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Credit default swap spreads as complements to credit ratings in pension fund solvency requirement calculations

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Eläkerahastojen tulee hallita sijoituksiin liittyvää luottoriskiä Suomen lain ja Finanssivalvonnan määrittelemällä tavalla. Tällä hetkellä luottoluokitukset ovat merkittävä vakavaraisuusvaateiden suuruutta määrittävä tekijä. Finanssikriisin jälkipyykissä luottoluokituslaitokset saivat osakseen suuren määrän kritiikkiä ja luottoluokitusten luotettavuus luottoriskin määrittäjinä kyseenalaistettiin. Tämä tutkielma selvittää mitä ongelmia on luottoluokitusten käytössä regulaation osana ja voisiko markkinaperusteisilla riski-indikaattoreilla, kuten luottoriskinvaihtosopimuksilla, täydentää nykyisiä suomalaisten eläkerahastojen pääomavarauslaskelmia.

ABSTRACT

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Pension funds need to manage their credit risk according to the Finnish law and Finland's financial authority's regulation. Currently one key component of the solvency requirement calculations are credit ratings defined by the credit rating agencies. After the financial crisis, there has been more critique on the credibility of the credit ratings. This thesis examines what are the current issues related to the usage of credit ratings in regulatory purposes and could a market based parameter like credit default swap spreads be incorporated to the Finnish pension fund solvency capital calculations.

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1 INTRODUCTION

Pension funds manage considerable number of assets and their importance to the financial markets and sovereign economies is incontrovertible. Default of a major pension fund would cause profound harm to the financial markets, which is why there is high scrutiny over the funds' risk management. Adequate risk control mechanisms address investment, operational and governance risks. Credit risk is a major component of pension funds investment risk and the management of the credit risk is regulated by the legislation and financial regulators. Current solvency requirement calculations rely heavily on credit ratings of securities and issuers. During the financial crisis the quality and integrity of credit ratings were questioned, but ratings have kept their regulatory use as there haven't been obvious substitutes for the ratings. In this thesis we offer alternative for the complete reliance on credit ratings.

1.1 Background and Motivation

In Finland, private and public sector pension funds managed approximately 184.5 billion euros worth of assets at the end of September 2016. The Finnish Pension Alliance's (TELA, 2016) statistics show that at the beginning of millennium major part of the funds were invested in fixed income assets, but currently most of the assets are invested in equity. In year 2000, the Finnish pension funds' assets were allocated approximately in following way: 60 percent bonds, investment loans and money market investments, 22 percent shares and other, 12 percent real-estates investments and 6 percent premium lending. 15 years later the investments in real-estates had stayed at the same level, amount of fixed income investments and cash had decreased to 39 percent and the number of shares had increased to 48 percent. The investment reforms carried out in 1997 and 2007 increased pension insurance companies' investments in equity and the trend has continued until today. In recent years, the monetary policies carried out by central banks has pushed bond yields down into even negative territory, which has made bonds less attractive form of investment compared to equity. However, as Finnish legislation (315/2015 7 a §) states that maximum 65 percent of the funds can be invested in equity the level of equity cannot increase above this level.

Pension funds are important buyers in the long-dated bond market. In balancing risk against return hurdles pension funds tend to buy significant amounts of corporate bonds. These intermediate- to long-term fixed income securities are a good match against typical liability profiles and, by offering extra return as compensation for credit risk, are more useful than government bonds for meeting return objectives, especially in current low yield environment. The amount of credit risk funds can prudently take is limited, however, whether constrained by themselves or by their regulators, so they tend to purchase investment-grade corporate bonds.

The regulation of pension funds' risk management has tightened since the financial crisis. Changes were made to make the financial sector less vulnerable in times of distress. The financial crisis made markets also question the quality and integrity of credit ratings, which are still commonly used in regulatory purposes. In studies criticising credit rating agencies and the regulatory reliance to them, many scholars suggested that the credit ratings could be replaced by market-based indicators. Still, there were only few concrete suggestions on how this could be done. This thesis attempts to contribute to the previous studies by showing how market-based parameter like credit default swap spreads could be incorporated to the solvency capital calculations.

1.2 Objectives of the Study

Objective of this study is to demonstrate what risks and benefits both credit ratings and market-based parameters pose when implemented in regulation, and how credit default swap spreads could be incorporated to pension fund capital requirements. The aim of the regulation is to protect important institutions like pension funds, but regulation should not become excessive burden neither distort the markets. The new model, complemented with marked-based indicator of credit risk, is intended to make the capital requirements treat securities from different issuers more fairly by reflecting both credit agencies and markets opinion of the issuers' credit risk. It should push regulation to a direction where reliance to credit rating agencies is diminished.

We use the current model to calculate the solvency capital requirements defined by the law of pension fund capital requirement calculation and investment diversification (315/2015) as a base to our proposed model. The model suggested is simple enough to be implemented in regulation, yet the capital requirements it produces should be sufficient to protect the financial system. The goal is to keep the complexity of the model at the same level as it currently is, even though a small increase in complexity can't be avoided as additional component is introduced to the calculation.

This study is limited solely to capital requirements on debt security investments. Also the effect of leverage and portfolio diversification is excluded from the scope of this study. We follow Finnish legislation, which differs from the Solvency II directive (2015/35) of European Union law. Still the methodology used could potentially be incorporated also in other contexts.

Previous studies on credit risk, informational value of credit ratings, business models of credit rating agencies, features of credit derivatives market and credit risk pricing are the base of this thesis. Credit ratings and credit default swap markets are connected by introducing the academic findings on how these two affect one and other. These studies highlight the important features of these two measures of credit risk, which should be thoroughly understood before applied to regulation.

1.3 Structure of the Study

The reminder of this study is organized as follows. Next Section presents the key concepts of this study: credit risk, credit ratings and credit default swaps. Section 3 introduces the different ways of measuring credit risk, the development of pricing the credit risk and the framework with which credit rating agencies produce their credit ratings. Section 4 presents how the solvency capital requirements are currently calculated and the new model which incorporates the marked based variables. It also describes the data used in the new model and in testing the model. Sections 6 concludes the study and suggests topics for further research.

