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Master in Finance

Thesis

ARE CREDIT RATING AGENCIES PREDICTABLE?

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Groupe HEC
2009

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Abstract:

In this paper, I decided to assess the credibility of CRA through the timeliness of their rating announcements. In order to determine whether ratings are timely assigned and whether they conveyed new information to the market participants, I decided to use a market-based benchmark. To that extent I derive risk-neutral default probabilities extracted from market data. I considered the entities that composed the S&P 500 index. For each value, I collected information regarding their stock prices, bond prices and CDS spreads when available. I extracted three sets of risk-neutral default probabilities implied by the pricing of each security. I used a Merton-type approach to derive default probabilities using as key input the stock prices, a reduced-form model in order to derive default probabilities from the CDS spreads, and a model introduced by J. Fons (1987) that allows to extract a term structure of default probabilities from bond prices.

This extraction allows to compare the performance of those three different models as well as providing some insight on the timeliness of those markets to issuers' creditworthiness information. This work also gives some insight on how to characterize those market derived measurement of credit risk in comparison with the CRA ratings.

I also did two series of tests in order to appraise whether market participants anticipate CRA rating actions: I first measured the impact of a rating announcement on the market implied default probabilities; and I also defined a regression model in order to attempt to predict CRA announcement using the market implied default probabilities. If market credit default probabilities assess fully all the public information and are more reactive than CRA, they will adjust before CRA takes any action. A downgrade/upgrade announcement should have a limited impact on that measurement. If the market derived default probabilities are assessing in a timely fashion issuer credit risk, they can be used to anticipate CRA downgrade/upgrade.

In addition, I consider whether the liquidity can be considered as another variable helping in the anticipation of credit quality change sanctioned by a rating event. The intuition is that liquidity is partly defined by the adverse selection cost and asymmetry of information among market participants. I found that indeed it can be considered as a useful variable in order to predict CRA downgrades.

As for the existing literature, there is evidence that market participants anticipate for CRA downgrade announcements, however the anticipation of upgrade is less clear cut. I reached the conclusion that CRA ratings and market implied default probabilities can better be considered complementary, rather than competitive assessments of the credit quality of a firm. Since those measurements reflects different approaches and to some extent different time horizons: the market implied default probabilities are a "point-in-time" measure of credit quality over a short to medium term horizon (the measures consider a time horizon of one-year), CRA ratings are a "through-the-cycle" measure with a long time horizon.

Acknowledgement: I would like to thank M. Foucault for his support as well as his useful advices all along the process.

Introduction:

Recently, the credibility of Credit Rating Agencies (CRA) has been strongly questioned. Their inability to appropriately estimate the credit risk conveyed by subprime mortgages, to foresee the credit crunch, as well as ratings failure such as the Enron case, have eroded their reputation. The new role they had been entrusted with the Basel II regulation has put the credit rating agencies under greater scrutiny by the regulators. Hence, the performance of credit rating agencies is a key issue in this debate. Several criticisms have been expressed against the main credit rating agencies, such as Fitch, Moody's and S&P. Their ratings are slow to adjust, jeopardizing/impairing their forecasting ability. Other criticisms were related to potential conflict of interest. In the present paper, I do not focus on this aspect of the criticisms.

In a response to the criticisms, Cantor (2003) states that the CRAs pursue two main objectives: accuracy and stability. He proposed a series of measures of accuracy based on the events of defaults observed on the sample of companies they rate, as well as a series of measures of stability built on a comparison with bond derived ratings. This paper enables to better understand the challenges of the rating process, namely that the CRA are facing a "trade-off between ratings accuracy and stability" (Cantor, 2006).

However, those metrics introduced by Cantor are ex-post measurements of rating performance. In order to assess in a timely fashion the performance of the CRA, I suggest to use a market-based benchmark. To that extent, I derive risk-neutral default probabilities extracted from the equity market, the fixed income market and the derivative market using standard models from the credit risk modelling literature.

This task is mainly feasible due to the extensive development credit risk modelling literature since the seminal work of Merton (1974). This paper paved the way to the development of structural models that combine accounting information and market information (either stock prices or bond prices). The development of derivative securities, and more specifically of the Credit Default Swaps (CDS), provides another metric of the market sentiment regarding the credit risk of a specific issuer. The reduced-form models where mainly used in order to price this new product. I decided to extract default probabilities from market data as a benchmark to assess the performance of rating. Since the purpose of ratings is to measure credit risk in terms of probability of default, expected losses or likelihood of timely repayment in accordance with contractual terms, the extraction of default probability seems the most "natural" benchmark. Note that I derived risk-neutral default probabilities, and not risk-adjusted default probabilities. Risk-neutral default probabilities are considered as an upper bounds to risk adjusted default probabilities, and they have the same sensitivities as risk-adjusted default probabilities (Delianedis & Geske, 2003). In addition, market participants usually price securities using risk-neutral default probability, and adjust the output by requiring a default risk premium.

Another procedure would have consisted of directly deriving market implied ratings, as Breger et al. (2002) suggested. The intuition is simple: bond spreads or CDS spreads for issuers belonging to the same rating category should be similar. They design a penalty function in order to find the boundary "spread" between two rating categories. This method has been developed into a commercial tool by Moody's (Market Implied Ratings®). Only one academic paper to my knowledge (Kou & Varotto, 2008) applies this methodology to bond spreads in order to assess and conclude that it can be used to predict rating changes. However, I have not considered this approach in order to derive a market benchmark to credit ratings. I want to assess the performance of credit ratings; therefore using a benchmark which is partly dependent on the ratings itself seems a poor fit for the purpose set. Besides, two main factors explain the market implied ratings: variations in the market spreads and rating down/upgrades that modifies the boundary levels

I preferred to use default probabilities derived from market data. Those default probabilities can be considered as the aggregation of the market participants' views on the credit risk of a specific entity. It allows to compare the market opinion on credit risk to the credit rating agencies opinion on credit risk on the same entity expressed by the rating they assigned. Note that I do not make the hypothesis of market efficiency. I only consider that market conveys information. The default probabilities extracted are supposed to reflect the aggregated view of the market participants. Moody's-KMV pronounces the same pledge/plead (Crosbie and Bohn, 2002)

However, numerous papers in the academic literature have previously explored the relation between market reactions and CRA announcements in order to assess the informational content of the CRA rating actions.

Results from earlier empirical studies were mixed. Katz (1974) finds that bond investors do not anticipate rating changes and react with delay to announcement to such changes, Weinstein (1977) finds that no evidence of a reaction to rating changes.

Contrary to Grier and Katz (1977) and Hettenhouse and Satoris (1976) that conclude that bond rating downgrades were anticipated by the bond market around or within a few months before the downgrade announcement, and that rating increases were not anticipated by the market participants, Pinches and Singleton (1978) found that both rating upgrades and downgrades were fully anticipated by market participants intervening in the equity market, and that anticipations were from 18 to 6 months prior to the CRA announcement.

Later studies are more conclusive. Hand et al. (1992) conclude that the announcement of a downgrade results in a statistically significant adjustment of corporate bond and equity prices. Goh and Ederington (1998) found that rating downgrades conveyed some additional information to the market, since negative post-downgrade returns are observed. However, this is not the case for rating upgrades, since the upgrades follow periods of positive returns.

Moreover, Goh and Ederington (1993) were the first to test whether the reaction of equity prices depends upon the reason for the rating announcement. They find that equity prices fall in response to downgrades motivated by deterioration in the issuer's financial prospects but do not react to downgrades motivated by an increase in leverage.

Kliger and Sarig (2000) test the significance of the reaction of investors to changes in ratings following the refinement of Moody's rating system in 1982. In 1982, Moody's refined its ratings by splitting each of the categories Aa, A, Baa, Ba, B into three subcategories. They show that investors indeed reacted to changes in ratings as if they revealed new information.

Delianedis & Geske (2003) study the properties and uses of option based estimates of risk neutral probabilities by applying the Merton (1974) model and the Geske (1977) model. They performed an event study using the risk neutral default probabilities and ratings migration in order to show the informational content of this market measure. They found that they possess early information about rating migrations.

Vassalou and Xing (2004) investigate the "credit spread puzzle": Holthausen and Leftwich (1986), Hand, Holthausen and Leftwich (1992) and Dichev and Piotroski (2001) found persistent abnormal equity return following downgrades, and no equity reaction to upgrades. Vassalou & Xing (2003) apply a new methodology that incorporates market opinion about credit risk of the entity. They use the risk neutral probability of default derived by the Merton (1974) model. Once taking into account the credit risk factor, the pattern exhibited by previous studies disappears. They also found that the risk neutral default probabilities start increasing from two years previous to the downgrade announcement, and decrease at the same path soon after the downgrade announcement, exhibiting an inverted V-shape curve. They argued that CRA downgrades might have a disciplinary effect on the management of the company.

Hull et al. (2004) explore the relation between credit default swap spreads and credit rating announcements. They performed a series of tests in order to assess to which extent credit rating announcement by Moody's are anticipated by the credit default swap market. They find that credit default swap spread provided useful information when the credit risk of an issuer is increasing, anticipating negative credit event announcements such as downgrade. However, they do not find significant evidence regarding the predictive power of credit default swap spread to detect upgrade announcements.

Norden and Weber (2004) found that the equity market and the CDS market anticipate downgrades and review for downgrade, concordant with Hull et al. (2004) results for the CDS market. In addition, they found that review for downgrade by Moody's and S&P showed the largest impact on both markets considered in their paper.

The present approach differs to some extent to the existing literature. I do not consider security price reactions, but the reaction in the market opinion in the credit quality of an issuer measured by market implied risk-neutral default probabilities. Contrary to the existing literature, I jointly consider the information present in three different markets: equity market, the derivative market and the fixed income market. This allows comparing the performance of default predictions, as well as giving an insight whether the market participants react differently according the market they are operating in. I introduce models that one can use to easily extract risk-neutral default probabilities from market data. Those models can have a practical use in order to help investors in the surveillance process of firms' credit quality. Moreover, those implied default probabilities are a common measure in order to assess the performance among rating agencies.

In the first section, I describe the different models used in order to extract risk-neutral default probabilities from market data, as well as data set used. In a second section, I present the results found and perform a series of test. Since I derived a “Market Credit Assessment” embedded in the risk-neutral default probabilities, I examine how those measures compare with the ratings assigned by the three main CRA. In addition, if market credit default probabilities assess fully all the public information and are more reactive than CRA, they will adjust before CRA takes any action. For that purpose I assess the impact of a down/up-grade announcement on the implied default probabilities. Moreover, if the market derived default probabilities are assessing in a timely fashion issuer credit risk, they can be used to anticipate CRA downgrade/upgrade. I perform a last series of test in order to assess this hypothesis.

Part I: Models, Data & Estimations

1. Models used to extract Default Probabilities from Market data

a. Default Probabilities extracted from CDS spreads

The Credit Default Swap (CDS) is an Over-The-Counter (OTC) derivative product for which the price is heavily correlated to the default probability of the reference obligor. Indeed, a CDS can be compared to an insurance contract against credit risk. The buyer of the credit derivative contract, or protection buyer, pays a premium, or CDS spread, in exchange for protection against the specified credit event, or trigger event, of a reference obligor during the life of the contract. The credit event can be default, bankruptcy or restructuring, downgrades, or other credit-related occurrences. If a trigger event occurs, the protection buyer delivers the bond or loan of the reference obligor to the protection seller in exchange of the face value of the bond or loan. The compensation is to be paid by physical settlement or cash settlement, whatever is specified in the CDS contract. In the physical settlement the protection buyer sells the distressed loan to the protection seller at par. In a cash settlement the protection buyer receives cash from the protection seller for the difference between the par value and the value of the distressed bond. The typical contract maturity is 5 years for corporate references. CDS spreads are quoted as spreads over the swap curve rather than the Treasuries curve, as the former curve better reflects the funding costs faced by market participants.

A CDS contract does not have to be used as insurance for a bond that an investor actually owns, but it can be used as a way to gain exposure to credit risk without holding any reference entity’s outstanding debt. A CDS contract can be entered even though there are no bonds available from the reference entity. Besides, there is no cash transfer at the beginning of the contract life. Therefore, CDS contracts can be an effective tool to diversify or hedge positions, as well as speculate on the coming evolution of the creditworthiness of the reference entity. It is therefore a good indicator of the market views on credit risk attached to the reference entity.

The link between default probability and CDS spread can be easily illustrated using the following one-period example. Assume a one-period CDS contract with a unit notional amount. The protection seller is exposed to an expected loss, L, equal to:

$$L = p * (1 - RR)$$

where p is the default probability, and RR is the expected recovery rate at default. The recovery rate and default are assumed to be independent. Under the risk neutrality assumption, it follows that the CDS spread, S, or “default insurance” premium, should be equal to the present value of the expected loss:

$$S = \frac{p * (1 - RR)}{1 + r}$$

where r is the risk-free discount factor. It follows that the default probability can be recovered if the CDS spread, the recovery rate and the risk-free discount factor are known. I do use this methodology in order to recover the default probability using 1-Year CDS spreads.

I will introduce a reduced-form model, or hazard model, that can be used in order to extract the default probability from CDS contract, following a presentation made by Duffie (1999). For the purpose of this paper, I extracted the default probabilities from 1-Year CDS spread using the simplified equation I have just introduced as well as the following reduced-form model in order to check the consistency of the probabilities found.

In a hazard model, default is modeled as a rare event. A default is considered to be the first event of a Poisson process. I assume that the CDS spread is paid in periods T(i) for i=1,…,n. The default probability in period T(i) is given by:

$$p\big(T(i)\big) = 1 - e^{-\lambda(i) * T(i)}$$

In the following presentation, I assume that default occurs at a risk-neutral constant hazard rate of λ.

In a typical CDS contract, there are two potential cash flow streams :

1. a fixed leg : the protection seller receives a series of fixed, periodic payments of CDS premium until maturity or until the reference entity defaults;
2. a contingent leg: the protection seller makes a payment only if the reference entity defaults.

It follows that the value of the CDS contract to the protection seller perspective is equal to the difference between the present value of the fixed leg, which the protection seller expects to receive, and the present value of the contingent leg which he expects to pay.

Value of the CDS (to the protection seller) = PV[Fixed leg] – PV[Contingent leg]

In order to calculate these values, I need the following inputs: the default probability of the reference credit, the recovery rate in case of default, and the risk-free discount factor. Another factor might intervene in the pricing of the CDS: the counterparty risk. I assume that there is no counterparty risk.

On each payment, the protection seller will receive a fixed, periodic payments calculated as the annual CDS premium times the accrual days between the payment dates. However, this cash flow is subject to default risk from the reference entity. It will effectively receive it if the reference entity has not defaulted before payment date. I assume no payment of accrued credit-swap premium at default. The present value of this payment is equal to:

$$S\big(T(i)\big) * e^{-(\lambda+y(i))*T(i)}$$

I will denote $a_i(\lambda) = e^{-(\lambda+y(i))*T(i)}$ where $a_i(\lambda)$ is equal to the value of receiving at t=0 one unit of account at the i^{th} coupon date in the event that the default occurs after that date. Since all these payments are to be made during the life of the CDS contract, I can write that:

$$\text{PV[Fixed leg]} = S(T) * A(\lambda, T) = S(T) * \sum_i a_i(\lambda)$$

In order to compute the contingent leg, I make the assumption that the reference entity defaults between $(i-1)^{th}$ and the i^{th} coupon payment date. The protection seller will make a contingent payment of (1-RR), where RR is the recovery rate. Since this payment is conditional on the probability that the reference obligor defaults during this time interval, I have to account for it. It can be formally written as follow:

$$S(T) * e^{-y(i)*T(i)} * (e^{-\lambda*T(i-1)} - e^{-\lambda*T(i)})$$

I will denote $b_i(\lambda) = e^{-y(i)*T(i)} * (e^{-\lambda*T(i-1)} - e^{-\lambda*T(i)})$ where $b_i(\lambda)$ is the value of receiving one unit of account at the i^{th} coupon payment date in the event that the default is between the $(i-1)^{th}$ and the i^{th} coupon payment date. Summing up all expected payments over the term of the contract, I can write that:

$$\text{PV[Contingent leg]} = (1 - \text{RR}) * \text{S(T)} * \text{B}(\lambda, \text{T}) = (1 - \text{RR}) * \text{S(T)} * \sum_{\text{i}} b_i(\lambda)$$

When two parties enter a CDS trade, the CDS spread is set so that the value of the swap transaction is zero. Hence, the following equality holds:

$$\text{PV[Contingent leg]} = \text{PV[Fixed leg]}$$

Given all the parameters, S, the annual premium payment is set as:

$$S(T) = \frac{B(\lambda, T)}{A(\lambda, T)} * (1 - RR)$$

One of the advantages of this model is that it can be easily extended to derive a term structure of hazard rates, thus allowing to determine a term structure of default probabilities.

b. Default Probabilities extracted from Corporate Bond Prices

Default probabilities can be extracted using Fixed-Income market information. The price of a corporate bond can be expressed as the present value of the future payments (coupon and principal). However, those payments are subject to default risk. In a seminal work, Fons (1987) formalized the previous intuition into a pricing formula of bond dependent on default probability, recovery rate and risk-free discount factor. In order to illustrate the intuition behind this model, let's consider the simple case of zero-coupon bond paying one unit at maturity T. I denote by r the risk-free discount factor, RR the recovery rate, p the default probability of the bond. If the bond is currently priced at B, the risk-neutrality hypothesis implies that:

$$\mathrm{B} = \frac{(1-\mathrm{p}) + \mathrm{p} * \mathrm{RR}}{1+\mathrm{r}}$$

It results that the default probability of the bond is a function of the recovery rate RR, the risk-free discount factor r, and the price of the bond B. By reversing the previous formula, I can write that:

$$\mathrm{p} = \frac{1-(1+\mathrm{r}) * \mathrm{B}}{1-\mathrm{RR}}$$

I will now generalize the methodology introduced by Fons (1987). Under the risk-neutrality assumption, the price of a bond with N period to redemption, paying a fixed coupon C and one unit notional, is given by its expected discounted cash flow:

$$B_t = \sum_{i=1}^{N} \frac{C}{1+r_{it}} + \frac{1}{1+r_{Nt}}$$

Where r_{it} is the risk-free rate corresponding to each cash flow period.

However, since the bond holder bears a risk of default from the issuer, the bond price can also be expressed as the actualized coupon and principal repayment weighted by the probability of being paid when promised.

It follows that the price B_t is also equal to:

$$B_t = \sum_{i=1}^{N} \frac{S_i * C + S_{i-1} * p_i * RR * (C+1)}{1+r_{it}} + \frac{S_N}{1+ r_{Nt}} \text{ where } S_i = \prod_{k=1}^{i}(1-p_k)\,, for\ \forall i \in [1;N]$$

S_i is defined as the likelihood that the issuer will "survive" *i* coupon payments from the issuance date without experiencing a default. It follows that, at the coupon payment i, either the bond holders receive its coupon if the firm has not defaulted before *i* (occurring with probability S_i), or he will receive only a fraction of the accrued coupons and principal if the firm has not defaulted up to *i-1* and default at *i*, event that occurs with probability $S_{i-1} * p_i$.

