Alarm System for Credit Losses Impairment under IFRS 9

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1.1. Framework

- Post Financial crisis IFRS standards
- *IFRS 9 : Financial Instruments* published by IASB on July 24, 2014
- Since equity securities have to be classified as Fair Value through P&L, impairment losses stand for financial instruments which are eligible to amortized cost (or Fair Value through OCI)
- Moving from an *incurred* approach toward an *expected* one
- New rules inspired by loan pricing and risk management : what about non-banking financial institutions (e.g. insurers with bonds) ?

1.2. Some figures

Table: 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**
Total financial investments	**411.02**	**450.04**	**339.56**	**342.04**
Debt instruments				
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
Total	**366.74**	**360.37**	**240.44**	**280.37**
	89%	80%	71%	82%

1.3. Overview of IAS 39 impairment disposals

Category	HTM	AFS		HFT
Eligible securities	Bonds	Bonds	Others (stock, funds, etc.)	Everything
Valuation	Amortized cost	Fair Value (through OCI)		Fair Value (P&L)
Impairment principle	Event of proven loss	Event of proven loss	Significant or prolonged fall in the fair value	NA
Impairment trigger	Objective evidence resulting from an incurred event (cf. IAS 39 §59)		Two critera (non-cumulative : cf. IFRIC July 2009) : significant **or** prolonged loss in the FV	NA
Impairment Value	Difference between the amortized cost and the revised value of future flows discounted at the original interest rate	In **result** : difference between reported value (before impairment) and the FV		NA
Reversal of the impairment	Possible in specific cases	Possible in specific cases	**Impossible**	NA

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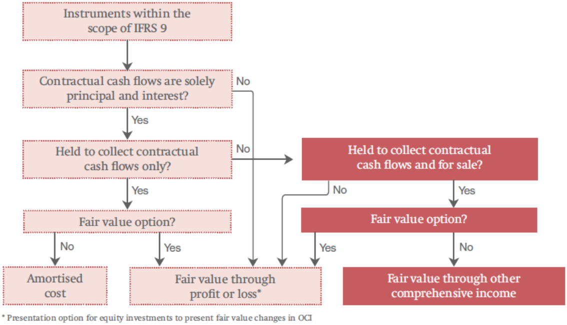
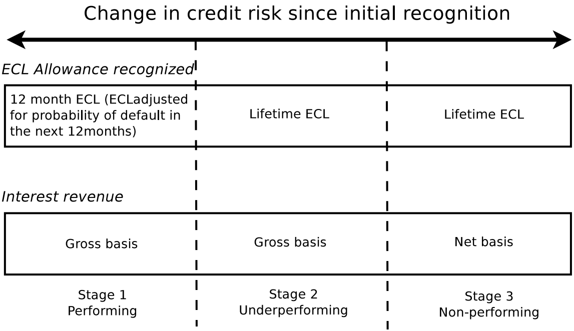
2.1. Overview of IFRS 9 disposals (measurement)



Classification & Measurement of financial assets

2.2. Expected Credit Losses



Overview of the general impairment model

2.2. Expected Credit Losses I

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 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.

2.2. Expected Credit Losses II

In practice, most credit risk watchers rely on ratings released by major agencies, e.g. Moody's, Standard & Poors and Fitch among others. There have been strong criticism about the accuracy of ratings, for example :

- lack of timeliness (cf. Cheng and Neamtiu (2009) and Bolton et al. (2012))
- too slowly downgrading (cf. Morgenson (2008))
- unability to predict some high-profile bankruptcies (cf. Buchanan (2009))

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3.1. Main idea

In order to assess a significant increase in credit risk, we propose a monitoring procedure based on implied default intensities of CDS prices.

It consists in modelling CDS prices and an alarm system based on quickest detection procedure (cf. Poor and Hadjiliadis (2009)).

3.2. Modelling I

Letting τ be the random time of the default event, the present value of the CDS fixed leg, denoted $\mathrm{FIL}(T_0, [\mathbf{T}], T, S_0)$, is given by

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

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.

3.2. Modelling II

Similarly, the present value of the floating leg $\mathrm{FLL}(T_0, [\mathbf{T}], T, L)$, that is the payment of the protection seller contingent upon default, equals

$$\mathrm{FLL}(T_0, [\mathbf{T}], T, L) = L_{\mathrm{GD}} \sum_{i=0}^{n} B(T_0, T_j) 1_{\tau \in [T_{j-1}, T_j]}, \tag{2}$$

where L_{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.