2 KEY CONCEPTS

Credit risk is the primary risk related to debt securities, which pension funds need to manage. Credit quality of an issuer or security will affect the pension funds capital requirements when purchasing a security. In current legislation credit quality of a security is determined by the credit rating given by a credit rating agency (CRA), though there are also other possible determinants that could be used.

2.1 Credit Risk

Credit risk can be divided into default risk, recovery risk and credit deterioration risk. Default risk refers to the risk that investor might lose all or part of the cash-flows related to the security due to issuer inability to meet its obligations. Recovery risk refers to risk of the extent of the loss incurred in the event of default. Credit deterioration risk is the risk that debtor's credit quality changes. Deterioration of credit quality should be reflected in issuers credit rating and credit default swap (CDS) spread.

2.1.1 Default Risk

Default risk is the risk that investor might lose all or part of the cash-flows related to the security due to issuer inability to meet its obligations. Moody's (2016) definition of default has three types of events: (i) missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period; (ii) bankruptcy, administration, legal receivership, or other legal blocks (perhaps by regulators) to the timely payment of interest and/or principal; (iii) a distressed exchange occurs where: (a) the issuer offers bondholders a new security or package of securities that amount to a diminished financial obligation or (b) the exchange had the apparent purpose of helping borrower avoid default. The definition is meant to capture the change in the original contracted relationship between the bond holder and issuer, which subjects the bondholder to an economic loss. Credit agencies produce cumulative default rates from their data of companies they rate. The table below indicates the probability of a company with given rating to default during a certain time period. Table 1 shows the average default probabilities during 1970-2009.

Table 1. Moody's cumulative default rates by original rating, 1970-2009

Age in Year	Aaa	Aa	A	Baa	Ba	High Yield
1	0.0%	0.0%	0.1%	0.2%	1.2%	4.5%
2	0.0%	0.1%	0.2%	0.5%	3.2%	9.3%
3	0.0%	0.1%	0.3%	0.9%	5.6%	13.9%
4	0.0%	0.2%	0.5%	1.4%	8.1%	17.9%
5	0.1%	0.2%	0.7%	1.9%	11.9%	21.4%
10	0.5%	0.5%	2.0%	4.9%	20.0%	34.0%
15	0.9%	1.2%	3.6%	8.8%	29.7%	43.3%
20	1.1%	2.5%	5.9%	12.3%	37.2%	49.6%

(Tuckman & Serrat, 2011)

From the table one can notice that investing in a Aaa rated company means one has in average 1.1 percent probability that the company will default in next 20 years, when with high yield company the probability of default is almost 50 percent. Still, focusing on the average default rates can sometimes be misleading. In reality, annual default rates can vary significantly over time. In distressed times the default probability can be significantly higher than the average default probability would suggest. Based on S&P data Tuckman et. al (2011) have counted that annual high yield default rates in Europe and emerging markets can vary from less than 1 percent to over 15 percent. The volatility has been highest during the 2007-2009 financial crisis and at the time of the Enron and WorldCom defaults in 2001 and 2002. In average there have been 4.5 percent probability that a high yield company would default over one year period during 1970-2009.

2.1.2 Recovery Risk

When investing in corporate bonds realized returns don't depend only on defaults, but also on loss given default. Recovery risk refers to the extent of the loss incurred in the event of default. The recovery rate is defined as the fraction of the principal amount ultimately returned to debtholders. It is an industry practice to use a recovery rate of 40 percent for assorted credit-market calculations (Tuckman et al. 2011). Table 2 shows Moody's average historical recovery rates for senior unsecured debt as a function of rating. Usually the recovery rate declines with the rating, but the average recovery rate of investment grade bonds and high yield bonds are quite the same. Only Aaa rated senior secured bonds have had significantly higher recovery rate than the industry standard recovery rate of 40 percent.

Table 2. Moody's average recovery rates for senior unsecured debt, 1982-2009

Rating	Aaa	Aa	A	Baa	Ba	B	Caa-C
Recovery	62.0%	44.4%	41.4%	43.8%	42.4%	37.5%	34.9%
Grade		Investment				Speculative	
Recovery		43.5%				37.5%	

(Tuckman & Serrat, 2011)

Just as default rates, also recovery rates in a particular year can be very different from the average historical recovery rates. Default and recovery rates are highly correlated over time. There is also additional problem in using average recovery rates, even when conditioned on the priority class of a debt issue. For example, subordinated debt can recover a lot more from an issuer with a relatively small amount of senior debt than from an issuer with a relatively large amount of senior debt.

2.1.3 Credit Deterioration Risk

Usually companies do not jump from high rating to default, but their credit rating gradually weakens over time before bankruptcy. This deterioration of the creditworthiness will affect the returns of the debtholder. Table 3 below presents the percentage probability of an issuer from moving from one rating to another during one year period.

Table 3. Moody's average one-year letter rating migration rates, 1920-2010

From/To:	Aaa	Aa	A	Baa	Ba	B	Caa	Ca_C	WR	Default
Aaa	86.556%	8.214%	0.827%	0.162%	0.032%	0.001%	0.001%	0.000%	4.206%	0.000%
Aa	1.195%	84.152%	7.238%	0.740%	0.167%	0.037%	0.006%	0.005%	6.392%	0.068%
A	0.079%	2.917%	84.575%	5.549%	0.683%	0.121%	0.029%	0.009%	5.946%	0.092%
Baa	0.041%	0.286%	4.467%	81.252%	4.996%	0.789%	0.131%	0.015%	7.742%	0.280%
Ba	0.007%	0.083%	0.474%	5.923%	73.373%	6.838%	0.576%	0.068%	11.367%	1.292%
B	0.006%	0.050%	0.154%	0.592%	5.768%	71.304%	5.551%	0.534%	12.260%	3.781%
Caa	0.000%	0.021%	0.029%	0.189%	0.808%	8.067%	62.742%	3.841%	11.945%	12.358%
Ca_C	0.000%	0.026%	0.113%	0.061%	0.468%	3.265%	7.691%	51.801%	13.225%	23.350%

(Moody's, 2011)

Table 3. demonstrates well that more than one letter changes are quite rare especially with investment graded companies. Over a period of one year credit ratings usually stay the same. Column WR stands for "withdrawn rating". Reasons for withdrawals include: debt maturity;

calls, puts, conversions, etc.; business reasons, or the issuer default. It is noteworthy that rating migration can also benefit the debtholder if issuer's rating increases.