Those two equations are identical except that cash flow of payment in the second formula is adjusted for default risk. In a risk-neutral world, an investor will be indifferent to receiving this risk-adjusted cash flow of payment and the certain cash flow of payment with the same expected value. It follows that the appropriate discount factor is the risk-free interest rate, r_{it}.

The previous formula can even be simplified by assuming a flat term structure of default probabilities, i.e.: the probability of defaulting in any of the coupons periods is the same. This assumption can be formally expressed as the following: $p_{t1} = p_{t2} = \cdots = p_{tN} = p_t$. If the recovery rate, RR, and the coupon payments, C, are constant, the last equation can be written as follow:

$$B_t = \sum_{i=1}^{N} \frac{(1-p_t)^i * C + \ p_t * (1-p_t)^{i-1} * RR * (C+100)}{1+r_{it}} + \frac{(1-p_t)^N * 100}{1+r_{Nt}}$$

Therefore, if the current bond price, the recovery rate, the coupon and risk-free yield curve are known, the default probability p_t can be easily extracted. In addition, the probability of default in the next M coupon pavements can be obtained using the following formula:

$$p_M = 1 - (1-p_t)^M$$

However, there are limitations to this approach. The main limitation is that, in this model, bond prices, and therefore bond spreads, are only explained by default risk (embedded through the default probability and the recovery rate) and evolution of the risk-free discount factor. A large body of the theoretical research shows that default risk only constitutes a portion of the credit spreads.

For instance, Elton et al. (2001) report that default risk related premium in credit spreads accounts for 19% to 41% of spreads depending on company rating. Delianedis & Geske (2001) estimate default spread using a modified version of the Merton (1974) model to include payouts, recovery, and taxes. The difference between the observed corporate credit spread and the theoretically measured default spread is defined as a residual spread that could include recovery, tax, jumps, liquidity, and market risk factors. They find concordant results compared to Elton et al. (2001). Huang and Huang (2003) using the Longstaff-Schwartz model find that distress risk accounts for 39%, 34%, 41%, 73%, and 93% of the corporate spread respectively for bonds rated Aa, A, Baa, Ba, and B. Ericsson and Renault (2005) also find that the components of bond yield spreads attributable to illiquidity increase as default becomes more likely. Gemmill and Keswani (2009), while examining the “credit spread puzzle”, concludes that bond spreads include premia for illiquidity and illiquidity risk.

c. Default Probabilities extracted from Stock Prices

Information regarding default risk and default probabilities can also be derived using stock prices. In their seminal work, Black and Scholes (1973) and Merton (1974) suggest that firm’s equity and debt can be considered as contingent claims written on its asset value.

Based on this hypothesis, the option pricing theory they developed can be applied to assess the value of a firm’s equity and the value of its debt. Indeed, the common stock of the firm can be considered as a standard call option on the underlying assets of the firm: shareholders have "sold" the company to their creditors but hold the option of buying it back it by paying back the face value and interest of their debt claims. Alternatively, the shareholders hold the firm's underlying assets as well as a put option with strike price equal to the face value of the debt.

Default occurs either when the underlying assets process reaches the default threshold or when the asset level is below the debt face value at the maturity. If the firm's assets are worth less than the face value of the debt at expiration, it is supposed that shareholders can "walk away" without repaying their debt obligations, using their option to effectively "sell" the firm to bondholders for the face value of the debt. In turn, bondholders hold a portfolio consisting of riskless debt and a short put option on the firm's assets.

In order to formalize and illustrate the insight derived from the Merton (1974) model mentioned above, I use the simple case of a firm issuing one stock and one zero-coupon bond with face value D and maturity T. It is also assumed that the issuing firm does not default prior to the debt maturity date. In addition the term structure of risk-free interest rate r, firm's asset volatility σ_v and the asset risk premium π_v are assumed to be constant. In addition, the asset value is assumed to follow a diffusion process in the following form:

$$\frac{dV_t}{V_t} = (\mu_t - \delta) * dt + \sigma_t dW_t^v$$

Where μ_t is the expected asset return, δ is the payout ratio, σ_v is the volatility of the firm asset value, and $W_t^v$is a Brownian motion.

At maturity time T, the payoff of the equity is:

$$E(V, T) = \max(0; V_T - D)$$

And the payoff of the zero-coupon bond is:

$$B(V, T) = \min(V_T; D) = D - \max(D - V_T; 0)$$

Bondholders only get paid fully if the firm's assets V_T exceed the face value of the debt D. Otherwise, the firm is liquidated and the assets "sold" are used to compensate them partially. The equity holders are residual claimants in the firm since they get paid after bondholders.

Note that the payoff of the equity and of the risky debt correspond to the payoff of a standard European option. The first equation states that equity value is equivalent to a long position on a call option with a strike price equal to the face value of the debt. It follows that E_t can be written as below, using the option pricing theory:

$$E_t(V, T) = V_t * e^{-\delta(T-t)} N(d_1) - D * e^{-r(T-t)} N(d_2)$$

Where $d_1 = \frac{\ln(V_t/D) + (r - \delta + \sigma_v^2/2)(T-t)}{\sigma_v\sqrt{T-t}}$ and $d_2 = d_1 - \sigma_v\sqrt{T-t}$.

The second equation states that the bond value is equivalent to a long position on a risk-free bond and a short position on a put option with strike price equal to the face value of the debt. Equivalently the value of the bond is equal to the difference between the asset value and the equity value.

$$B_t(V,T) = V_t e^{-\delta(T-t)} N(-d_1) + D e^{r(T-t)} N(d_2)$$

Under the risk-neutrality assumption, I can compute the probability of default over the interval [t;T] which is equal to:

$$p\left(V_t \leq D\right) = p\left(\ln(V_t) \leq \ln(D)\right) = N\left(-\frac{\ln(V_t/D) + (r - \delta - \sigma_v^2/2)(T-t)}{\sigma_v\sqrt{T-t}}\right)$$

Since, under the risk-neutral assumption, $\ln(V_t)$is normally distributed with mean $\ln(V_t/D) + (r - \delta - \sigma_v^2/2)(T-t)$ and variance $\sigma_v\sqrt{T-t}$.

Note that KMV methodology departs at this point from the previous assumption that the default probabilities are normally distributed arguing that “the normal distribution is a very poor choice to define the probability of default [since] the default point is in reality also a random variable [due to] firms often adjust[ing] their liabilities as they near default” (Crosbie and Bohn (2002)). They compute the Distance-to-default (DD), which corresponds to the number of standard deviation away from default at time T. It is considered as a key summary statistic of the credit quality of the obligor and can be easily computed as follow:

$$DD = \frac{[Market\ Value\ of\ Assets] - [Defaut\ Point]}{[Market\ Value\ of\ Assets] * [Asset\ Volatility]}$$

Using the notation previously introduced, the previous expression is equal to the following one:

$$DD = \frac{V_t - D}{V_t * \sigma_v}$$

KMV deduces the probability of default of an issuer by using a proprietary database that links the DD and default probability from historical data on default and bankruptcy frequencies.

Equivalently, in the Merton framework I used, it is computed as follow:

$$DD = \frac{\ln(V_t/D) + \left(r - \delta - \sigma_v^2/2\right)(T-t)}{\sigma_v\sqrt{T-t}}.$$

Due to this stand, I use the DD as a proxy for credit risk assessment derived from the equity market, rather than using probability of default as I did for the other measures derived from the fixed-income and the derivative markets. In addition, in order to support this stand, I measured the correlation between the probability of default derived from the equity market with the Fixed-Income market implied default probability and the CDS implied default probability, as well as the correlation between the DD and the Fixed-Income market implied default probability and the CDS implied default probability. Those results are presented in the third part of this paper. I found that the DD was more correlated to the other market derived probabilities of default that the one implied by the equity market under the normality distribution assumption.

The market value of assets (V_t) and the asset volatility (σ_v) are supposed to be known in order to compute either the DD or the equity implied default probability. However, those inputs are not directly observable, and therefore need to be estimated. Several approaches have been previously implemented in the academic literature to deal with those inputs in Merton type models.

The basic method consists in using the market value of equity and the book value of debt in order to proxy the market value of assets. The asset volatility can be computed by calculating the annualized volatility of the asset returns from firm's accounting data.

Another method which is used by Moody's KMV consists of solving a system of two nonlinear equations. The first one is the Black-Scholes Merton equation of the option (i.e.: equity) price E_t and the second one comes from Itô's lemma, linking the equity relative volatility σ_e, that can be estimated from historical equity quotes, to the relative volatility of assets σ_v. Those equations can be formally written as follow:

$$E_t(V,T) = V_t * e^{-\delta(T-t)}N(d_1) - D * e^{-r(T-t)}N(d_2)$$

$$\sigma_e = \frac{V_t}{E_t}\,\Delta\,\sigma_v$$

where $\Delta = \frac{\partial E_t}{\partial V_t} = e^{-\delta(T-t)}N(d_1)$, N(•) is the normal cumulative distribution function.

A third methodology that can be employed to proxy the market value of assets and asset volatility has been introduced by Duan (1994) *A likelihood function based on the observed equity price is derived by employing the transformed data principle to obtain the parameters related to the unobserved firm's asset. Maximum likelihood estimates and statistical inference can be directly obtained from maximizing the log-likelihood function. One of the distinctive advantages of the maximum likelihood estimation is that it directly provides an estimate for the drift of the unobserved asset value process under the physical probability measure, which is critical to obtaining the default probability of the firm*. [Wang, W. and W. Suo, (2006)]

In order to estimate the market value of assets (V_t), I computed the sum of the market value of equity and the book value of debt. Regarding the asset volatility (σ_t), I estimated it by solving the following equation :

$$E_t(V,T) = V_t * e^{-\delta(T-t)}N(d_1) - D * e^{-r(T-t)}N(d_2)$$

Where $d_1 = \frac{\ln(V_t/D)+(r-\delta+\sigma_v^2/2)(T-t)}{\sigma_v\sqrt{T-t}}$ and $d_2 = d_1 - \sigma_v\sqrt{T-t}$.

The default point has been assessed using the methodology employed by Moody's-KMV. It is computed as the short-term liabilities plus half of the long-term liabilities obtained from the firm's accounting data reported in COMPUSTAT.

I decided to use the modified version of the Merton (1974) model since it is the seminal paper that paves the way for extended structural models and approaches in the credit risk modeling field. Its intuition is at the basis of many extensions that relaxes certain assumptions made in the original paper. I will briefly introduce other structural models that could have been employed in order to derive default probability from stock prices.

The Merton (1974) model assumes that bond holders receive the entire value of the firm in distress and that interest rates are constant. Besides, it can also deal with zero-coupon bonds.

I can distinguish two categories of structural models according to its consideration vis-à-vis the determination of the default boundary. Numerous models have been developed where the default barrier is exogenously defined.

Black and Cox (1976) consider a firm's equity as a down-and-out call option on firm's asset value. The company defaults when its assets value hits a pre-specified default barrier. This barrier can be constant or time-varying. The default barrier is assumed to be exogenous determined. In addition, the risk-free interest rate, asset payout ratio, asset volatility and risk premium are all assumed to be constant.

Longstaff & Schwartz (1995) extends the Black & Cox (1976) model to the case when the risk-free interest rate is stochastic and follows the Vasicek (1977) process. Default occurs when the firm's asset value declines to a pre-specified level. In the event of default, bondholders are assumed to recover a constant fraction of the principal and coupon.

The Collin-Dufresne & Golstein (2001) model extends the Longstaff & Schwartz (1995) model and considers a general model that generates mean-reverting leverage ratios.

Other structural models consider that the default barrier is endogenously defined.

The Geske (1977) model suggests to consider the coupon on the bond as a compound option. On each coupon payment date, if the equity holders decide to pay the coupon due by selling new equity, the firm survives; otherwise, the company defaults and the bondholders receive the entire firm.

Leland and Toft (1996) assumes that firm defaults when its asset value reaches an endogenous default boundary. In order to avoid default, a firm would issue equity to service its debt, as in the Geske (1977) model. At default the value of the equity goes to zero. The optimal default boundary is chosen by shareholders to maximize the value of equity at default-triggering asset level.

2.Data & Estimations

In this paper, I focus on the companies composing the S&P 500 index. The components of this index are all US-based entities. This restrains the geographical area I are considering and avoid geographical differences in the rating process or specificities in the methodology used by the CRA. The timeframe used in this paper spans from January 1st 2004 to December 31st 2008. I derive risk-neutral default probabilities with a one-year horizon.

1. Ratings

I focus on the ratings assigned by the three major CRA: Fitch Ratings (Fitch), Moody's Investors Services (Moody's) and Standard and Poor's (S&P). I extracted the ratings from Reuters 3000 Xtra. I only considered Long Term Issuer rating that were assigned from 01/01/2004 to 31/12/2008.I also added the CRA announcements made from 01/01/2009 to 15/04/2009 in order to consider the largest number of observations for regression analyses. If they were not available, I took by default the Long-Term Local Debt ratings, since I focus on US-based companies, only USD issuances are of interest. Over the 500 entities sample I look at, 426 entities are rated by one of the three major CRA – 394 by S&P, 329 by Moody's and 300 by Fitch. Approximately 75% of the companies rated in the sample belong to the A or BB/Ba categories. They also are relatively well diversified in terms of sectors they are operating in, as shown in the Charts below.

In addition, I also extracted from Reuters 3000 Xtra the rating events and ratings events dates of announcement. By rating event, I define the following announcements made by the CRA and recorded in Reuters : Rating Upgraded, Rating Affirmed, Rating Downgraded, Rating Off Watch, Rating On Watch Down, Rating On Watch Up. I define positive rating event as announcement made by the CRA stating either an upgrade or a rating on watch up. By negative rating event, I mean an announcement made by the CRA of either a downgrade or a rating on watch down. I will concentrate in this paper on positive and negative rating event as defined previously. I provide in the following tables some additional statistics regarding the rating events. In the first table, I compute for each CRA considered the number of credit events recorded by Reuters 3000 Xtra from January 1st 2004 to April 15th 2009. In the second table, I computed for each CRA the number of up/down-grades with x numbers of notches for the same time period considered as above.

Chart 1 : Distribution of firms per rating categories (in numbers)

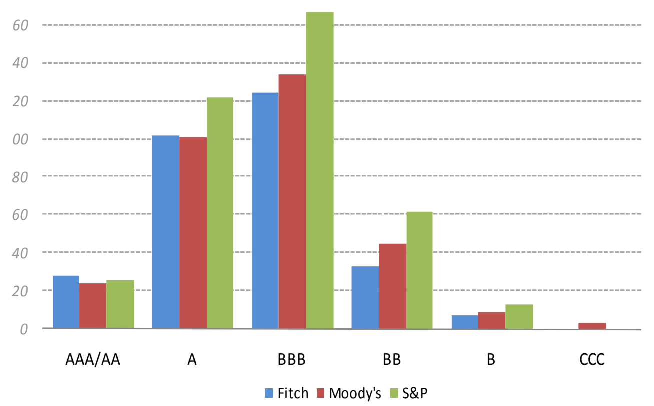


Chart 2: Distribution of firms per rating categories (in %)

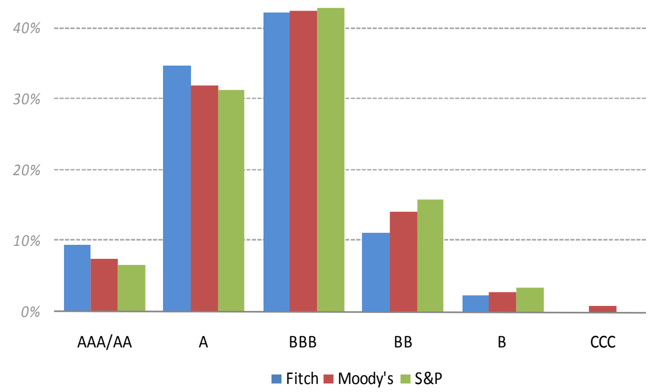


Chart 3: Number of Events by Rating Categories, from Jan. 1, 2004 to April 15 2009

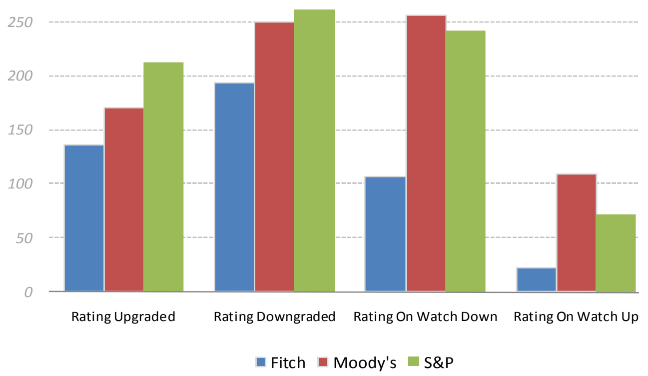
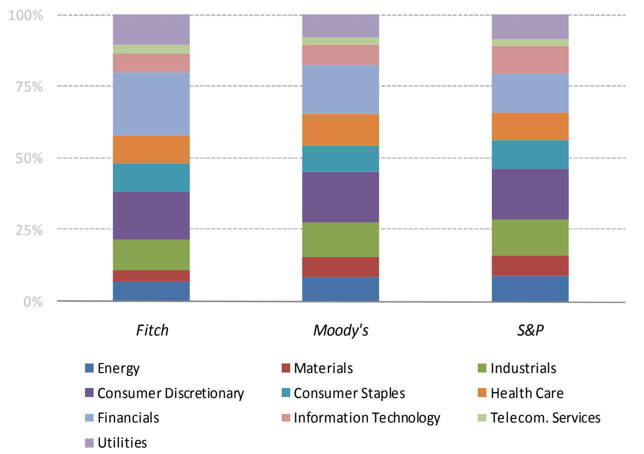


Chart 4: Distribution of the firms per sector



2. Corporate Bonds data

In order to derive default probability from fixed income market, I need to collect information regarding the price of bonds, as well as a proxy for risk-free discount rate and a recovery rate. I used TRACE database (Trade Reporting and Compliance Engine) in order to collect prices of the bonds issued by the sample companies. TRACE is an over-the-counter corporate bond market real-time price dissemination service provided by Financial Industry Regulatory Authority (FINRA). I selected plain-vanilla fixed-coupon bonds that did not bear any options attached such as callable, putable and convertible bonds in the subsample so that the price of the bond is not affected by those specifications. These constraints reduced the numbers of firms in this subsample from 500 to 183 companies. Since TRACE database provides information regarding bond price, volume, day and time of execution of the transactions, I aggregate those information to obtain daily observation by computing a daily volume weighed average price.