3.2. Modelling III

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 τ. Accordingly, the price is given as follows

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

where $\mathbb{E}$ denotes the risk neutral expectation (under probability measure $\mathbb{Q}$). For a given maturity, the market quote convention consists in the

3.2. Modelling IV

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

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

which yields to the following formulation of the premium

$$S_0 = L_{\mathrm{GD}} \frac{\sum_{j=0}^{n} B(T_0, T_j)\mathbb{E}\left[1_{\tau \in [T_{j-1}, T_j]}\right]}{\sum_{j=0}^{n} B(T_0, T_j)\alpha_j \mathbb{E}\left[1_{\tau > T_j}\right]}. \tag{3}$$

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

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

3.3. Market-Implied Default Intensities

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 US Bonds market.

Table: Average real world and market-implied default intensities based on Bonds market

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

3.4. Quickest detection problem I

We assume that the time varying intensity λ_t obeys to the following dynamics

$$\log \lambda_t = \underline{\mu} + \sigma\epsilon_t, \tag{4}$$

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

3.4. Quickest detection problem II

After the occurrence time θ the λ_t's evolve as follows :

$$\log \lambda_t = \overline{\mu} + \sigma \epsilon_t, \quad (5)$$

where $\overline{\mu}$ is the new drift, which is assumed to be deterministic and known. The quickest detection objective imposes that t_d^c must be as close as possible to θ. Meanwhile, we balance the latter with a desire to minimize false alarms.
For this detection strategy, it is shown that the cumulative sums (cusum for short) is optimal.

3.4. Quickest detection problem III

More formally, if one fix a given false alarm to π, which stands for the time until a false alarm, 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

$$V_t = \max_{1 \leq s \leq t} \left(\prod_{k=s}^{t} L(\log \lambda_k) \right), \quad V_0 = 0,$$

where $x \to L(x)$ is the likelihood ratio function. In view of our model the likelihood function $L(x)$ is given as follows

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

3.4. Quickest detection problem IV

- The log-likelihood process L works as a measure of the adequacy of the observation with the underlying model in 4.
- 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 (4)
  - greater than 0, we can interpret this as a deviation from the model in (4). This means that the 'real' model stands in between (4) and (5).
- In order to declare that the intensity is evolving with respect to the model in (5) one needs 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**.

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4.1. Educational example : AIG I

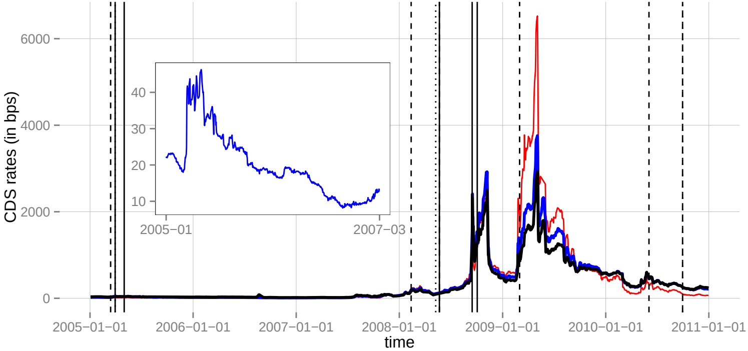


Figure: CDS spreads between January 1st, 2005 and December 31st, 2010 on AIG for different maturities : 1-year (red), 5-year (blue) and 10-year (black).

4.1. Educational example : AIG II

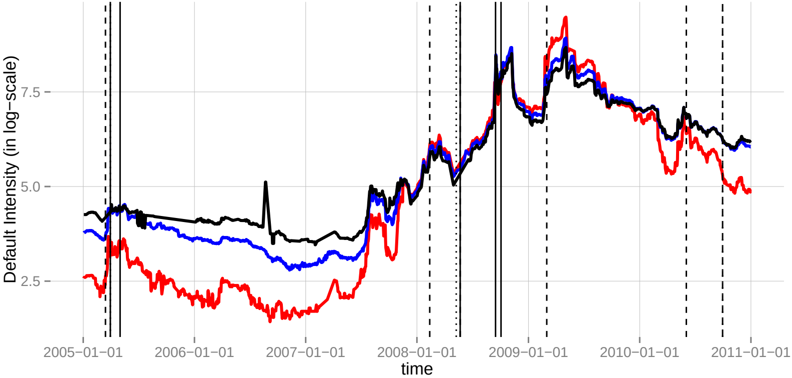


Figure: Time-series plot of AIG's market implied intensity process for different CDS maturities : 1-year (red), 5-year (blue) and 10-year (black)