2.2 Credit Ratings

Credit agencies have developed from the investors' need to understand the credit quality of security issuer. Credit quality analysis requires substantial information and expertise, making it inefficient for each investor to conduct their own assessment. Credit agencies act as information intermediaries between the issuer and investor. There are three major credit agencies: Moody's, Standard and Poor's (S&P), and Fitch. In Finland, official credit rating is not mandatory requirement for pension fund to invest into a debt security, thus not having one can affect the company's cost of capital.

2.2.1 Credit Rating Agencies

At the beginning of 1900's John Moody started producing single letter ratings from complex data and reports of railroad industry, and investors paid him for the access to this simplified information. The value of Moody's product was closely related to the quality of his ratings. If investors thought that Moody's ratings would not reflect the credit quality of the issuer they would not pay for such a product.

After the 1929s market crash regulators turned to credit agencies for measures of bond quality to be used in banking and insurance guidelines. A second wave of regulatory reliance began in 1975, when the US Securities and Exchange Commission (SEC) introduced the concept of Nationally Recognized Statistical Rating Organization (NRSRO) and regulators were further encouraged to rely on ratings from these private organizations. During this time the earnings mechanism of credit agencies shifted to collecting rating fees from the issuers introducing significant new conflict of interest.

Currently credit rating agencies operate on this issuer-pays business model. This means that credit agencies' revenues come from the company's the agencies rate. There are several problems to this model and we will address the critique on subsection 2.2.3. Some credit agencies are still using the original investor-pay or subscription model. With this model the

ratings are not publicly available, but investor must pay the agency to get access to the rating information. Also government-pay model has been suggested, but so far this model has stayed in theoretical level.

In issuer pay model rating fees are paid by debt issuers. These fees account for most of the rating agency revenues. Therefore, a substantial portion of the revenue coming from ratings is dependent upon the volume of ratable debt securities issued in the global capital markets. Still, annual fee arrangements with frequent debt issuers, annual debt monitoring fees and annual fees from commercial paper and medium-term note programs, bank deposit ratings, insurance company financial strength ratings, mutual fund ratings, and other areas partially mitigate the agencies dependence on the number of new debt securities issued in the global fixed-income markets. Many of the agencies offer also other kind of services, like consulting on data analysis and different kind of risk solutions, so their business does not rely solely on the rating fees.

Credit ratings are alphanumeric symbols indicating the creditworthiness of a security, issuer or borrower. There is some variation on how rating agencies present their ratings, for example Moody's four best ratings are AAA, Aa1, Aa2 and Aa3 when Standard and Poor's have AAA, AA+, AA and AA-. Bonds having ratings from Moody's Aaa (S&P AAA) to Moody's Baa3 (S&P BBB-) are referred as investment grade bonds. Bonds below the Baa3 rating are referred as the high yield bonds.

The rating agency markets are highly concentrated with the three biggest global rating agencies, Standard & Poor's, Moody's and Fitch dominating the industry. In year 2015 there were 26 credit rating agencies registered to the European Securities and Markets Authority (ESMA), but three biggest agencies' revenues accounted for almost 93 percent of the total markets. From the remaining rating agencies DBRS had 1,89 percent market share the rest 22 rating agencies had less than 1 percent market shares. (ESMA, 2016)

After the 2007-2009 financial crisis, regulators have started to pay attention to the issues related to credit agencies and especially in US there's been initiatives taken to reduce the reliance on credit ratings in regulation. The US securities and exchange commission (SEC) and European ESMA publish annual reports on credit ratings agencies. For example article

8d of the CRA Regulation requires ESMA to publish a list of registered CRAs and the types of credit ratings they issue. ESMA also calculates the CRAs' market shares using CRAs' revenues from credit rating activities and ancillary services at group level.

2.2.2 Benefits of Credit Ratings

The clearest benefit of credit rating is that a single letter rating is easy to understand and intuitive way of describing debt or issuers credit worthiness. As the ratings are usually paid by the issuers, investors can have free access to the ratings. Credit agencies have also access to confidential corporate information and deep expertise on assessing companies credit risk. Credit ratings are rather stable measures, that should reflect the corporate's financial fundaments and there is evidence from academic research that credit rating changes hold informational value in equity, bond and CDS markets even though there are also contrary results.

Credit agencies conduct substantial due diligence on the issuer before giving them a rating. There is also follow ups on the rating after the initial rating is given. When conducting their assessment on company, agencies get access to corporate information, which is not accessible for the general investor. They have many years of experience on assessing corporate credit risk and well thought processes and tools to conduct their assessment. They have also access to historical statistics on numerous other companies, which help them assess single issuer's credit worthiness relative to others.

Credit agencies aim at having rather stable ratings as it can be beneficial for the investor and the issuer. They look at company's financial situation in broader context so that unnecessary reversals of ratings could be avoided. Moody's Investor service changes the given rating only "when it is unlikely to be reversed within a relatively short period of time" (Cantor, 2001). Cantor explains that this rating policy is due to market expecting stable ratings and agencies acting to meet the investor expectations.