In order to extract the implied default probability, I also have to estimate a risk-free discount factor. I could have considered the Treasury Bond rate as a proxy for a risk-free discount factor. However, as Hull et al. (2004) point out that "*Treasury rates tend to be lower than other rates that have a very low credit risk for a number of reasons: (i) Treasury bills and Treasury bonds must be purchased by financial institutions to fulfil a variety of regulatory requirements. This increases demand for these Treasury instruments driving the price up and the yield down; (ii) the amount of capital a bank is required to hold to support an investment in Treasury bills and bonds is substantially smaller than the capital required to support a similar investment in other very low-risk instruments; (iii) In the United States, Treasury instruments are given a favourable tax treatment compared with most other fixed-income investments because they are not taxed at the state level*." For those reasons, many market participants prefer to use interest swap rates as a proxy for risk-free discount rate. Indeed, if I consider the strategy consisting in buying a bond with spread y% and at the same time hedging this position by buying a Credit Default Swap x%, it naturally follows that this strategy is equivalent of investing in a risk-free security that yields (y-x)% interest. Applying this analysis to a large number of corporations, Hull et al (2004) estimate that the benchmark risk-free rate being used by market participants is the swap rate less 10 basis points. I decided to use the interest swap rates as such for sake of simplicity. I use the interest swap rates reported by the Federal Reserve Bank in the H15 reports. Those interest swap rates are reported in a daily basis.

The last input of the model used to derive default probabilities from bond prices is the recovery rate estimation. If I assume that the recovery rate is nonzero, it follows that assumptions have to be made in the event of default regarding bondholders' claim. The literature provides some views on which recovery value to consider. Hull and White mentions that "*Jarrow & Turnbull (1995), Hull and White (1995) assume that the claim equals the no-default value of the bond. Duffie & Singleton (1997) assume that the claim is equal to the value of the bond immediately prior to default*." They suggest that it is best, in the event of default, to consider a claim equals to the face value of the bond plus accrued interests.

In Fons (1987), the recovery rate is defined as a fraction of par and suppose that recovery rate is exogenously given, based on the seniority and rating of the bond. In case of default, all future coupons are obviously lost. I also use an exogenous recovery rate that equals 40%, a figure that is widely used by market participants.

3. Credit Default Swaps

The Credit Default Swap spreads have been extracted from DATASTREAM database. I collected the end-of-the-day "default point" as defined by DATASTREAM for each entity of the S&P 500 index that has a one-year (Senior) Credit Default Swap. It follows that this subsample is reduced to 289 entities.

The two other inputs that are required by the model I used to derive default probabilities are the risk-free discount and the recovery rate. In order to be consistent with the different inputs used for the different models, the risk-free discount factor used is the interest swap rates reported by the Federal Reserve Bank as mentioned in the previous subsection. I set the recovery rate at 40%. It is the common assumption made by participants in the derivative market.

4. Equity

The application of the Merton model requires the most numerous data entries than the previous models implemented in this paper. I extracted closing day stock prices from DATASTREAM databases for the values composing the S&P 500 index. Accounting information was extracted from COMPUSTAT database, and is available in a quarterly basis. The Short Term, or Current, Liabilities and the Long Term liabilities were used to compute the Default point (D), as well as the market value of debt. In order to compute the market value of equity, the number of shares traded was necessary. I used the Common Shares Outstanding item from COMPUSTAT as a proxy. This data point was only available at a quarterly frequency. The risk-free interest rates used were the same one as described in the previous paragraphs, i.e.: the interest swap rate reported by the Federal Reserve Bank.

I provide below a summary table of the different inputs and estimations of the models parameters.

Table 1: Estimation of models parameters

Parameter	Description		Estimated as	Data sources
Bond Features	C	Coupon	Given	TRACE
	T	Maturity	Given	TRACE
	F	Face value	Given	TRACE
	RR	Recovery Rate	Assumption	-
CDS Features	S	CDS Spread	Given	DATASTREAM
	RR	Recovery Rate	Assumption	-
Firm Characteristics	V	Firm Value	Total Liabilities plus market value of equity	COMPUSTAT and DATASTREAM
	σ	Asset volatility		COMPUSTAT and DATASTREAM
	D	Default Point	Short Term Liabilities plus 0,5 * Long Term Liabilities	COMPUSTAT
Interest Rates	r	Risk-free discount factor	Interest Sw ap rate	Federal Reserve Bank

Part II: Empirical Tests

I have first derived measure of the market opinion towards the credit risk of firms. I will use those measures and assess whether they anticipate rating actions performed by the major rating agencies (Moody's, Fitch and S&P).

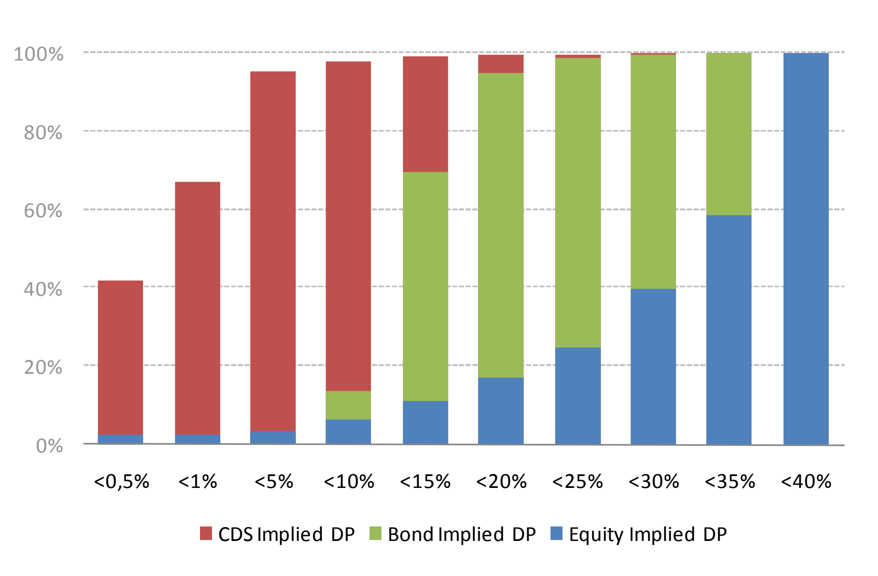
1. Description of the Results

I will in this section introduce the results of the extraction of default probabilities I performed over the values of the S&P 500 index that complied with the constraints and characteristics described above. I will use those market implied measures of credit risk as a benchmark in order to assess the performance of the rating assigned by the three major Credit Rating agencies(CRA), namely: Fitch, Moody's and S&P. In the first subsection, the results of the extraction will be described. In the second subsection, I will try to assess how those markets implied measures are sensitive to CRA announcements. In the third and last subsection, I will consider the opposite direction of the relation between markets implied default probabilities and CRA announcements, by assessing whether those market implied measures can be used in order to predict CRA actions.

a. Description of the Market Implied Default Probabilities

The first observation which is quite puzzling initially is that I do not find similar levels of default probability extracted from the three different markets I considered. The distribution of the default probabilities derived from the equity market, the derivative market and the fixed income market are shown in the following chart:

Chart 5: Cumulative of the Market Implied Default Probabilities (as of 02/06/2008)



This inconsistency in the level of default probability and its distribution is certainly due to the imperfect measurements and model risk used to derive those probabilities. Indeed, some of the model risks which can explain those differences in level are the following:

-Difference in the probability distribution function, as exhibited by KMV choice not to use the normal distribution;

-Gross approximation of some of the inputs, for instance: in the Merton-type model, the assessment of the market value of the firm and its asset volatility;

-The default probabilities obtained are risk-neutral; the utility function to be used in order to derive real-world default probability might be different according to the different markets;

-The models selected may make too simplistic assumptions and might underestimate other key variables that are taken into account by the market players – e.g.: no accrued interest for the case of the CDS pricing formula used, no difference of the term structure of the default probability, or variables such that liquidity, tax-related issues that are neglected in the models used.

However, the hypothesis that I want to test is whether changes in market implied measure of firm's creditworthiness can predict rating actions assigned by the major Credit Rating Agencies, such as Fitch, Moody's and S&P. Therefore, I focus on the variation of the implied default probabilities. Hence, the first consideration will be to assess whether those market derived measures are correlated to one another.

Therefore, I consider the coefficient of correlation between the different measurements obtained. I compute the coefficient of correlation for each entity that have a default probability derived from two different markets. I then calculate the mean and standard deviation for this particular sample and perform a standard test for the difference between two means applies, assuming normality:

$$t = \frac{\overline{X_a} - \overline{X_b}}{\sqrt{\frac{\sigma_a^2}{N_a} - \frac{\sigma_b^2}{N_b}}}$$

in order to reject or not the difference in correlation coefficients obtained.

The results are shown in the table 4 in the appendix. I find that default probabilities derived from the CDS market and the one derived using the Merton approach are not correlated. However, if I consider the Distance-to-Default (DD) measure as a measure of credit risk, the default probabilities derived from the CDS market and the DD measurement are correlated, with a correlation coefficient of -0,39. The negative sign of the correlation is due to the difference in interpretation of the variation of the two measures: a low DD means a high credit risk (and consequently a high default probability), and vice versa.

I perform the test described in the previous parachart in order to assess whether the correlation coefficient obtained using the DD measurement and the one using the default probability derived from the Merton approach. I find that those two measures are significantly different. That is reason why I do prefer to use the DD measurement as a proxy of credit risk derived from the equity market, instead of relying on the assumption that default probabilities are normally distributed.

The low correlation coefficients found might be explained by the difference in volatility of the derived default probability. The standard deviation of the default probability derived from the derivative market is about 1%, and the standard deviation of the DD proxy is around 20%. The equity derived measurements are noisier.

I reiterate the same computation as described above in order to assess the correlation between the DD proxy and the default probability derived from the bond prices. I find a lower correlation coefficient compared previously, being at -0,17. The volatility difference is still relevant between those two measures, since default probabilities derived from the bond prices exhibit a low volatility compared to the DD proxy for the sample of firms common to those two credit risk measures. The difference in volatility is statistically different at the 99% confidence interval.

The default probabilities derived from the CDS spread and the ones derived from the bond prices exhibit the highest level of correlation, with a coefficient of 0,55. The difference in volatility is not statistically different, this factor is not explanatory of the level of correlation observed.

I can also consider another method in order to compare the three market derived measures. If those three measures are coherent, the ranking of firms according to their creditworthiness using any of the three market implied measurements should be the same. Even though the distribution of the default probability is different and the variations are not perfectly correlated, the outcome of the usage I can make of those measurements should be similar.

In order to illustrate how to apply this method, let's consider the subsample of common entities for which I have derived the default probability from the equity market and from the fixed income market. For each observation date *t*, I rank the companies according their probability of default among the firms for which I have simultaneously information on the fixed income and equity market at date t. For instance, if I have derived at date t probability of default from the equity market and not from the fixed income market, I drop the firm value in the sample of firms to be ranked at the observation date t. I also rank the same sample of companies according to the default probability derived from the corporate bonds, using the same procedure as described above. In order to assess whether both market implied measures of credit risk provide similar ordering, I compute the difference of the rank between the default probability derived from the equity market and from the fixed income. I then compute for each entity the average difference in ranking over the sample period studied - 01/01/2004 – 31/12/2008.

I provide below the distribution of the rank difference for the three sets of comparisons.

Chart 6: Equity Implied DP / Bond Implied DP

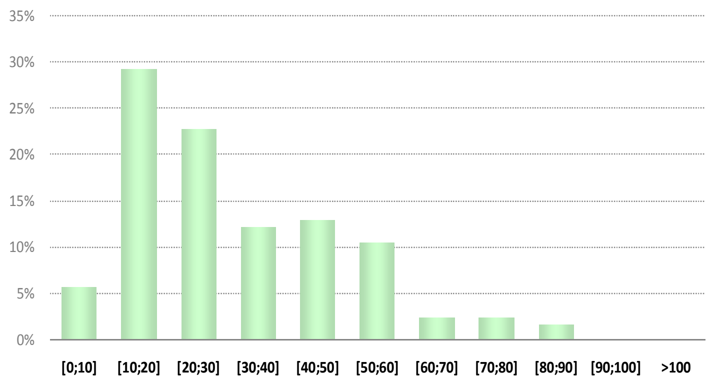


Chart 7: CDS Implied DP / Bond Implied DP

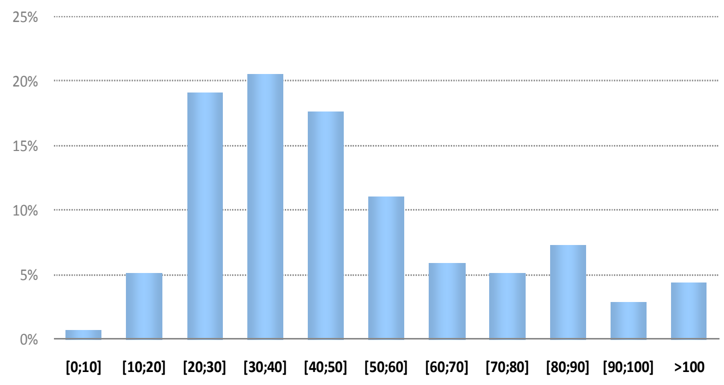


Chart 8: Equity Implied DP / CDS Implied DP

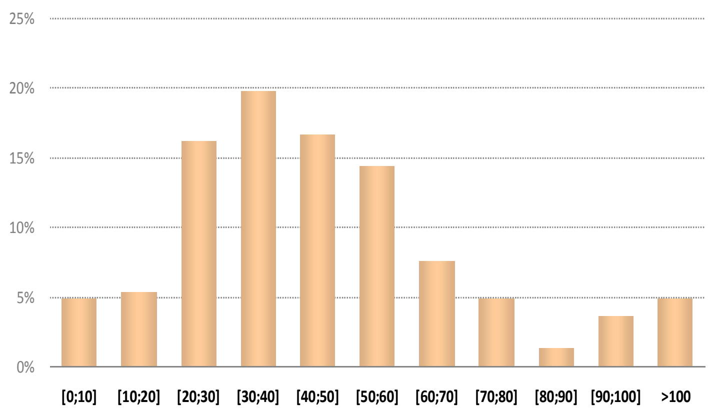
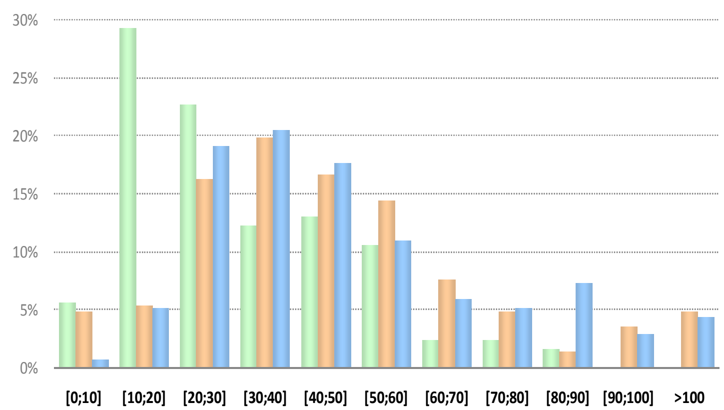


Chart 9: Comparison



I found that, according to this methodology, the equity and the fixed income market derived measures ranks similarly the sample of firms they both assessed. The median of the rank difference is set at 26 notches difference. The same metric is less satisfactory when comparing the ranking difference obtained between the CDS derived measure and the equity one, and the CDS derived measure compared with the fixed income market one, with a median of the 40 for the latter and 42 for the former. A statistical test does not reject the difference in ranking errors between those two sets of measures.

Another procedure that could have been implemented in order to achieve a similar result would have been to group entities according to the level of credit risk they show by breaking down the default probabilities into ranges. I will have to check whether the market implied measures distributes the firms into the same categories/groups. The main concern of this measure is that it requires a parametric calibration in order to determine the break points between the credit risk categories. For this reason, I have not chosen to apply this methodology.

b. Characterization of the Market Implied Default Probabilities compared to the CRA ratings

I try in that subsection to characterize the market implied default probabilities in comparison with the CRA ratings. The market implied default probabilities and the CRA ratings are both expressions of an opinion regarding the credit risk of an entity, for the latter the CRA and for the former the market. Therefore, if those opinions are similar, the ranking of the entities should be also similar.

I proceed with a methodology that follows the same intuition as the one described in the last subsection. However, since market implied default probabilities are a continuous figure from [0;1] and the CRA ratings are expressed as a letter, I cannot directly compared the rank of each firm. In order to overcome this problem, I do not consider the ranking of each entity, but how well the entities with a similar CRA rating are grouped. The companies with the same rating category should be gathered on a similar part of the market implied default probabilities scale. I first rank each entity, I assigned the rating given by the CRA in front of each firm, and then I compute the distance between each firm that have the same rating category. If the market implied default probabilities rank the companies in a comparable order as the CRA, the distance between two firms that have the same credit rating should be 1.

In order to assess if the ranking/grouping provided by the market fits the grouping provided by the CRA I can consider the median of the distance between each firms belonging to the same rating category with the median of the daily average distance. If this difference is large, the market implied measurement exhibits at least one outlier that is considered to be in a specific rating category by the CRA, where the market assigned a higher/lower default probability. This difference is then function of either overreaction of the market considering a specific entity, and/or delay for readjustment (either the CRA or the market opinion update).

Table2: Distance between each firms belonging to the same rating category

	Daily Average						Overall Sample					
Moody's Rating Category	Median	Avg	Stdev	Min	Max	Nb. Obs.	Median	Avg	Stdev	Min	Max	Nb. Obs.
Aaa	27	44	46	1	265	697	1	29	48	1	265	2368
Aa1/Aa2/Aa3	7	9	6	1	53	1305	1	8	14	1	118	19081
A1/A2/A3	2	2	1	1	5	1305	1	2	3	1	50	102133
Baa1/Baa2/Baa3	3	3	0	1	4	1305	1	3	4	1	68	86937
Ba1/Ba2/Ba3	6	7	3	1	19	1285	2	6	11	1	123	28086
B1/B2/B3	5	7	4	1	20	1283	4	7	10	1	100	9537
Caa1/Caa2/Caa3	19	32	33	1	152	1129	8	27	35	1	152	1740
Fitch Rating Category	Median	Avg	Stdev	Min	Max	Nb. Obs.	Median	Avg	Stdev	Min	Max	Nb. Obs.
Aaa	2	4	5	1	32	366	1	3	5	1	37	1752
AA+/AA/AA-	6	9	7	1	65	1304	1	8	15	1	155	18073
A+/A/A-	1	2	1	1	5	1305	1	2	2	1	45	61908
BBB+/BBB/BBB-	4	4	1	1	6	1305	1	4	6	1	79	57624
BB+/BB/BB-	5	5	2	2	14	1305	1	5	11	1	130	35917
B+/B/B-	8	11	7	1	31	1283	6	12	15	1	105	6540
CCC+/CCC/CCC-	5	9	8	1	36	912	5	8	8	1	41	1112
S&P Rating Category	Median	Avg	Stdev	Min	Max	Nb. Obs.	Median	Avg	Stdev	Min	Max	Nb. Obs.
Aaa	12	33	41	1	125	296	1	13	32	1	152	1659
AA+/AA/AA-	5	7	5	1	29	1305	1	7	15	1	157	20508
A+/A/A-	1	1	1	1	4	1305	1	1	2	1	47	63110
BBB+/BBB/BBB-	3	3	1	1	6	1305	1	3	5	1	65	60617
BB+/BB/BB-	4	5	2	1	13	1305	2	5	9	1	134	33250
B+/B/B-	5	6	4	1	15	1305	3	6	9	1	85	14473
CCC+/CCC/CCC-	-	-	-	-	-	-	-	-	-	-	-	-

I observe that in general the following categories are grouped together: A, BBB, BB and B. However there is difference in performance according to the different credit rating agencies: I notice that some outliers are persistent in the Aaa and Caa categories of Moody's; it is to a lower extent the case for the AAA category ratings assigned by S&P; Fitch ratings seem to be better grouped by the CDS implied default probabilities.

