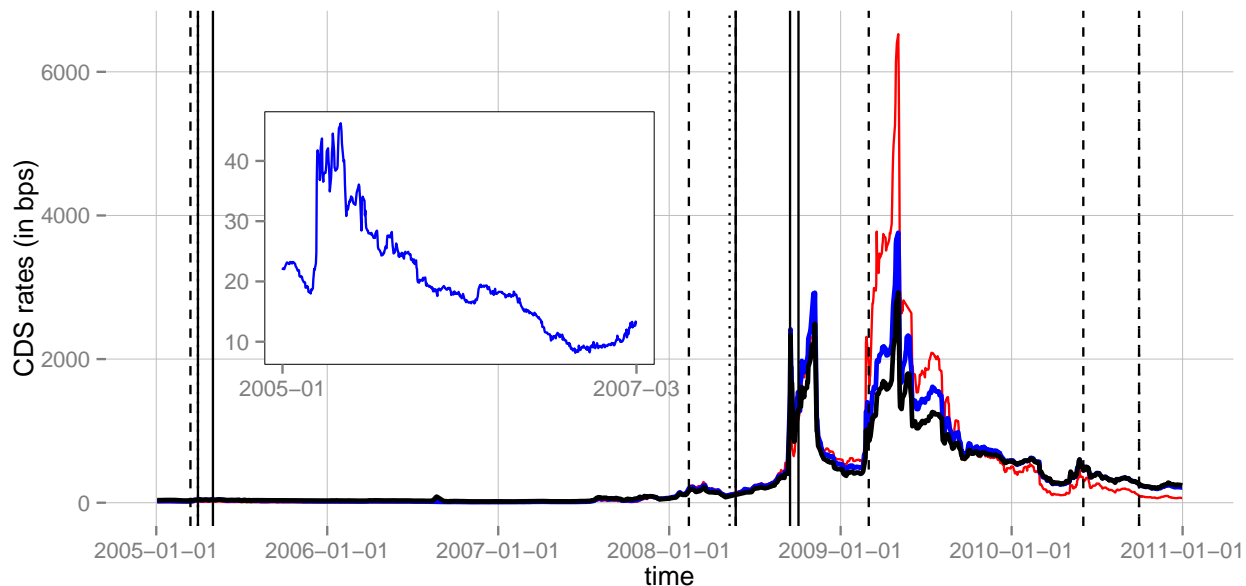
Based on these facts we will build our detection procedure on two distinct periods. We thus divide the sample into two parts: The first will run from January 2006 until the end of 2008 and the second is starting on 2009 until the end of the sample. As mentioned, the first period is characterized by quiet 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.

**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  $T$ . 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 3.4.

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 is assumed to be constant and

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<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.



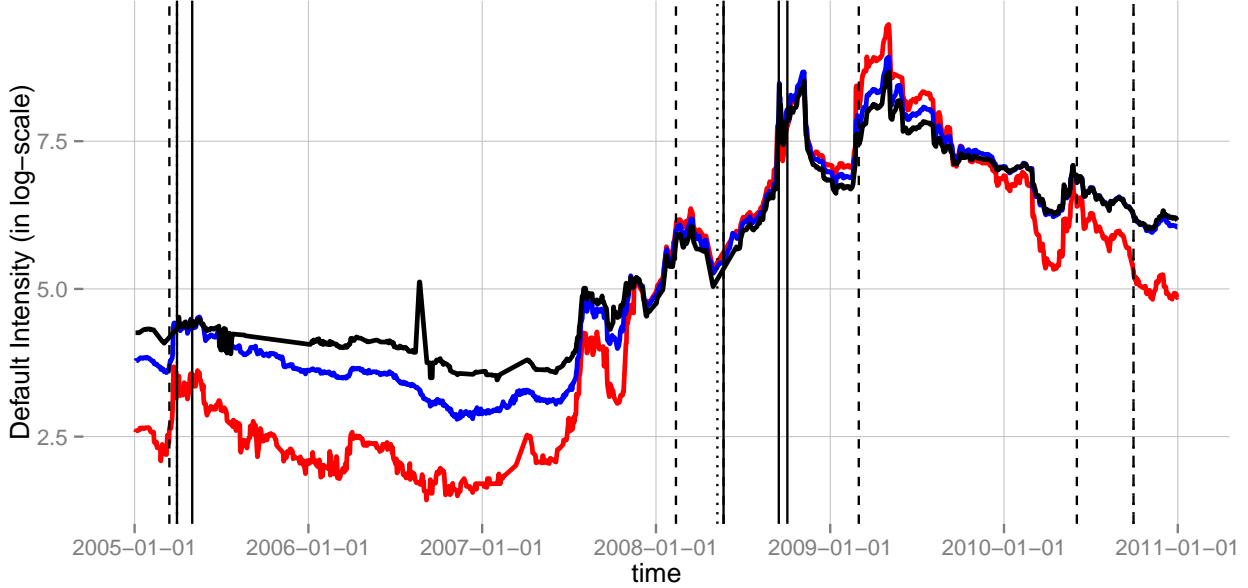
**Figure 1:** CDS spreads between January 1<sup>st</sup>, 2005 and December 31<sup>st</sup>, 2010 on AIG for different maturities: 1-year (red), 5-year (blue) and 10-year (black)