There has been a lot of studies made on how rating announcements affect stock, bond and derivatives markets. It seems that in general rating announcements have informational value on markets, though some of the changes are anticipated by the market participants. Hull et

al. (2004, pp. 2789-2811) studied how Moody's credit rating announcements affect CDS spreads. Their main conclusion was that reviews for downgrades had significant effect on spreads. Their results were in line with previous studies from stock and bond markets. Norden and Weber (2004, pp. 2813-2843) studied the impact of rating announcements from all three major rating agencies: Moody's, S&P, and Fitch, to CDS spreads and found similar results as Hull et al. (2004, pp. 2789-2811). Also Micu et al. (2005) found that reviews for downgrade have significant impact on CDS market and that the reviews are anticipated by the market. What was different from the previous research was that they identified significant decrease in CDS spreads due to positive rating announcements, which wasn't anticipated by the markets.

2.2.3 Critique on Credit Agencies and Usage of Credit Ratings

For many years there has been controversy surrounding the role of rating agencies in the financial system. The critique on credit agencies flared dramatically through the 2007– 2009 financial crisis. One big topic was that rating agencies had been earning a larger and larger percentage of their revenues from rating mortgage-related structured products. These products performed very poorly through the crisis, including securities that were rated Aaa/AAA. Later research including one from Griffin and Tang (2012, pp. 1293-1328) have shown that some of the ratings for these securities were inflated. What needs to be said though, is that research by He et al. (2012, pp. 2097-2137) shows that investors charged higher spreads on products with an inflated rating, which suggests that investors were aware of misaligned ratings and priced those in.

Regulatory bodies have outsource some of their responsibilities to CRAs by making rules that depend on ratings. Few clear examples include international bank capital rules under the Basel Accords and quality standards for the security holdings of U.S. money market funds. Regulatory bodies also choose which rating agencies can be used for regulatory purposes. These selections can build a special status and competitive advantage on the chosen rating agencies. Even if regulators have tried to promote rules that would make the CRA market more diverse, the biggest players have stayed the same.

Current regulation secures the revenues of CRAs. As issuer needs a valid credit rating so that no potential investor would be inhibited from buying the security, the revenues of the CRAs do not depend on the quality of their ratings. According to Moody's annual report (2015) the company has provided shareholders an annual return of 16 percent during 2000-2015. Since the year 2000 Moody's revenues have increased steadily and year 2015 was a record year for the company with its revenue being 3,484.5 million USD. 67 percent of the revenues came from Moody's credit rating activities. Similar picture applies for Standard & Poor's. Big profits aren't a proof of questionable business practises but large excess returns compared to other businesses can be seen as a warning sign.

Though it would seem wise to have more competition on the credit agency market, there is also evidence that suggests the opposite. More rigorous competition, could be seen to spur CRAs to develop their credit assessment methods leading to better quality credit ratings. Competition would also cut the excess returns currently witnessed on the industry. Study by Becker and Milbourn (2011, pp. 493–514) presents evidence that increased competition, when Fitch Ratings entered the industry, actually led to lower quality corporate ratings. The rating levels went up, the correlation between ratings and market-implied yields fell, and the ability of ratings to predict default deteriorated. Becker and Milbourn conclude that competition most likely weakens reputational incentives for providing quality in the ratings industry and, thereby, undermines quality.

The volume of different securities issued have expanded tremendously, but the growth of rating agency resources haven't increased in even pace. For example the report from SEC (2008, pp. 10-11) points out that before the financial crises the volume of certain securities increased substantially as did the revenues gained from these products, but in the case of few rating agencies the amount of staff assigned to rate those products did not increase in even pace. There has been also critique on the lack of transparency on calculations behind the ratings.

One major evidence against the credit ratings' ability to measure credit risk in a persistent way is how differently market participants measure the credit risk of companies having the same letter rating, but who operate in different business sectors. Cataldo and Yen (2011, pp. 48-51) point out in their research that the divergence in risk among issuers with same letter

ratings measured by average CDS prices are too big to be ignored by the professionals responsible for implementing and validating consistent credit standards. The table below summarises their findings on how differently CDS prices and letter ratings measure the credit risk in the example sectors.

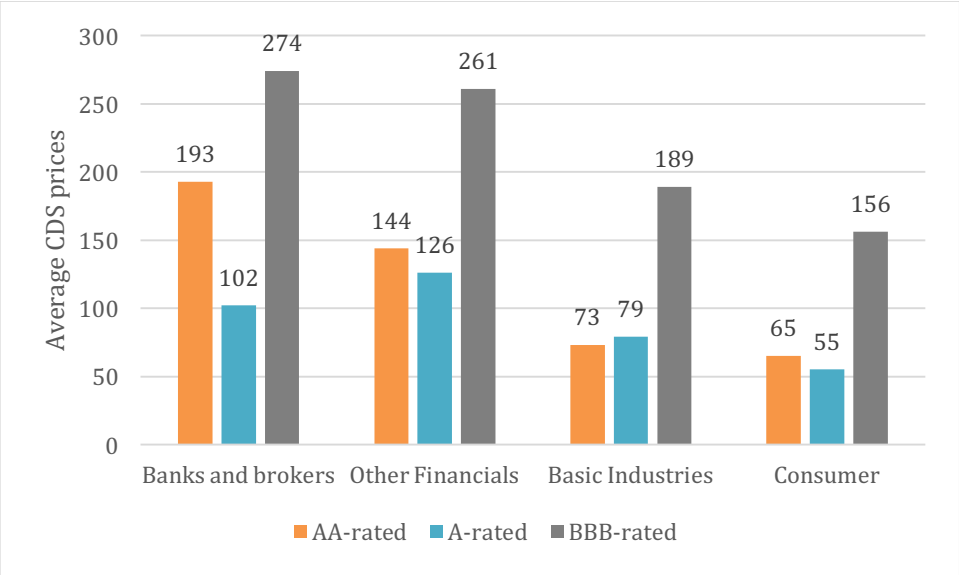

Figure 1. Average CDS prices of AA, A, and BBB-rated companies on different sectors.