Regarding the equity driven default probabilities, I observe that the A and BBB categories are appropriately gathered by this market implied opinions. There is a lower performance in gathering the AAA/AA categories with the same errors for the three CRA. This methodology also shows that there are large movements in the distance between two entities with a AAA rating for the S&P subsample, or with a CCC/Caa rating for the Fitch/Moody's subsamples. One explanation that can be advanced is that there are fewer firms with those ratings, and therefore bigger discrepancies in their relative credit risk assessed by the market participants.

Similarly to the equity driven default probabilities, the Fixed Income market derived default probabilities classify appropriately together entities with a A or BBB ratings. There are larger moves in the lower rating categories, i.e.: B and CCC rating categories, exhibited by the difference between the median and average of the distance between firms with the same rating category.

I conclude that the CDS implied default probabilities better grouped the firms with the same rating category than the two other metrics. A common feature of the three metrics is that they exhibit few consensus regarding the extremes categories (AAA/AA and B/CCC) than the CRA.

Another trait of the rating opinion provided by the CRA is that its evolution is similar to a step function. Another question that arises is whether I can see this pattern in the market implied default probabilities that I extracted? The intuition is that, similarly to the Credit Rating Agency, market participants observes an event and update their believes regarding the credit risk of the entity, creating sharp changes/jumps in the sample of default probabilities derived from the market.

Therefore, is needed a model that allows converting the continuous tracking of the daily market opinion on credit risk into a step curve. The main issue is that it requires to calibrate the model in order to exhibit step-function-like pattern. For instance, I can consider the following calibration: if the % change of the default probability was of 20 % or more during the three weeks preceding date t, and if the % change in the default probability is of 1% or less over the two weeks following date t, I then infer a change in regime at date t. I do not perform this type of test due to the arbitrary calibration issue.

Another way will be to apply the procedure first initiated by Breger et al. (2002) to derive market implied ratings. Instead of applying this methodology to bond spread or CDS spread, I could apply it using the default probabilities I previously extracted. The intuition is that spread/default probabilities for the entities belonging to the same rating category should be concentrated within a specific range. They define a "penalty function" in order to find the break-points between two different rating categories. This penalty function for the boundary is as follow:

$$P(b) = \frac{1}{m}\sum_{i=1}^{m} \max\,(s_i^+ - b\,;0) + \frac{1}{n}\sum_{i=1}^{n} \max\,(\,b - s_i^-\,;0)$$

where s_i^+ refers to the spread of bond i with the highest rating of the two rating categories considered in the penalty function, m is the total numbers of bonds currently rated with the highest rating, s_i^- refers to the spread of the bond i with the lowest ratings of the two rating categories considered in the penalty function and n the number of bonds with this rating, b is the limit point between two different rating categories.

It logically follows that b is found by minimizing the penalty function described above. This process has been employed by Moody's (2003) while assessing the timeliness of the ratings they assigned. If I reapply this methodology by substituting the default probability instead of the market spread, I could therefore convert default probability into ratings. As Moody's (2003) mentioned, this market driven measure is more volatile than the ratings they assigned: over the period 1999-2002, as a twelve-month average, 25% of issuers experienced a rating action by Moody's, whereas market-implied rating changes affected 91% of the issuers. This result also holds for large rating changes (7% against 43%) and rating reversals (1% against 76%) according to the same report. This is consistent with the CRA statement that they are to provide stable measure of credit risk to the market. This is also qualified in the academic literature as the "Through the cycle" rating, contrary to the "Point in time" rating. Numerous papers focused on the "through-the-cycle" properties of the CRA rating methodology such as Löffler (2004) and Altman & Rijken (2005), agreeing that the CRA methodology focuses on the permanent component of credit quality, lowering rating migrations, affecting their default prediction performance. Moody's(2003) agrees with this result and reports that, when considering a one year horizon, bond market-implied ratings are, on average, a better approximation of corporate defaults than their own ratings. However, the gap between these two measures is reduced as the time horizon lengthens.

However, there is an issue in applying this methodology. Market spreads, as well as market implied default probabilities, are continuous and provide a "point in time" assessment of the credit risk of a specific entity. The ratings assigned by the CRA are "through the cycle" measurement of credit risk. There is an implicit hypothesis that the CRA are slower than the market participants. Indeed, if there are macroeconomic factors affecting the overall credit of a specific category, the market spread are to increase for all; some will see theirs increasing more due to the fact that they are more sensitive to those conditions or that the market participants are more concerned by this stressful scenario. The model described above will reconsider those entities and reallocate to another credit rating category. The boundary will change until the CRA have readjusted their rating. The boundary is likely to go back to its original level. This framework implies that market implied ratings are much more volatile than the CRA ratings, since the defined boundary is sensitive to both market movements and CRA adjustments. I conclude that there is an intrinsic instability in this model.

I can use the information I extracted from market price in order to show that the CRA ratings are not assigned in a timely manner by performing a simple test. I first make the hypothesis that the implied default probabilities provide a reliable measure of the market opinion regarding the credit risk of a specific entity. If the rating agency provide timely opinion of the creditworthiness of the same entity, an upgrade or/and downgrade from one notch to another will intervene around the same default probability level. I therefore computed for each rating change the average default probability difference between downgrade and upgrade. I computed it for each sector, since CRA may record a different methodology according to the sector they are covering. Since all the companies in the sample are from the United States, I do not face any country contamination effect. I then performed a simple t-test on the average of the average default probability difference per market and per CRA.

I find that there is a statistical significance of that difference in the derivative market and in the equity market for all the CRA. Since the signed of this difference is statistical negative, it means that the downgrades by the CRA appear at a higher default probability level than the upgrades. Either CRA upgrades too early or they downgrades too late. However, I also found that this difference is not significant for the Fixed Income market.

Table 3: Difference between average default probabilities between downgrade and upgrade announcements

	CDS				Corp.Bonds				Equity			
	Nb. Obs.	*Avg*	*Stdev*	*t-stat*	*Nb. Obs.*	*Avg*	*Stdev*	*t-stat*	*Nb. Obs.*	*Avg*	*Stdev*	*t-stat*
Fitch Rating	33	-0,046	0,073	-3,633	27	-0,014	0,055	-1,334	24	0,118	0,181	3,205
Moody's Rating	36	-0,032	0,047	-4,113	18	-0,014	0,071	-0,849	38	0,122	0,200	3,767
S&P Rating	39	-0,042	0,083	-3,167	22	-0,007	0,057	-0,614	47	0,115	0,160	4,944

2. Impact of CRA announcements on the Implied Default Probabilities

In this subsection I consider the change in the market implied default probabilities that occurs before and after a CRA rating actions. I want to test whether market implied default probabilities anticipate the CRA rating actions, and whether a CRA rating action has an effect on these measurements, i.e.: whether CRA announcement provides significant and reliable new information to the market participants.

In that respect, I apply a methodology quite similar to a traditional event study. I define a time interval $[t_1;t_2]$ as the time interval lasting from t_1 business days after the event to t_2 business days after the event, where t_1 and t_2 can be positive or negative. For instance, [-60;-30] is time interval from 60 days before the CRA announcement to 30 days before; [1;10] is the time interval from 1 day after the event to 10 after the CRA announcement. I computed the market implied default probabilities change for interval $[t_1;t_2]$ as the market implied default probability observed for day t_2 minus the default probability observed for day t_1. When there was no default probabilities extracted for t_1 or t_2 being the interval extremes, I simply dropped that this observation from th sample.

The CRA announcements that I considered were a rating upgrade, a rating downgrade, a rating put on watch up and a rating put on watch down[1], since those announcements might be considered by the market participants as possible predictors of upgrade or downgrade. I consider that a rating upgrade and a rating put on Watch Up are qualified as “positive” events, and that a rating downgrade and a rating put on Watch Down are qualified as “negative” events. Contrary to Hull et al. (2004) who performed a similar event study using the CDS spread instead of market implied default probabilities, I did not “eliminate all events that were preceded by another event in the previous 90 business days”. I did not control for contamination, since I make the hypothesis that the credibility of the CRAs considered might not be perceived as equivalent by the market participants. Besides, I wanted to isolate the effect of *Watch Up/Down* procedures from a Rating Up/Down-grade procedure. However, in order to corroborate the results, I apply the same methodology by considering altogether the announcement effects of rating actions performed by Fitch, Moody’s and S&P simultaneously.

I considered whether the mean market implied default probability change for a rating event is significantly great than (less than) zero for negative (positive) events. I perform a standard *t*-test contrary to Hull et al. (2004) that use a bootstrap technique due to relatively small size of their sample (only thirty companies are considered in their sample). Vassalou & Xing (2004) performs a similar test but consider a much longer time frame. They shows that the Merton derived default probability anticipates up to two years ahead of the CRA downgrade announcements, however this credit risk measure remains stable after the CRA announcement and decreases at the same path it increased. They advanced the hypothesis that the management of the firm reacts to this signal by adjusting the financials accordingly.

I presented below the results for the general case where I do not make any differentiation according to the rating categories (Table 6 in the Appendix). The default probabilities extracted from the CDS spreads anticipate the rating downgrades and “Watch down” actions up to 90 days before the CRA announcements. The downgrades also affect the market opinion around the announcement dates, at 95% confidence. This effect disappears quickly for Fitch announcement, whereas the market participants seem to update their views up to 10 days after S&P and/or Moody’s announcements. CDS implied default probabilities do not have any specific features before or around Upgrades and “Watch Up” announcements. The default probabilities extracted from the corporate bond prices exhibit the same patterns as for the default probabilities extracted from the derivative market. However, no specific adjustments are statistically significant at and after downgrades or “Watch down” announcements, except for Fitch “Watch Down” announcements. The default probabilities derived by the Merton-type approach do not exhibit any specific features regarding downgrades. Nevertheless, it seems that they anticipate upgrades up to 30 days ahead of the CRA announcements. This result is relevant for the upgrades announcements performed by the three CRA considered in this paper.

[1] *Rating on watch up / on watch down have been taken from Reuters 3000 and translate the “On watch positive/negative» announcements from S&P and Fitch, “Review for upgrade/downgrade” announcements from Moody’s.*

I also look at the results adjusting for rating categories. The results are shown in the table 7, 8 and 9 in Appendix. Regarding the impact of Fitch announcements on the CDS spread implied default probabilities, I notice that downgrades affecting investment grade categories are anticipated by the market participants up to 90 days prior to the rating action. The CDS spread implied default probabilities show a strong movement during the month preceding a “Watch Down” announcements by Fitch for investment grades categories. The movement is still significant at the announcement date but dissipates quickly. I observe a similar anticipation by the market participants measured by the CDS spread implied default probabilities once considering Moody’s downgrade announcement. It affects all rating categories except the single B category. The market participants anticipate up to one month ahead “Review for downgrade” announcements performed by Moody’s. I observe the largest movements for the Baa category that culminate during the month prior to the “Review for downgrade” announcement; they still react at the announcement date. I also observe that for “Review for upgrade” by Moody’s, the default probabilities implied by CDS spread anticipates this announcement up to 30 days in advance for the Baa category and below. Regarding the anticipations of S&P announcements, I notice that S&P downgrades are anticipated by the market participants with a readjustment of the default probabilities derived from the CDS spread up to 90 days for investment grades, and 30 days for speculative grades. The “Watch Down” announcements performed by S&P are anticipated. However I observe a strong reaction on the day of the announcement for speculative grades that quickly disappears expect for BBB ratings.

I observe a large readjustment of the default probabilities derived from bond prices up to 90 days prior to a downgrade announcement by Fitch for all categories except for the BB category. A similar readjustment is visible up to 60 days prior to an upgrade announcement by Fitch for all rating categories except for BB category. I notice a more disperse reaction of the bond implied default probabilities prior to and after a “Watch Down” action performed by Fitch. I notice strong movement of this measure up to one month prior to Moody’s “Review for downgrade” announcements. A wider move is observed up to 90 days prior to the announcement for the Baa category. I also notice that the market participants seem to anticipate “Watch down” announcement by S&P up to 60 days in advance for all categories. However, they seem to update their views at the announcement day and after for BBB rating issuers.

Regarding the equity implied default probability, a readjustment is perceptible for the AA and BBB categories during the month preceding Fitch downgrade, and up to 60 days ahead of Fitch upgrade announcement for the BBB/BB/B categories. I also notice that the market participants anticipate up to one month ahead upgrades performed by Moody’s on B/Caa issuers.

3. Rating events conditional on the Market Implied Default Probabilities

In this subsection, I examine whether market implied default probabilities are useful in order to estimate the probability of a rating event. In the previous subsection, I considered whether market implied default probabilities were affected by CRA announcement. Here I consider whether market implied default probability change may predict rating events, by looking at the probability of a rating event conditional on the change in market implied default probabilities.

In that respect, I constructed a set of non-overlapping 30-day (90-day) time intervals for each reference entity and observed whether a particular rating event occurred in the 30 days (90 days) following the end of the interval. I eliminated intervals that did not include at least two market implied default probabilities observations on the reference entity. I constructed three different sets per market implied probabilities of the type described above, one for each CRA. I only considered two types of credit rating events: rating upgrade and rating downgrade.

Since the rating event that I are considering can take only two outcomes possible: either at date t a rating event has occurred, or it has not occurred. It naturally follows that the most appropriate test is to use a binary logistic regression where I examine the relationship between a binary dependent variable Y (Y_t = 1 if a rating event has occurred or Y_t=0 if it has not), with the independent variable X. Let's denote $p(x) = prob(Y = 1|x)$ the probability that a rating event occurred for X set at x. The variable Y follows a Bernoulli process with parameter p(x), for X set at x. The mean of Y, for X set at x, is equal to p(x) and its standard deviation is equal to p(x)(1-p(x)).

In the logistic regression model, the relationship between Y and the probability of a rating announcement is described by the following link function:

$$p = \frac{e^y}{1+e^y} = \frac{1}{1+e^{-y}} \; or \; y = \log\left({}^{p}/_{1+p}\right)$$

where p is the probability that a rating announcement occurs during the following time interval and y is the value of the unobserved continuous variable.

The model also assumes that Y is linearly related to the predictors. I can write in the case at hand:

$$y = a + b * x$$

where *x* is the predictor, i.e.: the implied default probability change over the defined time interval, *a* is a constant and *b* is the regression coefficient.

If Y were observable, I would fit a linear regression to Y. However, since Y is unobserved, I must relate the predictor to the probability of a rating announcement by substituting y.

The probability p(x) is written as follow:

$$p(x) = \frac{1}{1 + e^{-(a + b*x)}}$$

I used SPSS software in order to determine the regression coefficients. Those coefficients are estimated through an iterative maximum likelihood method.

In the present case, x is the market implied default probability change in a 30-day interval, p is the probability of a rating event during the 30 days following the end of the interval, a and b are constants. The market implied default probability change is defined as the last default probability observed in the interval less the first default probability observed in the interval. One sample set consists of observations for all combinations of intervals and reference entities for one specific market driven default probabilities measure and one specific CRA considered. I also performed the same regression considering a longer time span of 90-days.

In order to provide an intuitive measure of the impact of x on the probability p of seeing a rating event in the next time interval, I computed the increase in the probability of a rating event for a one-percent increase in x, keeping constant a and b coefficient found by the binary logistic regression. I refer to his measure as the "Probability Sensitivity Measure" (PSM).

The results are shown in Tables 10 and 11 in the Appendix. I first look at the results from the regression performed when the rating events tested were downgrades, and the time span considered is 30 days. I found that, for Fitch and Moody's samples, the coefficient b is significantly different from zero while considering the Wald test. It can be interpreted as the change in the implied default probabilities observed over a 30-day time interval has a predictive power in order to anticipate possible downgrade by those CRAs. The PSM is about 1%, i.e.: a 1% increase in the implied default probabilities over a 30-day time interval leads to a 1%-increase in the probability of a downgrade announcement in the following 30 days. I observed a stronger sensitivity for the default probability change derived from the bond prices. I also observed that the model perform poorly in order to assess the probability that S&P announces a downgrade.

The sensitivity of this probability is slightly more than half of the sensitivity observed for Fitch and/or Moody's downgrade announcements. The results are greatly improved if one considers a longer time span: the series of test I performed while replacing a 30-day time interval by a 90-day time interval show this amelioration. The high level of significance of the Wald test for the change in the default probabilities implied by the CDS and the bond markets points out the explanatory power of the regression coefficient b. This result is valid for Fitch, Moody's and S&P included. Observing the change in the default probabilities derived either from the CDS or the bond market allows to assess the probability of rating announcements by one of the "big" three CRAs. Similarly to the conclusion found once considering a 30-day time interval, I observe that the PSM is the strongest for change in the bond implied default probabilities. The regression model provides a good fit in assessing the probability that Moody's will downgrade while looking at changes in the equity implied default probabilities. Once considering the upgrade announcements, I found that there is a poor performance of the regression model whatever the time interval considered, expect for Fitch upgrade announcements while considering a 30-day interval change in the CDS implied default probabilities. The market measures I derived cannot appropriately predict upgrade announcements.

A natural alternative to looking at the implied default probability change is to look at the implied default probability level. I therefore consider the sample of observations from the previous experiment and set x equal to the average implied default probabilities level in an interval. The logistic model is the same as before. The results are shown in the Tables 12 and 13 in the Appendix. I find similar results as the one shown previously. The CDS and the bond implied default probabilities provide useful information in order to anticipate downgrade announcements by Fitch, Moody's and S&P that you consider either average level over 30-day or 90-day time interval. Regarding upgrade announcements, I found a poor performance of the logistic model applied except for Fitch upgrade announcement when the bond implied default probabilities are used as input in the model.