4.1. Educational example : AIG III

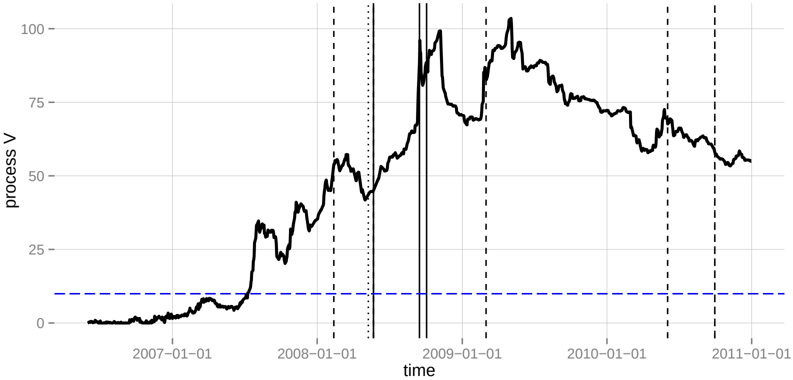


Figure: The evolution of the process V since the initial recognition in September 1, 2006.

4.2. Other illustrations

Table: The grade change column corresponds to the time the entity's grade witnessed the main downgrade during the period of interest.

	Main Change	Alarm		Grade Change	Alarm
Industrials			**Financials**		
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
Technology			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 (Ba3)	—	**Con. Goods**		
Consumer Services			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	—
Utilities			**Energy**		
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)	—
Healthcare			Repsol	5/16/05 (Baa1)	—
Sanofi	2/18/11 (A2)	3/7/08	**Basic Materials**		
Pfizer inc.	3/11/09 (Aa2)	—	Arcelor	11/6/12 (Ba1)	—
			Solvay	9/5/11 (Baa1)	—

4.3. Overview of the procedure

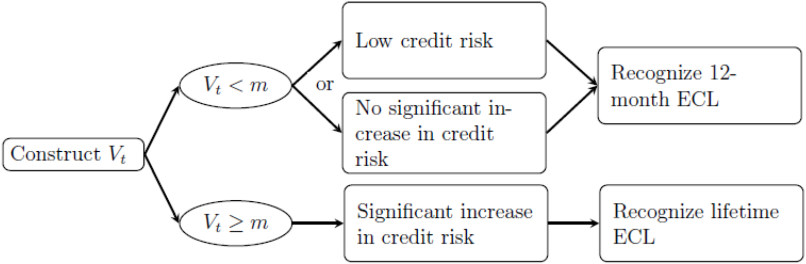


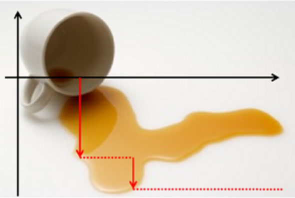
Figure: Summary of the main proposals. The time t refers to the current reporting date.

This approach should lead to further examination of bond issuers for which alarm sounded. The effective impairment should rely on closer investigation of their financial position, e.g. financial analyses and non-quantitative information.

Conclusion & Future Works

- Refinement to avoid *frequent false alarms*
- Considering more CDS examples
- Bayesian framework, where :
  - The sequential probability of change of regime is derived using the *market implied matrix transition probabilities*
  - Refined approximation of the post-change average DI
- Portfolio assessment of expected credit losses ;

DéCAF - What else ?



Work in progress :

- portfolio assessment of expected credit losses (Y. Salhi & P. Thérond) ;
- fol. of Azzaz et al. (2014) : multi-period framework for equity securities at FVOCI (A. Bienvenue, S. Loisel & P. Thérond)
- other stock price models : regime-switching, Levy, etc. (S. Loisel & P. Thérond)
- projecting French GAAP impairment losses for estimating market consistent liabilities (Y. Salhi, P. Thérond & J.P. Félix)

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