Interestingly, the higher the letter rating the bigger the difference between the sector with highest CDS price and lowest CDS price. These prices are quotes from 9/27/2010 and might reflect the systematic risk associated with the financial sector.

2.3 Credit Default Swaps

In credit default swap (CDS) transaction the buyer makes periodic payments to the seller and in return obtains the right to sell a bond issued by the reference entity for its face value if a credit event occurs. The rate of payments made per year by the buyer is known as the CDS spread. In a typical CDS contract, a bank or insurance company will purchase credit protection on a company in its credit portfolio from a protection seller, who receives quarterly premiums up until the derivative contract matures or until the firm defaults on its debt obligations. Upon default, the seller compensates the buyer at the difference between the face and market value of the company's debt.

2.3.1 Credit Default Swap Market

Credit default swaps are by far the most common credit derivatives traded world-wide. According to Bank for International Settlement's semi-annual report (2016), the size of the global CDS market in the first half of 2016 was 11.8 trillion US dollars covering approximately 99 percent of the OTC credit derivatives market. Though, the size of the market has declined steadily since 2007. BIS (2014) statistics show that at the end of year 2007 the notional amount of outstanding CDS contracts was 58 trillion US dollars. During the peak of 2007, credit derivatives came close to surpass foreign exchange derivatives as the second largest segment in the global OTC derivatives market. Currently credit derivatives account only for about 2 percent of the total OCT derivatives market.

Credit derivatives are fairly new instruments as their trading started during 1990s. The main point in CDS trading is that the contract allows one party to transfer its credit exposure on a reference entity to another party by means of bilateral agreement. CDSs can have maturities from a few months up to 10 years or more and their maturity is not necessarily the same as the maturity of the reference entity. Most CDSs are quoted for a benchmark time-to-maturity of 5 years and typical payment terms are quarterly or semi-annually.

The exposure to corporate default through CDS is in many ways similar to a cash or direct exposure to corporate debt. Though, there are two important differences. As a bilateral agreement is made, each counterparty is exposed to the counterparty risk. However, the counterparty risk can be mitigated by the taking and posting of collateral. Second, the financing risks of a cash position and a CDS position are quite different. A counterparty in a CDS contract can maintain exposure to credit through the CDS maturity date by meeting any collateral calls. By contrast, maintaining a position in corporate bonds requires financing, either with capital or through repo markets. Financing with capital can be expensive and financing though repo market is subject to significant liquidity risk.

In reducing systemic risks, central clearing has become a key element in authorities' agenda for reforming OTC derivatives markets. Multi-name products are more standardised than single-name products and as such they are more amenable to central clearing. Multi-name

products consist primarily of contracts on CDS indices. As CDS become more standardised, central counterparty clearing houses' share of newer contracts is likely to increase.

2.3.2 Benefits of Credit Default Swaps

Like demonstrated in previous section credit ratings have several problems as an objective measure of credit risk, including the agency problems related to credit agencies' business model. Market based measures, like CDS spreads, reflect how many different market participants view the credit risk of a specific entity. As CDSs are subject to real trading, market participants will have to "put their money where their mouth is" when they quote the prices and make their assessments of the entity's credit risk. In current regulatory environment rating agencies do not lose money if their ratings are proven to be incorrect, but market participants have strong financial incentives to make accurate estimations when trading is conducted.

Several studies, for example Hull et al. (2004, pp. 2789-2811), Norden and Weber (2004, pp. 2813-2843), and Micu et al. (2005) presented in previous section, have showed that CDS spreads anticipate reviews for downgrades. In general, marked based measures are faster to react to changes in company's credit risk than credit ratings. One reason for this is CRAs' goal to avoid rating revearsals and to keep the ratings stable. The study from He et al. (2012) also showed that market prices can incorporate information that is not publicly available.

There has also been active development of the CDS market. For example in year 2014 ISDA introduced new standard definitions for CDSs' to address some issues detected during the resent crisis. They introduced better sovereign credit event mechanisms and new credit event: Governmental Intervention. Governmental intervention is similar to a restructuring credit event, but the trigger has to be the result of an action by a government or a governmental authority. (Markit, 2014) Research from Parlour and Winton (2013, pp. 25–45) have demonstrated theoretically that for high-quality borrowers CDS trading can increase the lending efficiency. Allen and Carletti (2006, pp. 89–111) concluded that Borrowers' credit quality may improve if lenders share some of the benefits from CDS trading with the borrowers.

2.3.3 Critique on Credit Default Swaps

Credit default swap markets are currently well established with 11.8 trillion US dollar notional amount of outstanding contracts. The regulation and standardization of the market has come a long way since the trading with CDS contracts started. Still, there is critique on the transparency of the market as it is largely invisible to the people outside the relatively small circle of direct participants. Also the pricing information is not easily accessible, but usually requires access to expensive institutional data service. In case of pension funds this is not a problem as they have access to these sources.

The pricing information itself also poses some problems. CDS trading is executed by the banks and investment firms who act as market makers. The CDS pricing data can be collected from either the quotes of market makers or from the buy side quotes. Usually the quotes used are indicative values, meaning that they are not necessarily prices of actual executed trades. They are presented as the average prices of indicative bids and offers. As the prices do not represent actual transactions the quality of the pricing data depends heavily on the instance that provides it. The pricing quality might suffer, if the particular name is thinly traded or the source providing the quote isn't particularly interested in the name, thus have profound information on its credit quality. Cataldo and Yen (2011, pp. 48-51) point out that the market for high yield names is less liquid than the market for investment grade names, which is why the user of pricing information should be more cautious when interpreting the prices of high yield CDS names. Low trading volumes also increase the potential for aggressive speculation and price manipulation. Though, this feature applies to all markets. Also as OTC instruments CDSs carry counterparty risk.