Since the logistic model relies on a particular functional form linking the probability of a rating event and the explanatory variable, I develop a non-parametric test based on the underlying idea of the CAP (Cumulative Accuracy Profile) curves. I consider the same sample of observations defined as in the previous tests, i.e.: I consider the variation in the implied default probabilities (average level of implied default probabilities) during a 30-day interval (a 90-day interval) and observe whether a particular event occurs during the following 30-day interval (90-day interval) that is coded by 1 if it does, and 0 if it does not occur. I then rank the sample and divide it into two categories: a low variation in the implied default probabilities (low level of implied default probabilities), L, and a high variation in the implied default probabilities (high level of implied default probabilities), H. The categories are defined as follow:

> *L:* the set of observations in which the variation in the implied default probabilities (level of implied default probabilities) is less than the $(100\text{-}p)^{th}$ percentile of the distribution of all changes (levels);
>
> *H:* the set of observations in which the variation in the implied default probabilities (level of implied default probabilities) is greater than the $(100\text{-}p)^{th}$ percentile of the distribution of all changes (levels).

I then counted the percentage of rating events observed in each category. By iteratively changing the value of p, I can take into account the evolution of the proportion of rating events occurring in each category. It follows that it can be graphically represented, as in the charts 10-13 in the appendix. The x-axis in the chart represent the value of p^{th} percentile that divides the two categories, the y-axis represents the percentage of the events that occur when the variation in the implied default probabilities (level of implied default probabilities) is above the $(100\text{-}p)^{th}$ percentile of the distribution of variation in the implied default probabilities. For instance, if p is equal to 50 and the value in the y-axis is 60, it means that if I divide the sample at the 50^{th} percentile, 60% of the rating event will be observed in the subsample of implied default probability changes greater than the one observed at the 50^{th} percentile, i.e.: above the 100-p percentile of the distribution. Hence, the further away the curve is from the line y= -x, the more discriminative the variable will be. The closer the curve is to the axe of

equation y= -x, the less discriminative the variable is. For downgrades, if the curve is above the axis y= -x, the better is the variable performing in discriminating the observations in the sample, and vice versa for upgrades.
I find similar results as the one exhibited by the regression test. However, it seems that the level of the implied default probabilities is a more discriminative variable.

I perform another series of test where I assess whether liquidity can improve the fit of the binary logistic regression. It is supposed that asymmetric information between market participants is a possible source of illiquidity. The bid-ask spread is partly defined by the adverse selection cost due to asymmetric information. It is supposed that some market participants have as a good insight of the firm than the CRA analysts. However, since they are free from rating procedure, they can react faster to arrival of new information, benefiting from their informational advantage. As Odders-White & Ready (2004) mentioned: *firms that have a high probability of large changes in total firm value should have both poorer credit ratings and higher adverse selection costs in trading their equity*. They found that proxies for adverse selection costs permit to predict CRA rating actions. In order to test whether adverse selection costs can improve the regression model I defined previously, I decided to compute more generally a proxy in order to capture the liquidity of a firm's security. I use a measurement close to the Roll's serial covariance spread estimate (Roll, 1984). The latter states that under a set of hypothesis the bid-ask spread can be estimated using the following relationship:

$$Spread = 2 * \sqrt{-Cov(P_{t+1} - P_t; P_t - P_{t-1})}$$

where cov stands for covariance and P_t is the price of the security at time t.
As a proxy for liquidity of the security, I use the absolute value of the covariance defined above. Since I lack information of the volume traded in the CDS market, I decided to use this metric, and to apply it consistently to the security prices collected in the stock market, the bond market and the CDS market.

I first test whether the power of the implied default probabilities to predict rating changes can be decomposed in two parts: a component dependent on the liquidity, and constant. It can be formally written as the following linear relationship:

$$Y = (a + b * L) * X + c$$

where Y is the binary dependent variable Y (Y_t = 1 if a rating event has occurred or Y_t=0 if it has not), L corresponds to the state of the liquidity measure, X is the implied default probability change over a 30-day time interval, a and b are regression coefficients, c is a constant.
The results are shown in Tables 15 and 18 in the appendix. I test separately downgrade and upgrade occurrences, considering a set of 30-day non overlapping interval and a set one of 90-day non-overlapping time interval. I find that b is statistically significant for downgrade announcements performed by Moody's, while considering a 30-day time interval set. It can be interpreted as following: the liquidity allows to refine the

ability of the implied default probability measure to better anticipate Moody's downgrade announcement occurring the following month of the observation. No significant improvement is observed if I extend the time horizon from 30 days to 90 days.

Since the correlation between the liquidity proxy used and the implied default probabilities is low (see Table 16 and 19 in the Appendix), I decided to consider the liquidity variable as a complementary predictive variable in the regression. Formally, using the same notations as before, I test the following linear relation:

$$Y = a * X + b * L + c$$

As before, I perform a binary logistic regression model to assess whether those variables can be considered as predictors to CRA rating events. I observe that b is statistically significant for regression models where X is equal to the equity implied default probability change over a 30-day time interval, as well as for X equal to the CDS derived default probability change over a 30-day time interval, and the rating event considered being downgrade announcements. That means that L, the liquidity observed in the corresponding market, improves the predictive power of the implied default probabilities in assessing the probability of a downgrade announcement occurring the following time span. However, the reliability of this predictor decreases if I extend the time horizon. Liquidity is still a complementary predictor of downgrade announcements once one consider the equity derived default probability changes over a 90 day time interval. However, the regression model performs poorly when assessing the ability to anticipate upgrade announcements.

I also provide in the appendix (tables 17 & 20) the results of the regression model performed using the liquidity measure as the only predictor of rating changes. I found the same result as before, namely that it can be used to measure the probability of a downgrade announcement once one consider the liquidity in the CDS market and the equity market. However, it performs poorly in as a predictor of upgrade announcements.

As for the first application of the regression model, I reapply the non-parametric test described above. It allows providing a visual representation of the discriminative performance of the liquidity variable in anticipating rating events. I observe from the charts 14 and 15 in the Appendix that the liquidity measure performs better than the implied default probabilities in discriminating the rating event with respect to downgrade announcements. It is less performing with respect to upgrade announcements.

Conclusion :

In this paper, I decided to assess the credibility of CRA through the timeliness of their rating announcements. In order to determine whether ratings are timely assigned and whether they conveyed new information to the market participants, I decided to use a market-based benchmark. To that extent I derive risk-neutral default probabilities extracted from the equity, fixed income and derivative markets, applying standard models from the credit risk modelling literature. I considered the entities that composed the S&P 500 index. For each value, I collected information regarding their stock prices, bond prices and CDS spreads when available. I extracted three sets of risk-neutral default probabilities implied by the pricing of each security. I used a Merton-type approach to derive default probabilities using as key input the stock prices, a reduced-form model in order to derive default probabilities from the CDS spreads, and a model introduced by J. Fons (1987) that allows to extract a term structure of default probabilities from bond prices.

This extraction allows to compare the performance of those three different models as well as providing some insight on the timeliness of those markets to issuers' creditworthiness information. I found that the default probabilities derived from those securities are not perfectly correlated contrary to one might expect. I can advance some possible explanations in order to understand the difference between those three metrics: inputs and hypothesis are different between the three models used, the informational content provided by the security prices might be different between those markets, and some security prices might be more sensitive to specific type of information in one market than another. Comparative studies on the application of the credit risk models to the same sample of entities are scare in the academic literature. This paper also provides some insight in the evolution of default probability perception from the market participants once aggregating information extracted from different markets. Some papers model the different metrics of credit risk such as the probability of default, expected losses or likelihood of timely repayment using information taken from different markets, they make the implicit hypothesis that those markets are equally conveying information regarding credit quality. The results found in the present study shows that this hypothesis can be questioned.

In addition, the market implied default probabilities can be used in order to characterize the CRA ratings comparatively to this market-based benchmark. I found that the CRA were not consistent through time when downgrading and upgrading issuers. If the rating agency provides timely opinion of the creditworthiness of the same entity, an upgrade or/and downgrade from one notch to another will intervene around the same default probability level. I therefore computed for each rating change the average default probability difference between downgrade and upgrade. I observed that it is statistically significant that this difference is not equal to zero. Either CRA delays downgrades decisions, or integrate faster than the market participants' positive signals leading to an upgrade. This finding is consistent with the common view that market-based benchmark provides a "point-in-time" assessment of the creditworthiness of an issuer, and CRAs provide a "through-the-cycle" assessment.

I also apply two series of test in order to appraise whether market participants anticipate CRA rating actions: I first measured the impact of a rating announcement on the market implied default probabilities; and I also define a regression model in order to attempt to predict CRA announcement using the market implied default probabilities. Bond and CDS derived default probabilities showed sign of anticipation of negative rating events. This observation does not apply to the default probabilities implied by stock prices. I observe that "Watch down"/"Review for downgrade" announcements have an impact on the default probabilities derived from the CDS spreads on the announcement day and after. The default probabilities derived from the equity market only exhibits statistically significant move during the month preceding upgrade announcements. The second test shows that downgrades are well predicted by the binary logistic regression that uses either CDS implied default probabilities or bond prices derived default probabilities. The predictive power of the model is even improved once one consider longer non overlapping time interval. The implied default probabilities are better predictors of Fitch downgrades, than Moody's and S&P. However, I do not find any predictive power of the binary logistic model so as to anticipate upgrade announcements.

In order to refine the logistic regression, I consider whether liquidity can be another helpful variable in the relationship linking market-based data and CRA rating actions. The intuition is that liquidity is partly defined by the adverse selection cost that better informed investors inflict to uninformed investors. Therefore, I make the implicit hypothesis that some market participants have as a good insight of the credit quality of the firm as CRA analyst. They can react quickly to new information affecting the credit risk of the firm, since they are free from any rating procedure. I found that the liquidity is indeed another variable that can help anticipating CRA rating actions.

Those tests confirm the common view that CRAs are not as reactive as the market participants in updating their views when considering news worsening the credit quality of the issuer, and delaying downgrade announcements compared to upgrade announcements. Another possible explanation is that market reactions are stronger when bad news occurs than good ones.

The results of the present study can be used in order to define surveillance system providing mark-to-market views on the evolution of the credit quality of companies. However, CRA ratings and market implied default probabilities should not be considered as competitive measures of issuers' credit quality, but as complementary. Since those measurements reflects different approaches and to some extent different time horizons: the market implied default probabilities are a "point-in-time" measure of credit quality over a short to medium term horizon, CRA ratings are a "through-the-cycle" measure with a long time horizon.

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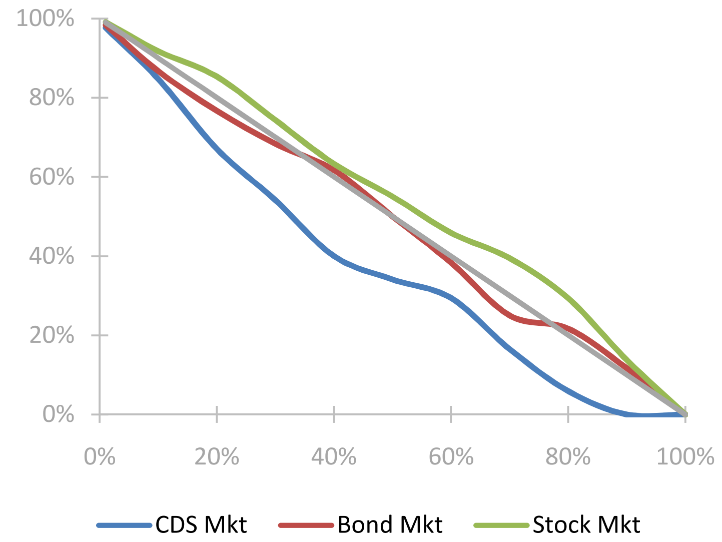
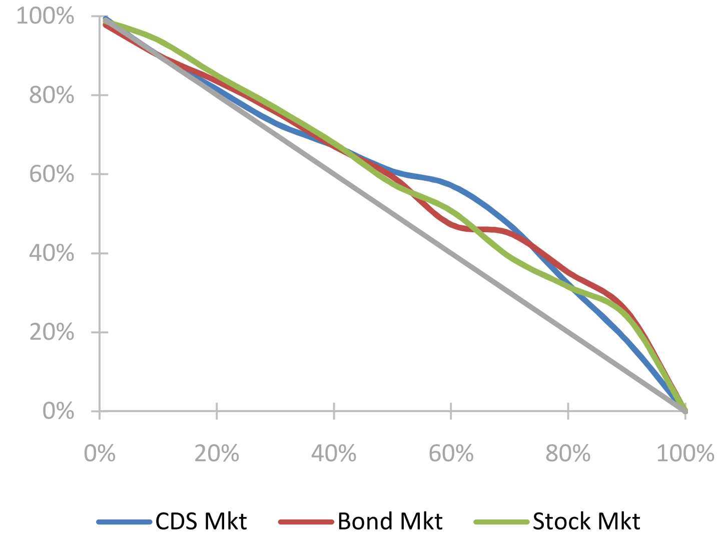
APPENDIX

Chart 10: Pseudo CAP curves generated from Variations in the Implied DP to discriminate Downgrades

Fitch



Moody's



S&P

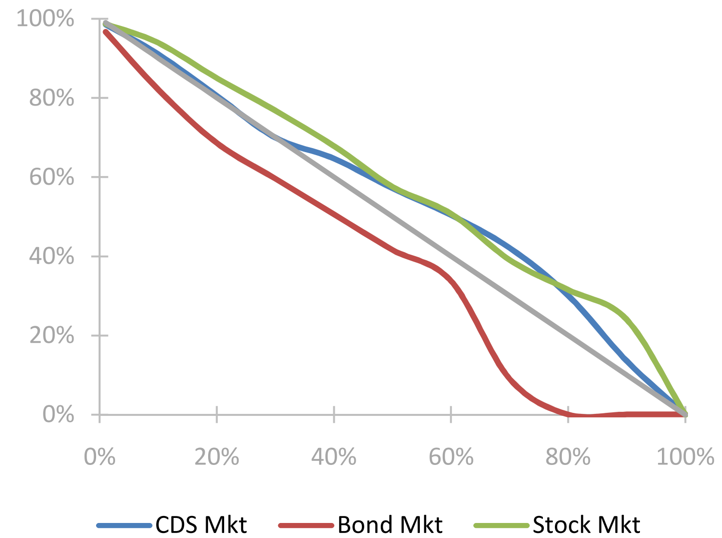


Chart 11: Pseudo CAP curves generated from Variations in the Implied DP to discriminate Upgrades

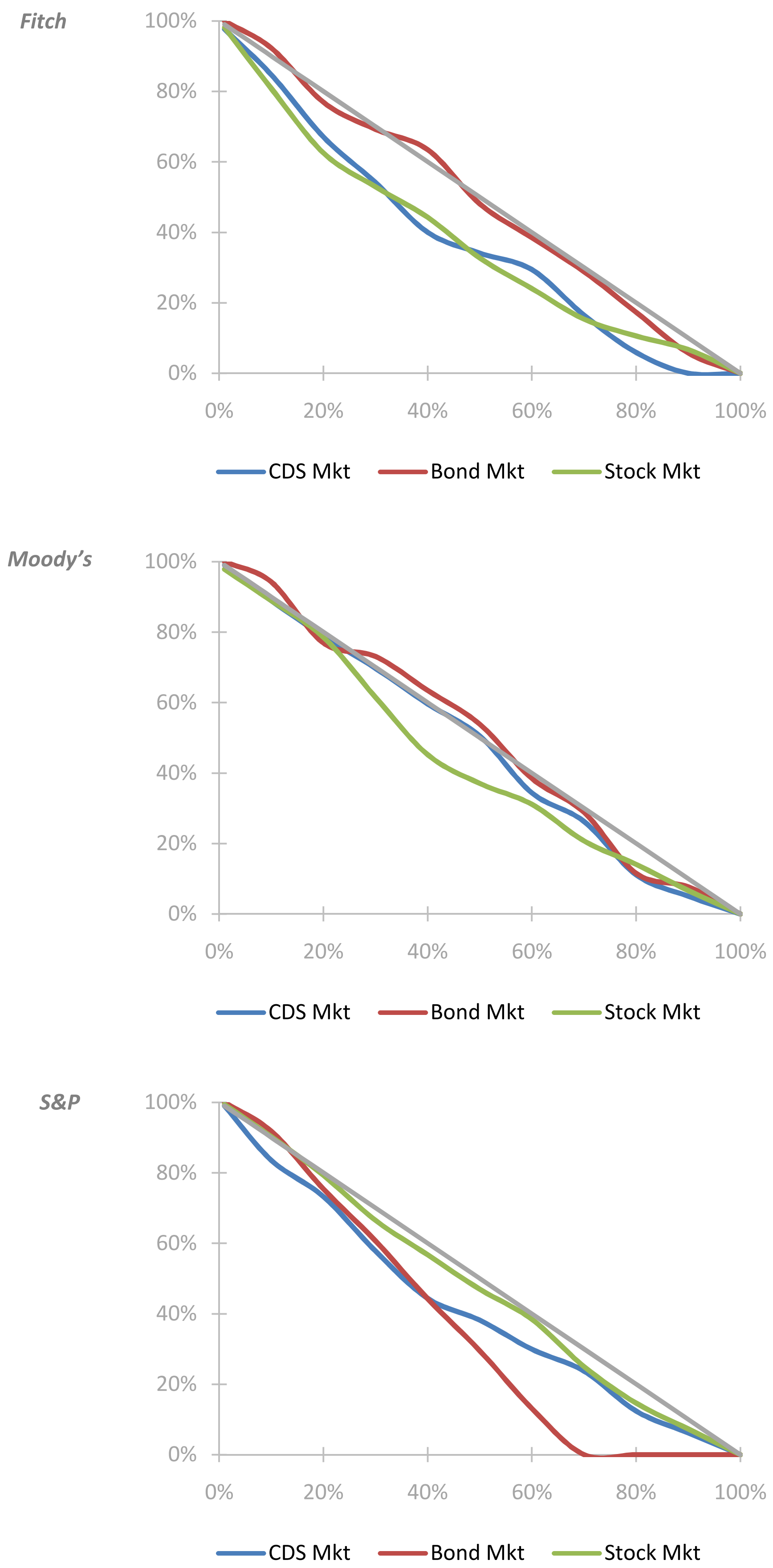


Chart 12: Pseudo CAP curves generated from the Levels of Implied DP to discriminate Downgrades