is fixed at 40%, which is the rate commonly used in empirical studies as well as by major rating agencies. We then substitute the fitted curve of  $B(t, T_j)$  for the CDS spreads in Equation 3.4. To derive the implied intensities for each observation date  $t$  we equate Equation 3.4 to the market quotes. Figure 2 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' of the grade<sup>5</sup>. The downgrades dates are collected in Table 3 from five periods of stable rating. For example, during the period P1, the AIG rating was at Aa1 level.

In Figure 2, 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>





**Figure 2:** *Time-series plot of AIG's market implied intensity process for different CDS maturities: 1-year (red), 5-year (blue) and 10-year (black)*

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 3, 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 3. It provides information on the p-value of normality test of the intensity during each period. In other words, we test whether the model (3.5) is valid during the period: Larger the p-value, smaller the significance meaning that the model (3.5) 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 may invoke 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 (3.5) 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 by the rating agencies.

**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 thereby being able to trigger an alarm to depreciate the asset of interest. Before proceeding, let us recall the main

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

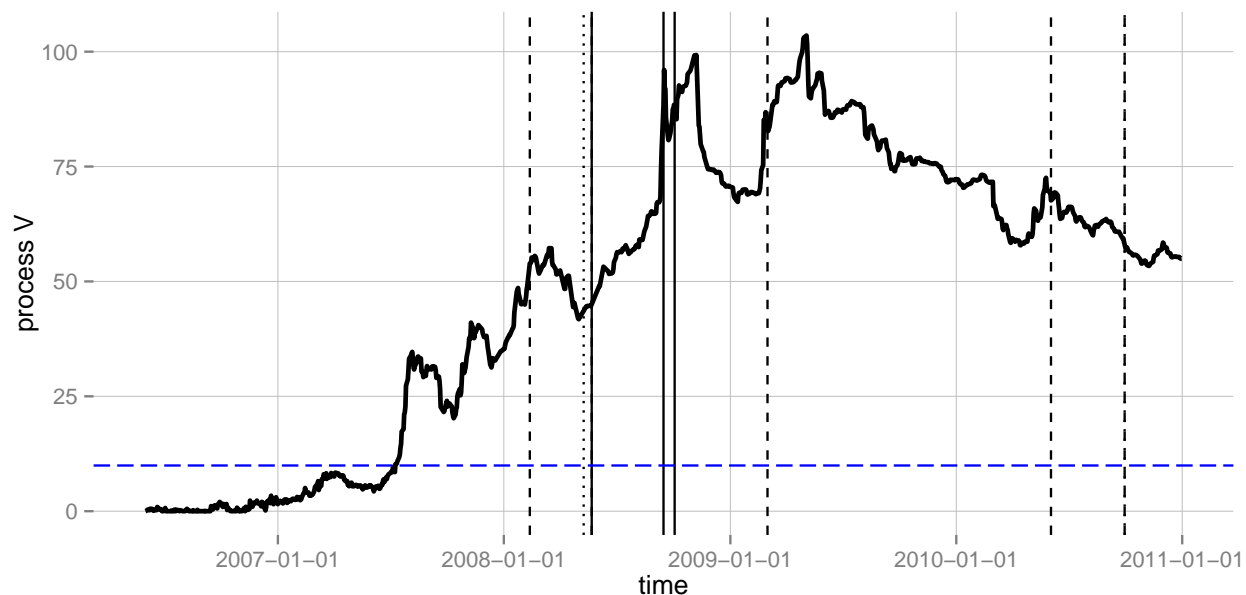
inputs of our approach:

- The historical DI average  $\underline{\mu}$ : It must match the average during the observation period. 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 3](#)). 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 2](#). The same reasoning shall 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 classes. A suitable candidate is the market average for rating class. According to [Table 2](#), average DI ranging beyond 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 3.7](#). 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 shown that the process  $V$  can also be built using the following simple recursive formula:

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

with  $V_0 = 0$ . Then, it suffices to rise an alarm once  $V$  goes beyond  $m$ . [Figure 3](#) illustrates



**Figure 3:** *The evolution of the process  $V$  since the initial recognition in September 1, 2006.*

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. From then on, 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 3](#). We thus consider  $\underline{\mu} = 0.78\%$ ,  $\bar{\mu} = 6.05\%$  and the level triggering the alarm is equal to 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.

In order to understand this credit event alarm, we can refer to the major events during 2007 and particularly two important early events in the financial crisis. First, 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 is 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 respect to some settings: The maturity of the CDS and the granularity of 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 2](#). Note that the behaviour of these intensities is substantially similar. Nevertheless, we can see that the default probability increases 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. This difference, however, tends to shrink in times of crisis, see [Table 3](#). [Table 4](#) shows the results for different

**Table 4:** *Comparative results for the detection with different sets of assumptions on the data periodicity (daily, weekly and a weekly average) and the CDS maturity (1-year, 5-year and 10-year)*

<b>Initial Recognition</b>	<b>Periodicity</b>	<b>1Y</b>	<b>5Y</b>	<b>10Y</b>
<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

maturities for a monitoring 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  $\underline{\mu}$  equal to the average DI over the period ranging from the origination (first column) back to the last change of the rating. The critical value is set  $1.4 \times \underline{\mu}$ .

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 triggered in the same year, i.e. 2006. It must be said that the data's quality used is mostly responsible for this alarm. First, notice that in mid-2006 the 10-year intensities as so is the spreads jump in mid-2006, which may certainly trigger the alarm in absence of any change of regime. 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 attractiveness, 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.

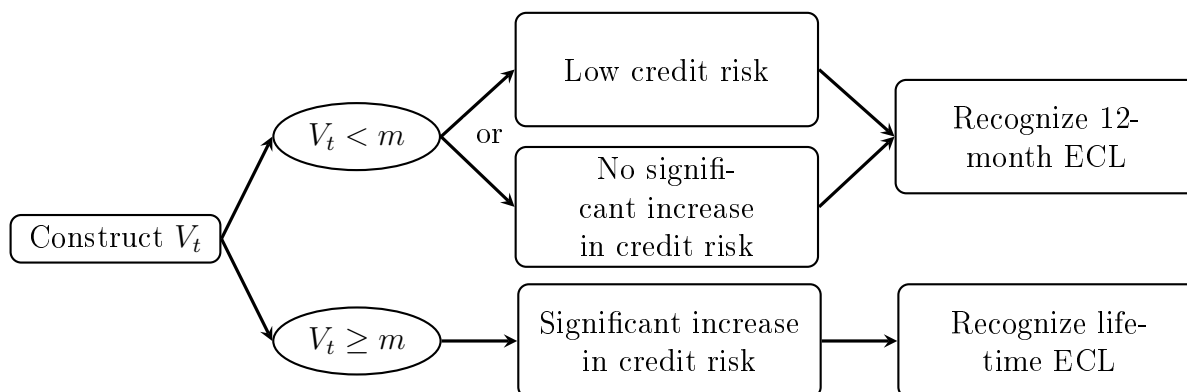
**4.2.2 Data Periodicity.** In [Table 4](#), we show the detection times when using different data. First, we consider weekly data which are the CDS prices of each Wednesday of the week during our sample period. Next, we also average out the intensity over weeks and consider the resulting quantity.

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. Averaged over a longer period could possibly remedy this.

## 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 this contracts and used it to detect changes on the underlying entity creditworthiness. The latter is shown to be a good proxy for anticipating credit events. It also fills into the standard requirement stated by the IASB's ED 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 events. Any change in the latter may invoke 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 4](#). Even if the method turns out to



**Figure 4:** Summary of the main proposals. The time  $t$  refers to the current reporting date.

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, most of insurance financial instruments can be easily associated with a CDS contract since there are mainly issued from well referenced entities.

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