Subrahmanyam et al. (2014, pp. 2926-2960) noticed in their research that likelihood of a rating downgrade and bankruptcy of the reference firms both increase after CDS trading begins. Even if CDSs aren't considered to affect the fundamentals of the underlying assets, CDS trading can affect decision makers' incentives and induce suboptimal real decisions. If a bank hedges its credit risk exposure to the borrower, it might not be as vigilant in monitoring the borrower, which may have change to take on more risky projects. It's also likely that CDS-protected creditors will be tougher during debt renegotiations, refusing debt workouts and making distressed borrowers more vulnerable to bankruptcy. Black and Hu (2008, pp.

663–709) had acknowledged this empty creditors problem, where CDS-protected debtholders have the same legal rights as creditors, but they do not have positive risk exposure to borrower default. Bolton and Oehmke (2011, pp. 2617–2655) formally modelled the problem and concluded that under mild assumptions lenders would choose to become empty creditors by buying CDS protection. These lenders would also be tougher in debt renegotiation if the firm would become financially distressed.

3 MEASURING CREDIT RISK

When studying whether credit default swap spread could be used as complementary parameter for credit ratings in solvency capital requirements, it is necessary to understand how these two measures are constructed, and establish the connection between the two measures of credit risk. The following section identifies the factors affecting CDS prices and credit ratings.

3.1 Credit Risk Pricing

In determining the credit risk structural models like Merton (1947, pp. 449-470) and Black-Cox model (1976, pp. 351-367) have been pioneering the field. These structural models are firm value based and have generally three determinants of credit spread: leverage, asset volatility and level of risk-free interest rate. Problem with the structural models were that their implementation needed inputs that are directly unobservable for most of the companies. Models included assumption that company's assets follow continuous diffusion process, there is complete information available of the company's current assets value and default boundary and that default is not a surprise event. These assumptions lead to result that there were no short-term default risk and short-term credit spreads were under-priced. To eliminate the predictability of default, researches like ones from Kijima and Suzuki (2001, pp. 661-620); and Hilberink and Rogers (2002, pp. 227-263) incorporated jumps in the assets value process. Other solution to eliminate the predictability of default was represented by Duffie and Lando (2001, pp. 633-664); Cetin et al. and Yildirim (2002); and Giesecke (2006, pp. 2281-2303) in form of incomplete information models. Some issues still remained.

To address the problems of structural models, researchers constructed new reduced from models where the parameters were set using information available at the markets. The originators of this field were Litterman and Iben (1991, pp. 52-64); and Jarrow and Turnbull (1995, pp. 53-85). In current trading practices, there are generally three models used to value credit default swaps: hedge-based valuation, bond yield-based valuation, and discounted cash flow method (Gökgöz et al. 2014). Hedge-based approach is based on fact that contracts with the same cash flows occurring at the same time should be equal. The bond yield-based valuation assumes that the price of CDS should be the difference between price of risk free

and risky bond. Discounted cash flow approaches rely on the equality of cash inflows and outflows. The present value of the expected CDS premium should then be equal to the present value of the expected default payment under the constant recovery rate assumption. From the price of the CDS one can derive an estimate of implied default probability. The implied default probability can be seen as market's view on the riskiness of the underlying security or issuer.

3.2 Credit Rating Framework

The actual models, which credit rating agencies use for assessing company's credit rating are business secrets and as such not publicly available for review. Still, to demonstrate the reliability of their ratings agencies have disclosed some information on their rating process. The figure 2 below demonstrates S&P's (2013) corporate criteria framework for issuer ratings.

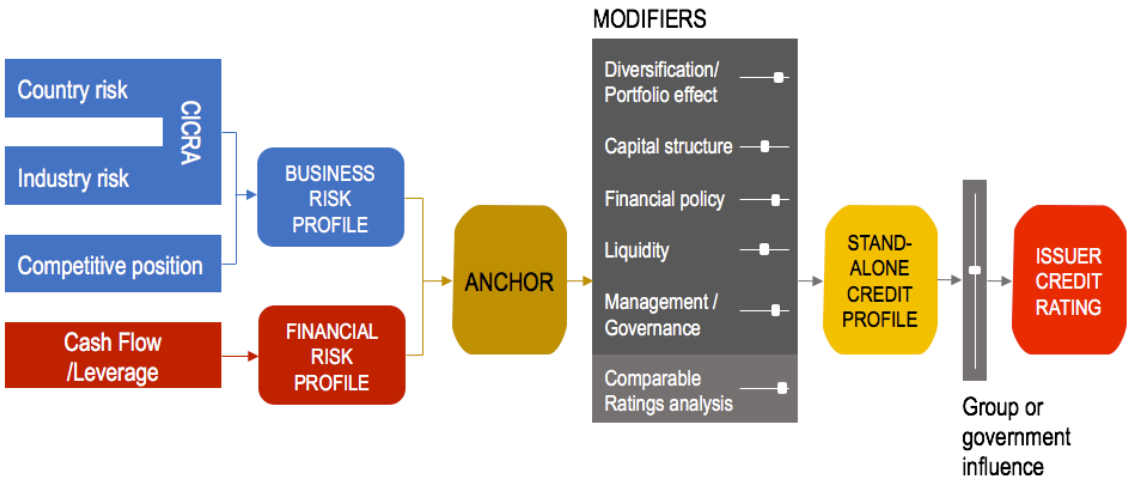

Figure 2. Standard & Poor's Ratings Services corporate criteria framework

S&P combines corporate and industry country risk (CICRA) and competitive position to assess corporate issuer's business risk profile. Cash flow and leverage analysis determines a company financial risk profile. These two combined will become corporate issuer's anchor. As a general rule, the analysis weighs the business risk profile more heavily for investment

grade anchors, while the financial risk profile carries more weight for speculative-grade anchors. Anchor is the base for the corporate issuer's credit rating. The table 4 presents how the business and financial risk profiles are combined to construct the anchor.