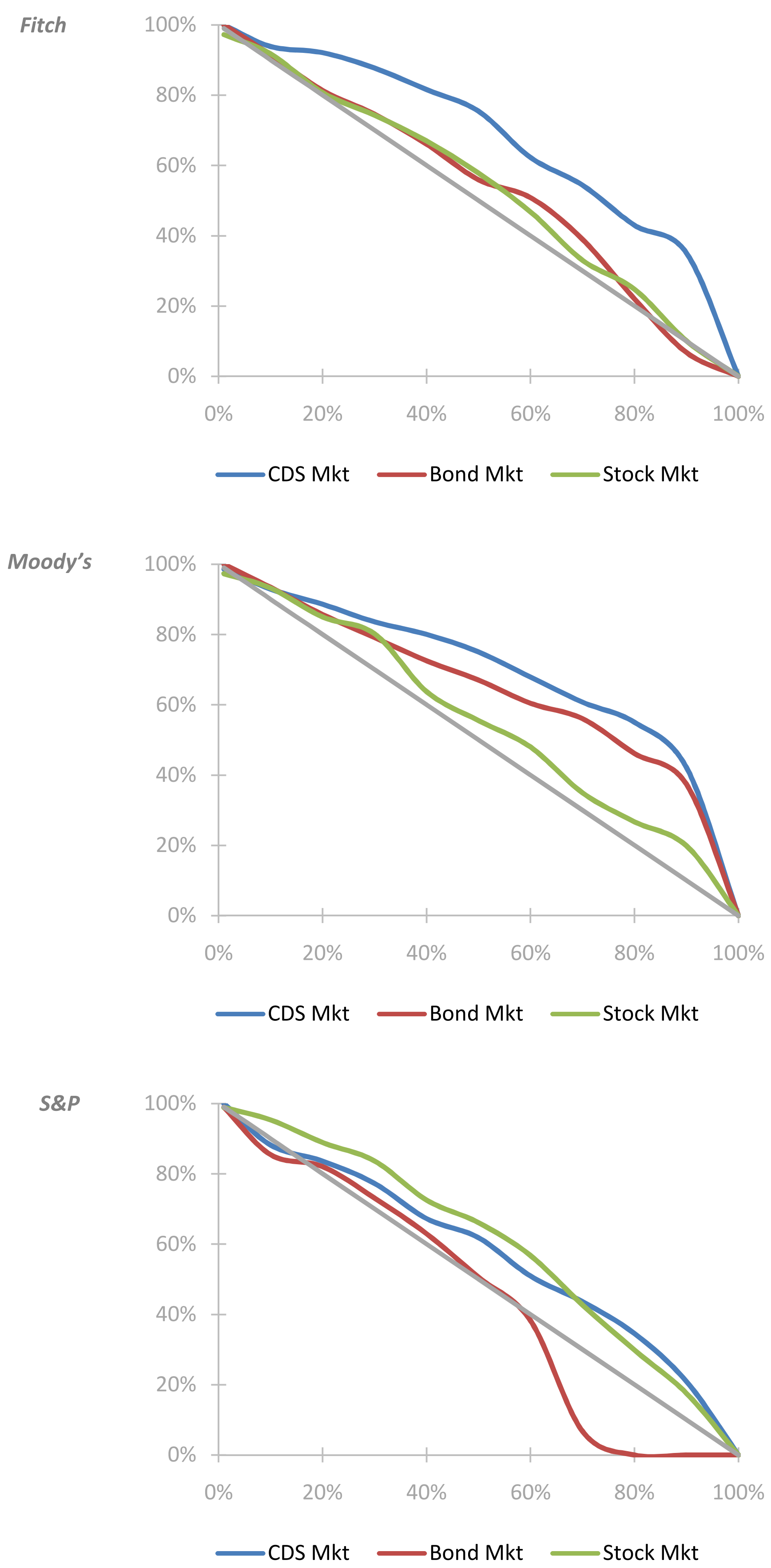


Chart 13: Pseudo CAP curves generated from the Levels of Implied DP to discriminate Upgrades

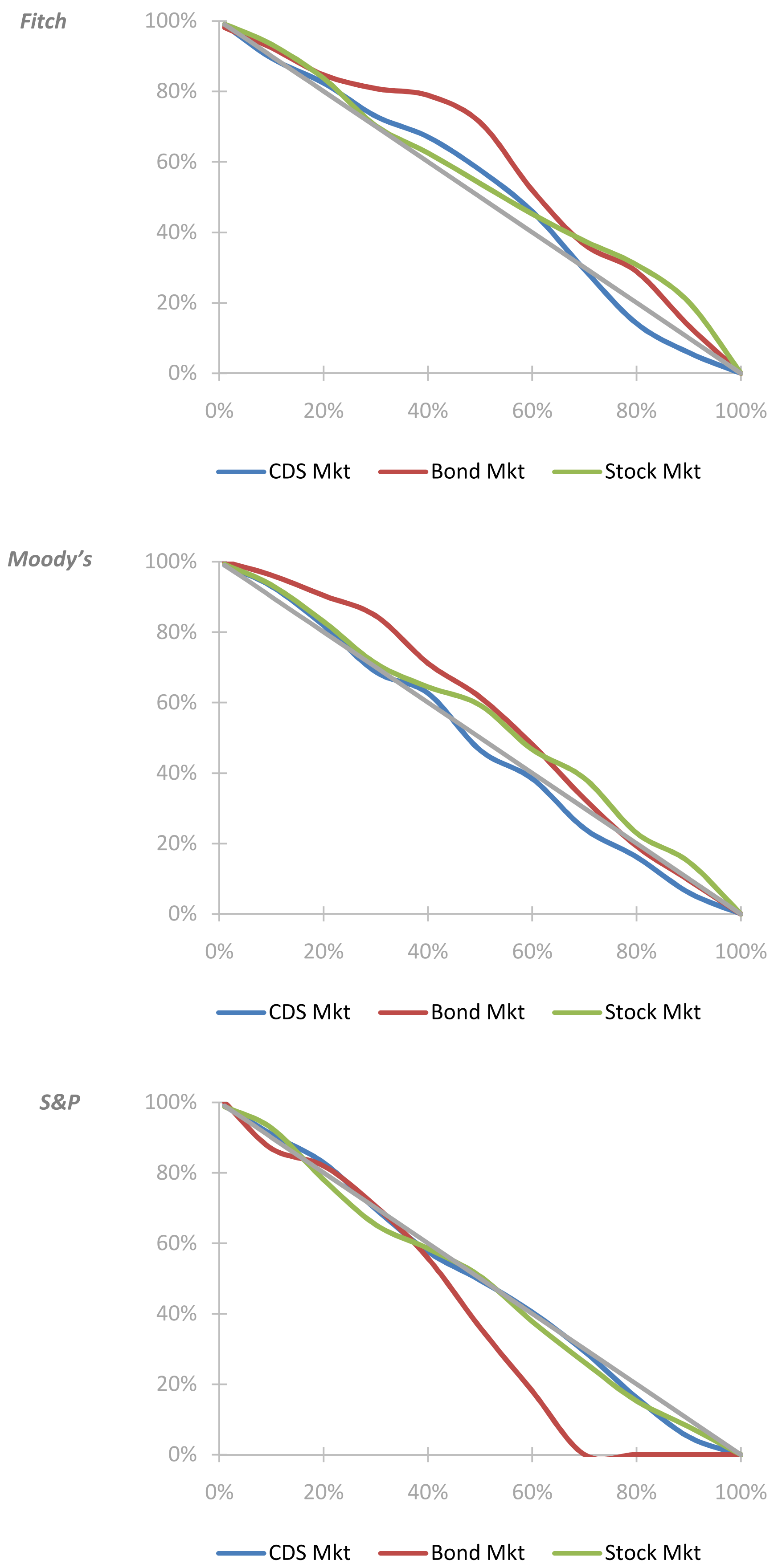
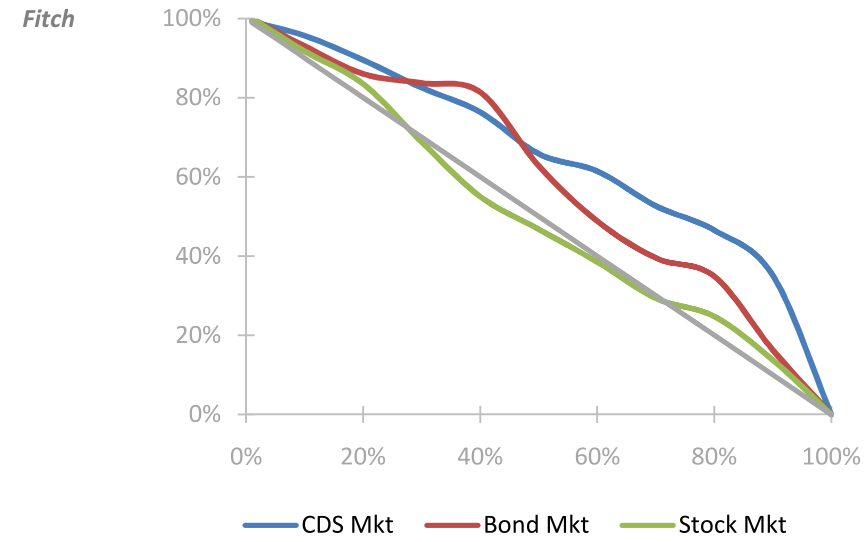
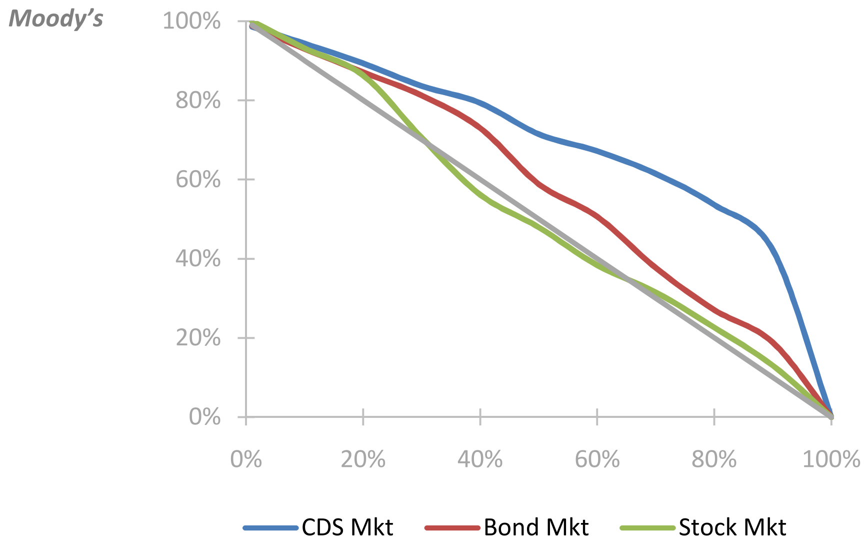


Chart 14: Pseudo CAP curves generated from the Liquidity measure to discriminate Downgrades





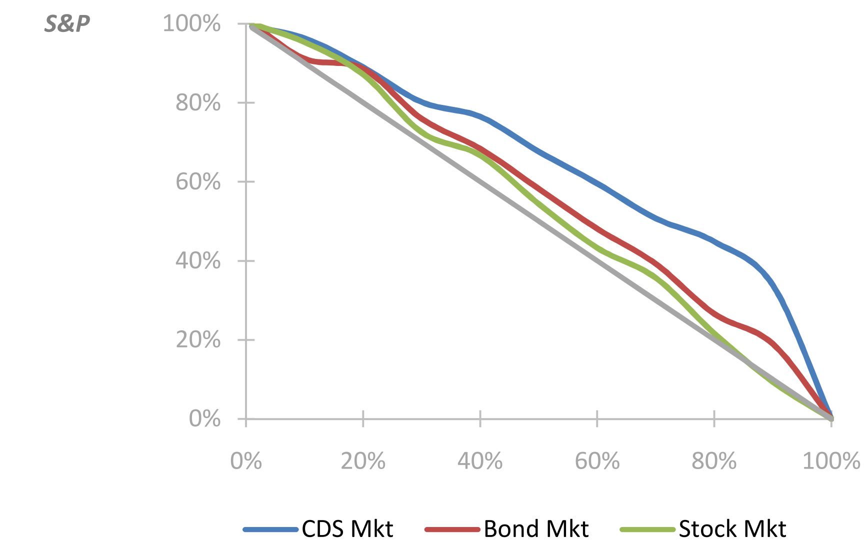
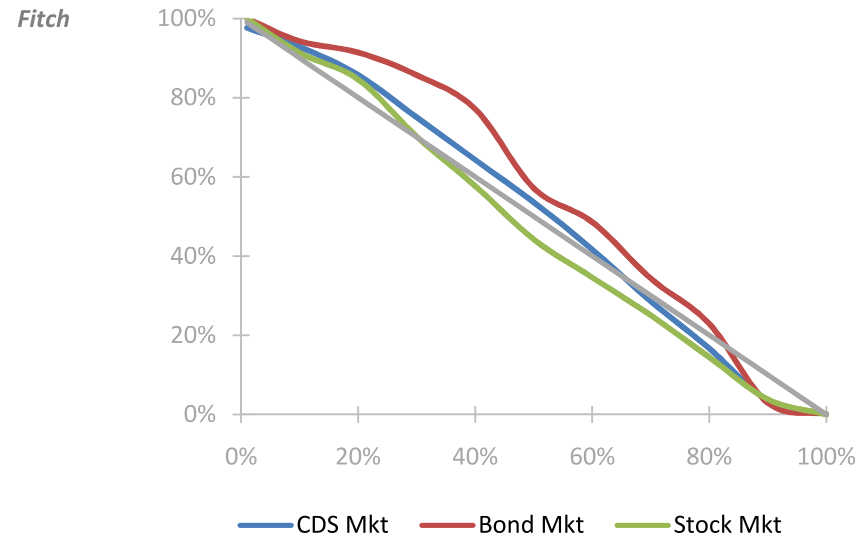
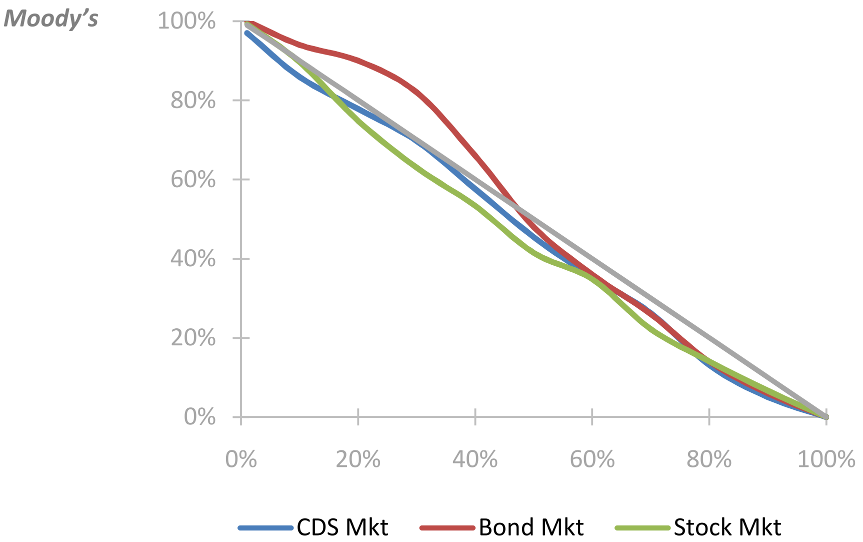


Chart 15: Pseudo CAP curves generated from the Liquidity measure to discriminate Upgrades





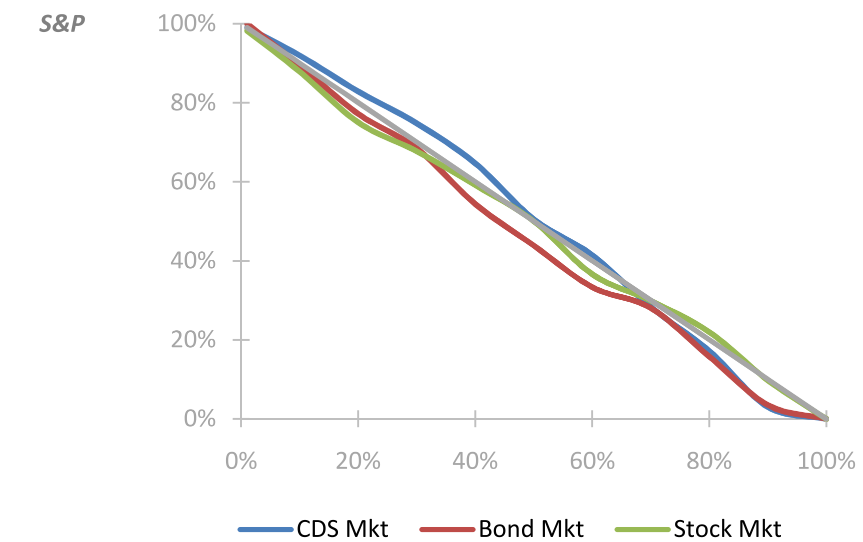


Table 4: Coefficient Correlation between the different implied measures of credit risk

	CDS.C	Corp.Bonds.DP	EQ.DD.S	EQ.DD.Merton	EQ.DP
CDS.C		0,556	-0,356	-0,394	0,049
Bonds.DP			-0,173	-0,174	-0,031
EQ.DD.S				-	-
EQ.DD.Merton					-
EQ.DP					

CDS.C: Default probability extracted from the CDS spread using direct calculation;
CDS.I: Default probabilities extracted from the CDS spreads using reduced-form model;
Bonds.DP: Default probabilities extracted from the bond prices;
EQ.DD.S: Distance-to-default computed using the simplified calculation;
EQ.DD.Merton: Distance-to-default computed from the Merton-type model;
EQ.DP: Default Probabilities computed from the Merton-type model.

Table 5: Volatility Measures

I calculate the standard deviation for each firm in the sample. The figure below represents the average standard deviation for the sample as well as the standard deviation of the volatility of the sample

Volatility Measure	*Avg*	*Stdev*
CDS.C	0,009	0,013
CDS.I	0,015	0,017
EQ.DD.S	0,181	0,451
EQ.DD.Merton	0,226	0,126
EQ.DP	0,034	0,023
Corp.Bonds.Measure	0,020	0,020
Corp.Bonds.DP	0,032	0,026

CDS.C: Default probability extracted from the CDS spread using direct calculation;
CDS.I: Default probabilities extracted from the CDS spreads using reduced-form model;
Bonds.DP: Default probabilities extracted from the bond prices;
EQ.DD.S: Distance-to-default computed using the simplified calculation;
EQ.DD.Merton: Distance-to-default computed from the Merton-type model;
EQ.DP: Default Probabilities computed from the Merton-type model.