Table 4. Standard & Poor's Ratings Services corporate criteria framework: Combining the business and financial risk profiles to determine the anchor

	Financial risk profile					
Business risk profile	**1 (minimal)**	**2 (modest)**	**3 (intermediate)**	**4 (significant)**	**5 (aggressive)**	**6 (highly leveraged)**
1 (excellent)	aaa/aa+	aa	a+/a	a-	bbb	bbb-/bb+
2 (strong)	aa/aa-	a+/a	a-/bbb+	bbb	bb+	bbb-/bb+
3 (satisfactory)	a/a-	bbb+	bbb/bbb-	bbb-/bb+	bb	b+
4 (fair)	bbb/b-	bbb-	bb+	bb	bb-	b
5 (weak)	bb+	bb+	bb	bb-	b+	b/b-
6 (vunerable)	bb-	bb-	bb-/b+	b+	b	b-

(Source: S&P (2013))

After the anchor is defined additional factors are used to modify the anchor. These modifiers are: diversification/portfolio effect, capital structure, financial policy, liquidity and management/governance. The assessment for each factor can raise or lower the anchor by one or more notches or the assessment can stay unchanged. Comparable rating analysis can lower or raise the anchor by one notch based on a holistic view of the company's credit characteristics. The last step before the having the issuer credit rating the stand-alone credit profile is adjusted for group or government influence. Any ongoing support or negative influence from a government (for government-related entities), or from a group, is factored into stand-alone credit profile.

S&P bases their rating assessments on qualitative and quantitative factors. The three analytical factors within the business risk profile: corporate risk, industry risk, and competitive position, are blend of qualitative assessments and quantitative information. Quantitative assessments distinguish risk factors, such as a company's competitive advantages, that is used to assess its competitive position. Quantitative information includes, for example, historical cyclicality of revenues and profits that are reviewed when assessing industry risk. It can also include the volatility and level of profitability that S&P considers to asses a company's competitive position. The analysis of financial risk profile focuses on quantitative measures.

In theory, both CDS spreads and credit ratings incorporate the same publicly available market information. On top of this, CRA's have also access to some confidential information disclosed to it while conducting the due diligence. If CRAs would incorporate all the market information and have access to information CDS market participants don't, CDS spreads should not have any additional explanatory power over the credit ratings. The evidence on which of the two have greater explanatory power on company's credit risk is conflicting. It is also unknown, how much CRAs use market-based indicators like CDSs when assessing companies. What seems to be a fare assumption is, that the two measures capture a slightly different aspects of company's credit risk. Thus, one could argue that complementing capital requirements with market-based indicator like CDS spread could capture a fuller picture of company's credit risk.

4 SOLVENCY REQUIREMENTS

Solvency requirements are set to ensure that insurers can meet their obligations to policy holders and beneficiaries. They are designed to prevent excessive risk taking as funds need to hold capital reserves that reflect the risk level of their investments. The capital requirements of a pension fund depend not only on the risk of individual assets, but also on the composition on pension fund's portfolio. This research focuses on capital requirements connected to the credit risk of bond investments, so the effect of portfolio diversification is left out. This section introduces the current method of calculating solvency capital requirements and how CDS spreads could be incorporated into the calculations.

4.1 Current Solvency Requirement Calculation

Solvency requirement calculations rely heavily on the ratings of the biggest rating agencies. If official rating is not available, pension fund needs to define the asset's risk category with its own models. In these cases, the use of market based indicator of credit risk could be applied, though it is possible that pension funds would follow the official calculation method as much as possible and use the peer ratings of the issuer and the debt to define asset's risk category. When using its own models pension fund needs to justify its methodology to Finnish financial regulator. The law of pension fund capital requirement calculation and investment diversification (315/2015 11§ 1) defines three credit categories presented in table 5.

Table 5. Credit categories defined by the law of pension fund capital requirement calculation and investment diversification (315/2015 11§ 1).

Credit categories	Fitch Ratings	Moody's Investors Service	S&P's Rating services
Category 1	AAA - AA-	Aaa - Aa3	AAA - AA-
Category 2	A+ - BBB-	A1 - Baa3	A+ - BBB-
Category 3	BB+ or below	Ba1 or below	BB+ or below

These categories need to be used when assessing asset's credit risk. If the credit rating of an asset is higher than its issuer's or guarantor's rating, the rating of the asset should be used. In case the asset has no rating, but the debt's guarantor has better rating than the issuer, the guarantor's rating is used to determine the asset's risk class. Ratings from other party than

one of the three major rating agencies can be used if the rating can be seen reliable. However, if there is a rating from either Fitch, Moody's or Standard & Poor's pension fund is obligated to use their ratings. If there is rating from two agencies, the lower rating will determine the credit category. If there is rating from more than two agencies the median rating should be used. Credit categories are used in defining the assets risk category, which determine assets expected loss coefficient S_j and the expected return m_j for the category. Risk categories are presented in table 6.

Table 6. Risk categories for debt instruments and expected loss S_j and return m_j for category *j* defined by the Act from Council of State (447/2015).

Risk categories	$\mathbf{S_j}$	$\mathbf{m_j}$
Category 7: Assets of public entities in credit category 1	0.000	0.000
Category 8: Other assets in credit category 1	0.015	0.005
Category 9: Assets in credit category 2	0.025	0.010
Category 10: Assets in credit category 3	0.050	0.020

In case of category 7: rated government and other public entity debt, the expected loss coefficient S_j gets value 0.000. In theory this is justified as governments have the right to tax its citizens, which is seen as unlimited collateral. Central banks have also the power to print more money. Still, the problems sovereign countries in Europe had after the financial crisis, highlighted that even debt issued by public entities do carry credit risk. When viewed against this background the expected loss coefficient set to zero would seem to carry the purpose that funds would favour securities issued by public entities over corporate securities. This would increase the demand of government securities and ensure their cheap funding.