Table 6: Impact of CRA announcement on market implied default probabilities for all categories

**: indicates that the variation in the market implied default probability is greater than zero at the 5% confidence level*

Impact on CDS derived DP		Nb.Obs.	Time Interval								
			[-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]
Fitch	Downgrade	124	0,255	*	0,296	*	0,377	*	0,044		0,054
	On Watch Down	69	0,358	*	0,108		0,437	*	0,053	*	0,035
	Upgrade	104	0,029		-0,008		0,016		-0,004		0,004
	On Watch Up	14	0,115		-0,009		0,014		-0,043		-0,003
Moody's	Downgrade	146	0,229	*	0,270	*	0,245	*	0,041	*	0,045
	On Watch Down	149	0,130	*	0,164	*	0,426	*	0,081	*	0,086
	Upgrade	112	0,014		0,040		0,021		0,004		-0,001
	On Watch Up	75	0,047		0,029		-0,020		-0,016		-0,018
S&P	Downgrade	145	0,271	*	0,361	*	0,237	*	0,037	*	0,091
	On Watch Down	135	0,163	*	0,133	*	0,348	*	0,092	*	0,090
	Upgrade	117	0,122	*	0,043		0,029		0,000		0,026
	On Watch Up	44	-0,021		0,146		-0,019		-0,056		0,005

Impact on Bond Mkt derived DP		Nb.Obs.	Time Interval								
			[-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]
Fitch	Downgrade	85	0,054	*	0,056	*	0,081	*	0,002		0,006
	On Watch Down	54	0,007		0,016	*	0,082	*	0,037	*	0,006
	Upgrade	58	0,002		0,015	*	0,003		-0,007		-0,003
	On Watch Up	5	0,014		0,011		-0,006		-0,007		0,005
Moody's	Downgrade	101	0,026	*	0,071	*	0,025		0,008		-0,023
	On Watch Down	108	0,013		0,072		0,048	*	0,023		0,017
	Upgrade	58	0,004		0,003		0,019	*	0,000		0,004
	On Watch Up	43	0,007		-0,004		0,004		-0,003		0,010
S&P	Downgrade	98	0,034	*	0,069	*	0,031	*	0,020		0,006
	On Watch Down	89	0,047	*	0,013		0,083	*	0,020		0,015
	Upgrade	66	0,004		0,019	*	-0,003		0,001		0,011
	On Watch Up	27	0,016	*	-0,010		0,007		-0,002		0,008

Impact on Equity Mkt derived DP		Nb.Obs.	Time Interval								
			[-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]
Fitch	Downgrade	110	0,002		-0,014		-0,033		-0,007		0,295
	On Watch Down	62	0,008		0,007		-0,004		-0,002		-0,010
	Upgrade	103	0,009		0,139		0,029	*	0,001		0,010
	On Watch Up	10	0,037		0,011		-0,002		0,000		0,007
Moody's	Downgrade	142	-0,005		0,126		-0,040		-0,008		0,008
	On Watch Down	153	-0,001		-0,010		-0,019		-0,003		-0,005
	Upgrade	132	0,105		-0,018		0,031	*	-0,007		0,000
	On Watch Up	81	0,014		0,012		0,184		0,003		0,013
S&P	Downgrade	166	-0,009		-0,026		-0,024		-0,003		-0,008
	On Watch Down	159	0,086		0,073		-0,039		-0,008		0,000
	Upgrade	164	0,100		0,001		0,025	*	0,004		-0,002
	On Watch Up	56	-0,001		0,022		0,215		0,001		0,022

Table 7: Impact of CRA announcement on the CDS implied default probabilities (DP)

**: indicates that the variation in the market implied default probability is greater than zero at the 5% confidence level*

Fitch Rating Announcement		Nb.Obs	Time Interval [-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]	
Downgrade	AAA/AA	14	0,317	*	0,316	*	0,860		-0,089		0,097	
	A	39	0,356	*	0,411	*	0,425	*	0,016		0,082	
	BBB	50	0,129		0,292	*	0,284	*	0,096		0,045	
	BB	8	0,259		-0,034		-0,037		0,083		-0,010	
	B	8	0,470		0,078		0,358		0,061		0,030	
	CCC	1	0,248		0,362		0,161		-0,013		-	
On Watch Down	AAA/AA	10	0,459		0,381	*	0,864	*	0,034		-0,028	
	A	29	0,335		0,097		0,384	*	0,056	*	-0,007	
	BBB	21	0,458		0,017		0,432	*	0,065	*	0,137	*
	BB	3	0,008		-0,197		0,053		-0,008		0,125	
	B	3	0,049		0,195		0,012		0,075		-0,174	
	CCC	1	-0,065		0,281		0,312		0,036		0,129	
Upgrade	AAA/AA	0	-		-		-		-		-	
	A	16	-0,070		0,070		0,099		0,059		-0,044	
	BBB	44	0,020		-0,040		0,067		-0,027		-0,008	
	BB	29	0,037		0,019		-0,041		-0,002		0,030	
	B	12	0,093		-0,034		-0,112	*	0,010		0,045	
	CCC	1	0,992		-0,330		-0,298		-0,245		-0,041	
On Watch Up	AAA/AA	0	-		-		-		-		-	
	A	0	-		-		-		-		-	
	BBB	6	-0,088		-0,081		-0,006		-0,023		-0,011	
	BB	3	0,678		0,014		0,029		-0,026		0,020	
	B	2	-0,113		0,004		-0,139		-0,074		0,000	
	CCC	1	0,101		0,297		0,536		-0,177		-0,056	

Moody's Rating Announcement		Nb.Obs	Time Interval [-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]	
Downgrade	Aaa/Aa	14	0,485		0,197		0,295	*	0,033		-0,026	
	A	34	0,156	*	0,278	*	0,416	*	0,017		0,146	*
	Baa	54	0,288	*	0,262	*	0,188	*	0,054		0,024	
	Ba	19	0,022		0,379		0,211	*	0,042		0,011	
	B	12	0,165		0,116		-0,036		0,073		-0,030	
	Caa	5	0,174		0,434		0,348	*	0,006		0,109	
On Watch Down	Aaa/Aa	17	0,199		0,142		0,783	*	0,033		-0,025	
	A	38	0,105		0,050		0,367	*	0,088		0,081	
	Baa	68	0,133	*	0,266	*	0,430	*	0,067	*	0,154	*
	Ba	10	0,033		0,040		0,272		0,246		-0,006	
	B	8	0,174		0,135		0,071		0,113	*	-0,058	
	Caa	2	0,150		-0,031		0,626	*	0,006		-0,004	
Upgrade	Aaa/Aa	2	0,000		0,000		0,000		0,000		0,000	
	A	15	0,080		0,114		0,001		0,061		0,009	
	Baa	42	-0,025		0,102		0,032		-0,004		0,012	
	Ba	32	0,021		-0,044		0,088		0,007		-0,024	
	B	11	0,081		0,009		-0,105	*	-0,047		-0,005	
	Caa	3	0,044		-0,090	*	-0,159		0,050		0,007	
On Watch Up	Aaa/Aa	1	0,000		0,000		0,000		0,000		0,000	
	A	12	0,051		0,046		0,191		-0,013		-0,013	
	Baa	38	0,121	*	0,030		-0,058	*	-0,006		-0,009	
	Ba	13	-0,042		0,012		-0,070	*	-0,045		-0,011	
	B	5	-0,225	*	0,052		-0,052		0,007		-0,104	
	Caa	1	-0,240		-0,026		-0,170	*	-0,111		-0,036	

S&P Rating Announcement		Nb.Obs	Time Interval [-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]	
Downgrade	AAA/AA	12	0,818	*	-0,160		0,887		-0,033		-0,050	
	A	45	0,262	*	0,406	*	0,127		0,008		0,107	*
	BBB	53	0,240	*	0,475	*	0,218	*	0,058		0,133	
	BB	19	0,145		0,255		0,138	*	0,049		0,054	
	B	6	-0,083		0,330		0,375	*	0,163	*	0,072	
	CCC	1	0,173		0,652		0,167		0,017		0,017	
On Watch Down	AAA/AA	9	0,497	*	0,297	*	0,675		0,122		-0,170	*
	A	41	0,037		0,032		0,381	*	0,072		0,094	
	BBB	58	0,174		0,265	*	0,283	*	0,103	*	0,153	*
	BB	10	0,040		-0,181	*	0,442		0,088	*	0,049	
	B	13	0,380		-0,008		0,245		0,081	*	0,037	
	CCC	0	-		-		-		-		-	
Upgrade	AAA/AA	2	0,020		-0,010		0,010		0,000		0,023	
	A	23	0,062		0,014		0,108		0,053		0,009	
	BBB	47	0,118		0,085		0,061		-0,006		0,082	
	BB	29	0,203	*	-0,051		-0,038		-0,024		-0,021	
	B	12	0,078		0,183		-0,071		-0,015		-0,041	
	CCC	0	-		-		-		-		-	
On Watch Up	AAA/AA	1	0,000		-0,038		0,000		0,000		0,000	
	A	7	-0,019		-0,013		-0,009		-0,015		0,010	
	BBB	15	-0,002		0,152		-0,012		-0,032	*	-0,010	
	BB	13	-0,104	*	0,087		0,008		-0,095	*	0,046	
	B	6	0,109		0,498		-0,114		-0,103		-0,050	
	CCC	0	-		-		-		-		-	

Table 8: Impact of CRA announcement on the bond implied default probabilities (DP)

**: indicates that the variation in the market implied default probability is greater than zero at the 5% confidence level*

Fitch Rating Announcement		Nb.Obs	Time Interval									
			[-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]	
Downgrade	AAA/AA	10	0,039		0,141		0,197		-0,007		0,016	
	A	32	0,054	*	0,030		0,065		-0,001		-0,016	
	BBB	31	0,034	*	0,050	*	0,042		0,001		0,008	
	BB	4	0,109		0,012		0,159		0,006		0,034	
	B	3	0,217	*	0,003		0,055		0,049	*	0,095	
	CCC	1	0,245		0,538		0,535		0,017		-	
On Watch Down	AAA/AA	10	-0,027		0,019	*	0,113	*	0,110		-0,047	
	A	27	0,014		0,010		0,097		0,021	*	-0,004	
	BBB	14	0,024	*	0,013		0,014		0,009		0,046	*
	BB	0	-		-		-		-		-	
	B	1	0,038		-0,033		-0,019		-0,001		0,005	
	CCC	1	-0,130		0,264		0,528		0,214		0,241	
Upgrade	AAA/AA	0	-		-		-		-		-	
	A	13	-0,028		0,034	*	0,023		-0,009		-0,001	
	BBB	23	0,025	*	0,017	*	0,006		-0,011		-0,010	
	BB	14	-0,011		0,005		0,016		-0,008		0,000	
	B	6	0,000		0,024	*	-0,088	*	0,013		0,006	
	CCC	2	0,032		-0,079		0,029		-0,002		0,010	
On Watch Up	AAA/AA	0	-		-		-		-		-	
	A	0	-		-		-		-		-	
	BBB	1	0,049		-0,046		0,001		0,000		0,000	
	BB	3	0,004		0,024		-0,004		0,000		0,002	
	B	1	0,007		0,027		-0,017		-0,036		0,018	
	CCC	0	-		-		-		-		-	

Moody's Rating Announcement		Nb.Obs	Time Interval									
			[-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]	
Downgrade	Aaa/Aa	13	0,039		0,092		0,029		0,025		0,043	
	A	33	0,015		0,132		0,048		0,035		0,001	
	Baa	35	0,024	*	-0,014		-0,038		-0,020		-0,111	
	Ba	9	0,040		0,123		0,107		0,002		0,022	
	B	6	0,034		-0,024		-0,011		0,006	*	0,011	
	Caa	3	0,054		0,378		0,330		-0,007		0,178	
On Watch Down	Aaa/Aa	12	-0,007		0,023		0,105	*	0,087		-0,014	
	A	39	-0,007		0,138		0,050	*	0,038		-0,001	
	Baa	46	0,039	*	0,044	*	0,025	*	0,001		0,042	*
	Ba	4	-0,017		-0,014		0,041	*	-0,010		0,026	*
	B	4	-0,014		-0,040		0,044	*	0,003		0,000	
	Caa	1	0,017		0,106		0,430		-0,011		-0,007	
Upgrade	Aaa/Aa	1	0,041		0,089		0,053		0,000		-0,033	
	A	9	0,011		0,010		0,029		0,002		0,021	*
	Baa	24	-0,004		-0,006		0,012		0,001		0,008	
	Ba	12	0,009		0,009		0,039	*	0,003		-0,017	
	B	7	-0,003		-0,002		-0,009		-0,004		0,015	
	Caa	3	0,026		0,010		0,018		-0,026		0,013	
On Watch Up	Aaa/Aa	1	-0,152		0,071		0,105		-0,033		0,021	
	A	8	-0,008		0,015		0,001		0,009		0,026	
	Baa	20	0,014		-0,015		0,001		-0,003		0,012	
	Ba	8	0,010		-0,004		0,004		-0,013		-0,002	
	B	4	0,040		-0,004		-0,014		0,000		-0,001	
	Caa	2	-0,009		0,005	*	0,023		-0,004		-0,026	

S&P Rating Announcement		Nb.Obs	Time Interval									
			[-90;-60]		[-60;-31]		[-30;-1]		[-1;1]		[1;10]	
Downgrade	AAA/AA	5	0,170		0,157		-0,019		0,039		0,015	
	A	36	0,043	*	0,044		0,018		0,033		-0,012	
	BBB	40	0,0050746		0,058	*	0,028		0,009		0,008	
	BB	9	0,052		0,129		0,047		-0,005		0,025	*
	B	4	0,034		0,033		0,160		0,038		0,055	
	CCC	1	0,039		0,721		0,279		0,104		0,094	
On Watch Down	AAA/AA	4	0,033		-0,012		0,303		0,165		-0,061	
	A	31	0,036	*	0,029		0,043		0,002		0,015	
	BBB	34	0,025	*	0,016		0,068		0,010	*	0,028	*
	BB	7	0,149	*	0,027		0,078		0,015		0,015	
	B	6	0,129	*	-0,082	*	0,194		0,062		0,021	
	CCC	0	-		-		-		-		-	
Upgrade	AAA/AA	0	-		-		-		-		-	
	A	15	0,014		0,035	*	-0,040		0,002		0,032	*
	BBB	26	-0,003		0,015		0,009		-0,001		0,001	
	BB	18	-0,002		0,009		0,010		0,004		0,010	
	B	5	0,021		0,023		-0,010		-0,006		0,002	
	CCC	0	-		-		-		-		-	
On Watch Up	AAA/AA	0	-		-		-		-		-	
	A	8	0,005		-0,002		0,004		0,000		0,003	
	BBB	11	0,033	*	-0,019		0,012		-0,006		0,017	
	BB	6	0,002		-0,002		0,016		0,000		0,007	
	B	2	0,013		-0,007		-0,034		0,005		-0,015	*
	CCC	0	-		-		-		-		-	

Table 9: Impact of CRA announcement on the equity implied default probabilities (DP)

**: indicates that the variation in the market implied default probability is greater than zero at the 5% confidence level*

Fitch Rating Announcement		Nb.Obs	Time Interval [-90;-60]	[-60;-31]	[-30;-1]	[-1;1]	[1;10]
Downgrade	AAA/AA	10	0,015	-0,006	-0,043	0,004	0,000
	A	39	0,001	-0,026	-0,032 *	-0,011 *	0,017
	BBB	50	0,005	-0,005	-0,038 *	-0,004	0,002
	BB	7	-0,033	0,004	0,024	-0,016	4,017
	B	2	-0,010	-0,084	-0,042	-0,017 *	-0,020
	CCC	0	-	-	-	-	-
On Watch Down	AAA/AA	5	-0,017	0,008	0,020	0,041	-0,055
	A	27	0,022	-0,004	-0,010	-0,006	-0,008
	BBB	23	0,000	0,019	-0,010	0,001	-0,008
	BB	5	0,011	-0,023	0,007	-0,037	0,011
	B	2	-0,039	0,082	0,044	0,000	0,000
	CCC	0	-	-	-	-	-
Upgrade	AAA/AA	0	-	-	-	-	-
	A	15	0,046	0,767	0,036	-0,010	0,006
	BBB	37	-0,001	0,021 *	0,043	0,001	0,026
	BB	28	-0,002	0,028 *	-0,002	0,003	0,001
	B	14	0,025	0,063 *	0,054 *	0,008	-0,005
	CCC	3	-0,021	-0,004	0,066	0,002	-0,010
On Watch Up	AAA/AA	0	-	-	-	-	-
	A	0	-	-	-	-	-
	BBB	2	0,037	-0,019	-0,028	-0,006 *	-0,020
	BB	3	0,076 *	0,044	0,002	-0,017	0,014
	B	3	0,017	0,021	0,038	0,012	0,014 *
	CCC	1	-0,015	-0,062	-0,088	0,052	0,011

Moody's Rating Announcement		Nb.Obs	Time Interval [-90;-60]	[-60;-31]	[-30;-1]	[-1;1]	[1;10]
Downgrade	Aaa/Aa	10	-0,088	1,264	-0,126	0,004	-0,021
	A	46	0,007	0,020	-0,027	-0,011	0,009
	Baa	58	0,013	-0,036 *	-0,016	-0,002	0,010
	Ba	14	-0,064	0,436	-0,112 *	-0,039	0,016
	B	7	-0,006	-0,072	-0,045	-0,001	0,005
	Caa	0	-	-	-	0,007	0,088
On Watch Down	Aaa/Aa	11	-0,005	0,010	0,018	-0,005	-0,013
	A	49	-0,003	-0,005	-0,004	-0,002	-0,012
	Baa	71	0,002	-0,014	-0,018	-0,003	0,004
	Ba	14	0,001	-0,025	-0,023	-0,004	-0,013
	B	5	-0,034	-0,011	-0,067	-0,010	-0,012
	Caa	0	-	-	-	-	-
Upgrade	Aaa/Aa	1	0,063	-0,089	0,099	0,046	0,057
	A	17	-0,027	-0,040 *	0,057 *	-0,005	-0,013
	Baa	46	0,288	-0,036	0,028	-0,001	0,001
	Ba	37	0,010	0,010	0,016	0,001	-0,005
	B	21	-0,003	0,023	0,043 *	0,002	0,014
	Caa	3	0,040	0,067	0,074 *	0,003	0,021
On Watch Up	Aaa/Aa	1	0,077	-0,008	-0,087	0,019	-0,007
	A	15	0,006	0,007	0,012	0,002	0,014
	Baa	41	0,011	0,007	0,333	0,003	0,024
	Ba	17	0,009	0,030	0,029	-0,001	-0,012
	B	5	0,064	0,001	0,058 *	0,010	0,005
	Caa	1	0,016	0,025	0,030	0,007	0,044

S&P Rating Announcement		Nb.Obs	Time Interval [-90;-60]	[-60;-31]	[-30;-1]	[-1;1]	[1;10]
Downgrade	AAA/AA	6	0,015	0,005	-0,028 *	0,008	0,005
	A	56	0,004	0,169	-0,011	0,004	0,002
	BBB	70	0,004	0,145	0,000	-0,002	-0,013
	BB	24	-0,069	0,218	-0,099 *	-0,003	-0,019
	B	2	-0,205	0,112	0,229	-0,181	-0,042
	CCC	0	-	-	-	-	-
On Watch Down	AAA/AA	4	-0,043	2,693	-0,160	-0,037	0,008
	A	53	-0,002	-0,010	-0,065 *	-0,003	0,016
	BBB	72	0,003	-0,010	-0,011	-0,006	-0,013
	BB	19	0,736	-0,046	-0,026	-0,021	0,012
	B	6	-0,021	0,013	-0,058	0,000	-0,006
	CCC	0	-	-	-	-	-
Upgrade	AAA/AA	0	-	-0,006	0,000	-0,007	0,002
	A	24	0,005	-0,008	0,053	-0,016	0,017
	BBB	61	0,013	-0,017 *	0,019	0,002	0,001
	BB	53	0,021	0,024	0,012	0,002	-0,016
	B	22	0,633	0,002	0,045	-0,005	0,000
	CCC	0	-	-	-	-	-
On Watch Up	AAA/AA	0	-	-	-	-	-
	A	6	0,006	0,010	0,000	0,010	0,027
	BBB	20	-0,019	0,034 *	0,012	0,004	0,036
	BB	23	-0,010	0,017	0,488	-0,014	0,001
	B	6	0,088	0,012	0,058 *	0,032	0,042
	CCC	0	-	-	-	-	-

Table 10: Regression Coefficients on Market Implied DP change over 30-day time interval

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-4,1977	-4,0238	-4,0462	-4,4114	-4,2816	-4,3063
b	0,7338	0,6746	0,4780	-1,0829	-0,4758	-0,5337
Wald	11,6434	11,2993	4,7709	11,6251	2,7160	3,3757
Sig.	0,0006	0,0008	0,0289	0,0007	0,0993	0,0662
PSM	0,0107	0,0117	0,0081	-0,0128	-0,0064	-0,0070

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-4,3975	-4,2600	-4,3178	-4,4250	-4,3241	-4,3522
b	-0,8060	-0,6134	-0,3567	0,2291	0,3319	-0,0922
Wald	10,4399	11,8205	3,8042	0,3321	2,0202	0,1453
Sig.	0,0012	0,0006	0,0511	0,5644	0,1552	0,7031
PSM	-0,0096	-0,0084	-0,0046	0,0027	0,0043	-0,0012

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-4,3142	-4,0502	-4,0400	-4,5659	-4,5761	-4,4016
b	1,7537	1,6285	1,0084	-0,6795	0,2501	0,1239
Wald	6,8651	7,3509	3,8959	0,2618	0,0502	0,0140
Sig.	0,0088	0,0067	0,0484	0,6089	0,8227	0,9058
PSM	0,0230	0,0276	0,0172	-0,0069	0,0025	0,0015

Table 11: Regression Coefficients on Market Implied DP change over 90-day time interval

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-3,2068	-3,2688	-3,1042	-3,2631	-3,3914	-3,1853
b	0,8364	0,7271	0,7423	-0,3293	-0,3206	-0,0602
Wald	46,9626	32,0107	34,2469	2,7596	2,4617	0,1216
Sig.	0,0000	0,0000	0,0000	0,0967	0,1167	0,7273
PSM	0,0314	0,0258	0,0306	-0,0117	-0,0101	-0,0023

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-4,1604	-3,1549	-3,1941	-4,5116	-3,2453	-3,2095
b	-0,3475	-0,5209	-0,2622	0,2427	0,2111	-0,0358
Wald	0,5174	9,4272	3,8952	0,2778	1,0674	0,0455
Sig.	0,4720	0,0021	0,0484	0,5982	0,3015	0,8310
PSM	-0,0052	-0,0204	-0,0099	0,0026	0,0076	-0,0013

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-3,2910	-3,1342	-3,1243	-3,4222	-3,4452	-3,2709
b	3,6651	4,2134	4,0706	-2,2585	-1,4915	-1,4473
Wald	40,9838	48,6625	50,4061	2,8487	1,2252	1,6988
Sig.	0,0000	0,0000	0,0000	0,0914	0,2683	0,1924
PSM	0,1290	0,1717	0,1673	-0,0684	-0,0444	-0,0507

Table 12: Regression Coefficients on Market Implied DP average level over 30-day time interval

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-4,3788	-4,3212	-4,2525	-4,2954	-4,1781	-4,1723
b	7,6463	10,0209	8,0824	-6,9267	-7,6455	-9,8964
Wald	78,8201	139,2103	74,5549	1,8517	2,3413	2,9585
Sig.	0,0000	0,0000	0,0000	0,1736	0,1260	0,0854
PSM	0,0971	0,1362	0,1163	-0,0889	-0,1096	-0,1411

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-4,4223	-4,3659	-4,3246	-3,6424	-3,8245	-4,3453
b	0,0841	0,2117	0,0271	-1,5249	-0,9155	-0,0104
Wald	0,1131	4,2307	0,0228	4,7286	2,5602	0,0026
Sig.	0,7366	0,0397	0,8800	0,0297	0,1096	0,9593
PSM	0,0010	0,0026	0,0003	-0,0377	-0,0191	-0,0001

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-5,5148	-5,6087	-5,3238	-5,0334	-5,0261	-4,6376
b	8,9783	11,5963	9,4692	3,4945	3,5047	1,8475
Wald	39,1918	54,6954	43,6392	1,9895	1,6323	0,4393
Sig.	0,0000	0,0000	0,0000	0,1584	0,2014	0,5075
PSM	0,0375	0,0447	0,0479	0,0229	0,0231	0,0177

Table 13: Regression Coefficients on Market Implied DP average level over 90-day time interval

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-3,2744	-3,3764	-3,2382	-3,2262	-3,3762	-3,0996
b	12,8284	12,7750	14,4631	-4,6452	-3,2728	-6,6273
Wald	58,5959	57,9525	61,2876	0,8779	0,4822	1,4791
Sig.	0,0000	0,0000	0,0000	0,3488	0,4874	0,2239
PSM	0,4784	0,4334	0,5620	-0,1670	-0,1030	-0,2653

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-3,8801	-3,2968	-2,9317	-4,3941	-2,7973	-3,2075
b	-0,5162	0,2827	-0,4457	-0,2145	-0,8085	-0,0027
Wald	0,3091	1,3084	1,3113	0,0492	2,1040	0,0001
Sig.	0,5782	0,2527	0,2522	0,8244	0,1469	0,9924
PSM	-0,0102	0,0097	-0,0214	-0,0026	-0,0436	-0,0001

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-4,1735	-4,7234	-4,6461	-4,9152	-3,9674	-3,6542
b	5,3276	14,2102	13,6627	13,9726	3,7478	2,6705
Wald	2,4971	29,7974	31,1038	29,9822	0,9637	0,6022
Sig.	0,1141	0,0000	0,0000	0,0000	0,3262	0,4378
PSM	0,0817	0,1331	0,1377	0,1083	0,0696	0,0665

Table 14: Coefficient of correlation between variations of market implied Default Probabilities and the Liquidity measure

	Liquidity Measure	
	30-day time interval	90-day time interval
Variation of CDS implied DP	0,14	0,09
Variation of Bond implied DP	0,00	0,07
Variation of Equity implied DP	-0,05	-0,01

Table 15: Regression coefficients on Market Implied DP over 30-day time interval.

The relation tested is : Y = (a+b*L)*X + c where L is the liquidity, X is the variation in the implied DP

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	2244,870	6882,065	0,453	-1,084	-0,463	-0,524
Wald	1,255	9,681	4,222	11,371	2,515	3,194
Sig	0,263	0,002	0,040	0,001	0,113	0,074
b	0,706	0,570	2165,169	-1176,280	-2951,866	-2377,621
Wald	10,570	7,673	0,997	0,017	0,121	0,063
Sig	0,001	0,006	0,318	0,896	0,728	0,802
c	-4,196	-4,031	-4,047	-4,421	-4,281	-4,306

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	2,289	3,796	1,648	-0,998	0,802	0,469
Wald	1,187	15,716	2,234	0,197	0,222	0,099
Sig	0,276	0,000	0,135	0,657	0,637	0,753
b	-0,062	0,365	-0,058	0,008	-0,103	-0,079
Wald	0,026	6,194	0,026	0,000	0,083	0,041
Sig	0,872	0,013	0,872	0,985	0,774	0,840
c	-4,465	-4,194	-4,036	-4,414	-4,536	-4,366

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-0,818	-0,690	-0,345	0,228	0,337	-0,094
Wald	10,715	16,770	3,430	0,325	2,070	0,149
Sig	0,001	0,000	0,064	0,569	0,150	0,699
b	0,001	0,001	0,000	0,000	0,000	0,000
Wald	0,095	5,311	0,457	0,000	0,028	0,005
Sig	0,757	0,021	0,499	0,985	0,867	0,946
c	-4,397	-4,272	-4,318	-4,425	-4,324	-4,352

Table 16 : Regression coefficients on Market Implied Default Probabilities over 30-day time interval

The relation tested is: Y = a*X+ b*L + c where L is the liquidity, X is the variation in the implied DP

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	0,7106	0,6338	0,4336	-1,0668	-0,3725	-0,4562
Wald	10,8086	9,7593	3,8741	10,8712	1,4884	2,2607
Sig	0,0010	0,0018	0,0490	0,0010	0,2225	0,1327
b	2133,2	3375,5	3667,7	-29167,0	-240058,7	-191207,1
Wald	5,6725	6,9548	5,1405	0,4244	2,3022	1,9138
Sig	0,0172	0,0084	0,0234	0,5147	0,1292	0,1665
c	-4,2035	-4,0367	-4,0526	-4,3996	-4,2012	-4,2379

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	2,5122	1,8471	1,0397	-2,3419	0,2639	0,4457
Wald	2,5971	7,0904	4,0734	1,4751	0,0540	0,2207
Sig	0,1071	0,0077	0,0436	0,2245	0,8162	0,6385
b	0,0188	0,0031	0,0066	-0,0850	-0,0433	-0,3620
Wald	0,1439	0,2756	3,3966	0,1821	0,1248	1,5231
Sig	0,7045	0,5996	0,0653	0,6696	0,7239	0,2172
c	-4,3961	-4,0733	-4,0918	-4,4945	-4,5397	-4,2960

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-0,8486	-0,6018	-0,3427	0,3007	1,2620	-0,0923
Wald	10,3407	11,6475	3,5752	0,4451	9,2824	0,1454
Sig	0,0013	0,0006	0,0586	0,5047	0,0023	0,7029
b	-0,1387	0,0012	0,0013	-1,2427	-113,0088	0,0000
Wald	0,0955	7,7791	8,0008	0,1124	0,6308	0,0004
Sig	0,7573	0,0053	0,0047	0,7374	0,4271	0,9831
c	-4,3957	-4,2661	-4,3234	-4,4208	-4,3122	-4,3520

Table 17: Regression coefficients on Market Implied Default Probabilities over 30-day time interval.

The relation tested is: Y = b*L + c where L is the liquidity.

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&p	Fitch	Moody's	S&p
b	2321,1987	3818,0761	4083,8671	-43883,0573	-262354,2	-213144,2
Wald	6,1996	7,6135	6,5757	0,7448	2,6346	2,2446
Sig	0,0128	0,0058	0,0103	0,3881	0,1046	0,1341
c	-4,1205	-3,9664	-4,0125	-4,3864	-4,2068	-4,2437

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&p	Fitch	Moody's	S&p
b	0,0219	0,0031	0,0065	-0,1003	-0,0414	-0,3557
Wald	0,2515	0,2827	3,3159	0,2331	0,1169	1,4842
Sig	0,6160	0,5950	0,0686	0,6292	0,7324	0,2231
c	-4,3391	-4,0191	-4,0670	-4,5004	-4,5361	-4,2902

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&p	Fitch	Moody's	S&p
b	-0,0304	0,0011	0,0013	-0,9396	-62,4623	0,0000
Wald	0,0381	7,3827	8,1258	0,1027	0,1927	0,0002
Sig	0,8453	0,0066	0,0044	0,7486	0,6607	0,9881
c	-4,3752	-4,2473	-4,3149	-4,4202	-4,3045	-4,3511

Table 18: Regression coefficients on Market Implied Default Probabilities over 90-day time interval.

The relation tested is: Y = (a+b*L)*X + c where L is the liquidity, X is the variation in the implied DP

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	0,8244	0,7147	0,7335	-0,3104	-0,3055	-0,0023
Wald	44,4674	30,1894	32,6837	2,3140	2,1276	0,0001
Sig	0,0000	0,0000	0,0000	0,1282	0,1447	0,9902
b	1963,05	2065,08	1460,22	-8952,83	-7446,47	-42609,56
Wald	0,4269	0,4438	0,2119	0,1246	0,0875	0,4492
Sig	0,5135	0,5053	0,6453	0,7241	0,7674	0,5027
c	-3,2064	-3,2679	-3,1031	-3,2606	-3,3888	-3,1802

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	3,4087	3,9482	3,8219	-1,7919	-1,0916	-0,8403
Wald	31,9621	39,0045	38,0765	1,5396	0,5528	0,4465
Sig	0,0000	0,0000	0,0000	0,2147	0,4572	0,5040
b	0,0794	0,0596	0,0663	-0,8970	-0,9546	-1,2899
Wald	1,5397	1,3935	1,4122	0,5955	0,6769	0,4770
Sig	0,2147	0,2378	0,2347	0,4403	0,4106	0,4898
c	-3,3137	-3,1268	-3,1468	-3,4013	-3,4421	-3,2360

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-0,4225	-0,5770	-0,2702	0,2329	0,2159	-0,0276
Wald	0,6894	11,9080	4,1536	0,2434	1,1021	0,0262
Sig	0,4064	0,0006	0,0415	0,6218	0,2938	0,8713
b	0,0265	0,0032	0,0012	0,0024	-0,0005	-0,0010
Wald	0,1016	5,4762	0,4746	0,0078	0,0252	0,1492
Sig	0,7500	0,0193	0,4909	0,9298	0,8738	0,6993
c	-4,1601	-3,1634	-3,1946	-4,5108	-3,2454	-3,2096

Table 19: Regression coefficients on Market Implied Default Probabilities over 30-day time interval

The relation tested is: Y = a*X+ b*L + c where L is the liquidity, X is the variation in the implied DP

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	0,8265	0,7166	0,7201	-0,3198	-0,3139	-0,0338
Wald	45,5153	30,8597	31,5225	2,5584	2,3314	0,0366
Sig	0,0000	0,0000	0,0000	0,1097	0,1268	0,8483
b	3317,93	3541,24	5931,60	-7970,17	-5633,87	-31133,38
Wald	1,0663	1,1886	1,8908	0,1108	0,0798	0,3404
Sig	0,3018	0,2756	0,1691	0,7392	0,7776	0,5596
c	-3,2105	-3,2722	-3,1065	-3,2575	-3,3868	-3,1717

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	3,5248	4,0465	3,9255	-1,9923	-1,4074	-1,0758
Wald	34,8140	41,6844	40,8494	2,0803	1,0080	0,8702
Sig	0,0000	0,0000	0,0000	0,1492	0,3154	0,3509
b	0,0125	0,0111	0,0112	-0,2020	-0,0804	-0,3696
Wald	1,7877	1,4470	1,4626	0,4949	0,1532	1,2045
Sig	0,1812	0,2290	0,2265	0,4817	0,6955	0,2724
c	-3,3202	-3,1346	-3,1539	-3,3493	-3,4188	-3,1558

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-1,7494	-0,5101	-0,2601	1,4958	0,2147	-0,0386
Wald	2,9516	9,1978	3,8915	1,8817	1,0668	0,0545
Sig	0,0858	0,0024	0,0485	0,1701	0,3017	0,8155
b	-1094,3578	0,0029	0,0030	-569,4066	-0,0164	0,0026
Wald	0,6507	4,4575	4,5351	0,2311	0,0556	3,0283
Sig	0,4199	0,0347	0,0332	0,6307	0,8135	0,0818
c	-4,1462	-3,1623	-3,2008	-4,4938	-3,2428	-3,2148

Table 20: Regression coefficients on Market Implied Default Probabilities over 30-day time interval.

The relation tested is: Y = b*L + c where L is the liquidity.

CDS Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	4982,9522	4910,8753	9458,1928	-14223,6204	-9621,7	-32950,9
Wald	2,7288	2,5345	5,0716	0,1853	0,1313	0,3814
Sig	0,0986	0,1114	0,0243	0,6669	0,7170	0,5369
c	-2,9599	-3,0653	-2,9143	-3,2854	-3,4174	-3,1756

Bond Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	0,0169	0,0163	0,0162	-0,2482	-0,1	-0,4
Wald	3,6386	3,5959	3,4760	0,7445	0,2498	1,3842
Sig	0,0565	0,0579	0,0623	0,3882	0,6172	0,2394
c	-3,0726	-2,8600	-2,8733	-3,3882	-3,4525	-3,1813

Equity Implied DP	Downgrade			Upgrade		
	Fitch	Moody's	S&P	Fitch	Moody's	S&P
a	-754,4032	0,0029	0,0030	-553,4317	0,0	0,0
Wald	0,1316	4,6281	4,4689	0,0783	0,0568	3,0100
Sig	0,7168	0,0315	0,0345	0,7796	0,8116	0,0828
c	-4,1205	-3,1409	-3,1904	-4,4787	-3,2402	-3,2142

Complementary information about Ratings

Number of Firms in Sample (as of 02/06/2008)

Nb	Fitch	Moody's	S&P
AAA/AA	28	24	26
A	102	101	122
BBB	124	134	167
BB	33	45	62
B	7	9	13
CCC	0	3	0
CC/C	0	0	0
D	0	0	1

%	Fitch	Moody's	S&P
AAA/AA	9,5%	7,6%	6,6%
A	34,7%	32,0%	31,2%
BBB	42,2%	42,4%	42,7%
BB	11,2%	14,2%	15,9%
B	2,4%	2,8%	3,3%
CCC	0,0%	0,9%	0,0%
CC/C	0,0%	0,0%	0,0%
D	0,0%	0,0%	0,3%

Distribution of the firms by sector and CRA (as of 02/06/2008)

Nb	Fitch	Moody's	S&P
Energy	21	28	36
Materials	12	23	27
Industrials	32	40	50
Consumer Discretionary	50	58	70
Consumer Staples	30	30	38
Health Care	29	36	39
Financials	66	56	52
Information Technology	20	23	39
Telecommunications Services	9	9	9
Utilities	31	26	34

%	Fitch	Moody's	S&P
Energy	7,0%	8,5%	9,1%
Materials	4,0%	7,0%	6,9%
Industrials	10,7%	12,2%	12,7%
Consumer Discretionary	16,7%	17,6%	17,8%
Consumer Staples	10,0%	9,1%	9,6%
Health Care	9,7%	10,9%	9,9%
Financials	22,0%	17,0%	13,2%
Information Technology	6,7%	7,0%	9,9%
Telecommunications Services	3,0%	2,7%	2,3%
Utilities	10,3%	7,9%	8,6%

Number of Events by CRA (01/01/2004 - 15/04/2009)

Rating events	Fitch	Moody's	S&P
Rating Upgraded	136	170	213
Rating Affirmed	1099	849	1097
Rating Downgraded	193	249	261
Rating Off Watch	3	15	35
Rating On Watch Down	106	255	242
Rating On Watch Up	22	109	72

Numbers of Event by Magnitude (01/01/2004 - 15/04/2009)

Downgrade (in Notch #)	Fitch	Moody's	S&P
-1	163	199	228
-2	38	55	41
-3	6	7	6
-4	2	1	3
-5	1	1	1

Upgrade (in Notch #)	Fitch	Moody's	S&P
1	136	142	190
2	21	27	20
3	2	3	3
4	0	0	1
5	0	0	0