The total solvency capital requirement is counted with the following formula:

$$V_{total} = -\sum_i \mu_i + \sqrt{\sum_i \sum_j p_{ij} (V_i + \mu_i)(V_j + \mu_j) + \sum_j \beta_j^2 B_j^2} + \sum_k K_k \qquad (1)$$

where V_j is the risk value of the risk category j, and μ_j is its expected return. ρ_{ij} is the correlation between the risk classes j and i, B_j is the smaller value, from risk class j, of the sum

of the long positions and the sum of the short positions. Finally, K_k is the amount the counterparty risk k limit is exceeded (315/2015 8 §). The constant β_j, representing the risk exposure due to the difference of long and short positions, and the correlation among the risk classes ρ_{ij} are both regulated by an Act from the Council of State (315/2015). When considering a single investment i belonging to risk category j the formula is reduced to form:

$$V_i = -\mu_i + \sqrt{p_j(V_j + \mu_j)(V_j + \mu_j)} \tag{2}$$

$$V_i = |V_j| \tag{3}$$

See Appendix 1. for the derivation. The risk value V_j for a category j is counted by the formula defined by an Act from the Council of State (315/2015 12 §):

$$V_i = \left|\sum_i A_i \, min\left[(1 + L_i)S_j; 1\right]\right| \tag{4}$$

When calculating the risk value for the debt margin risk, constant S_j is replaced with the difference of the product of S_j and the duration of the investment exposed to debt margin risk, with the expected rate of return of the risk category while setting A_i to the value of one. (315/2015 14 §).

$$V_i = \left|min\left[(DUR_i S_j - m_j); 1\right]\right| \tag{5}$$

Duration is the weighted average time until cash flows from the investment are received. For zero-coupon bond duration equals its maturity. Pension funds should estimate the security's duration in reliable way approved by the financial regulator. The figure below demonstrates the connection of security's duration and the required solvency capital.

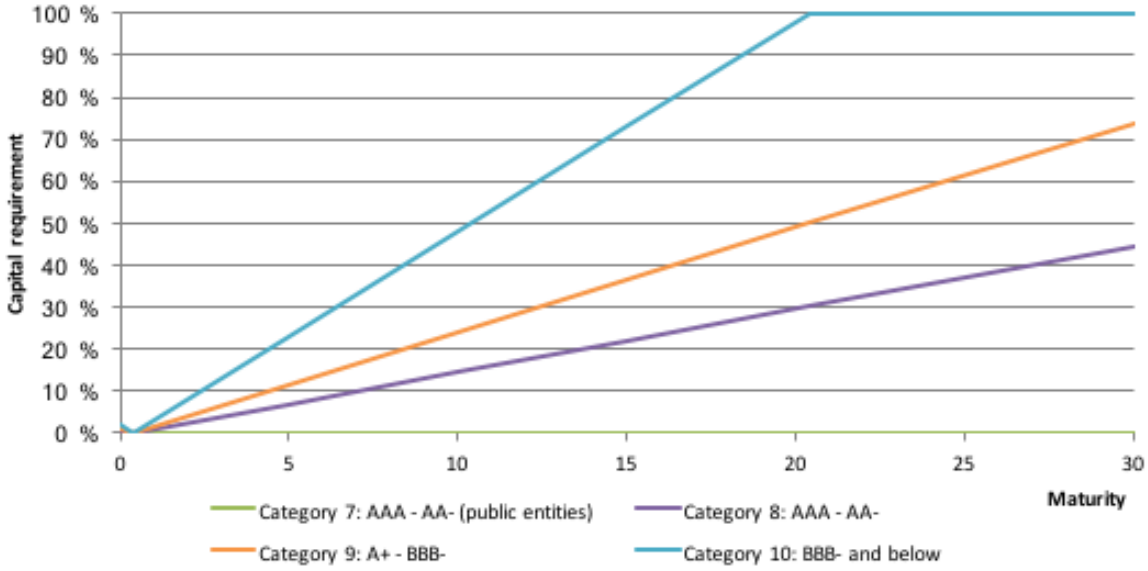

Figure 3. Current capital requirements for debt securities in different risk categories against their durations.

As seen from the figure, the capital requirements for different assets depend heavily on their credit ratings. This has impact on pension fund's portfolio allocations. Capital requirements increase with the security's duration. In Category 10, which includes corporate and public entity high yield debt securities the capital requirement equals the total investment when security's duration is around 20 years. Though, one should remember that in case of high yield securities long maturities are rare.

4.2 Model Using Credit Default Swap Spreads

The aim of the model is to consider the market's view of company's credit risk when assessing the needed capital requirement for an investment. The model should be rather intuitive and easy to use, so that it could be used in regulatory context. Implementing the formula to determine the capital requirement should not became excessive burden for the pension fund, yet is should reflect the markets expectation of the credit risk in valid manner.

4.2.1 Data

In theory, credit default swap spread describe purely the underlying company's credit risk. In reality, factors like liquidity also affect the spread. We use the spreads of 5-year single name CDS contracts to determine the companies' credit risk as they are the most standardized and liquid of the CDS contracts. For our model, we consider the spreads to be reliable enough estimates of the companies' credit risk and do not adjust them in any way.

All data is obtained from Bloomberg and it consists from daily CDS closing spreads for 748 companies and public entities, and two CDS indices during the time period 10.08.2012-03.03.2017. The companies have different credit ratings, and are form different sectors and countries. Pension funds diversify their investments and the data was to reflect that. The countries included are; Finland, Germany, France, United Kingdom, United States and Japan. For some companies, there were no CDS quotes available to the whole time period, thus this was not a problem for the analysis. Also credit rating information for the companies was accessed through Bloomberg.

The two indices used as benchmarks are Markit CDX North American Investment Grade and Markit CDX North American High Yield. Markit Ltd. selects the companies included to the indices in a way that they represent the most liquid segment of the market. As CDS markets are global, using North American indices should be applicable. North American CDS market is the biggest and most developed, which makes it a good benchmark. The following figure 4 shows the development of the two indices during our sample period.

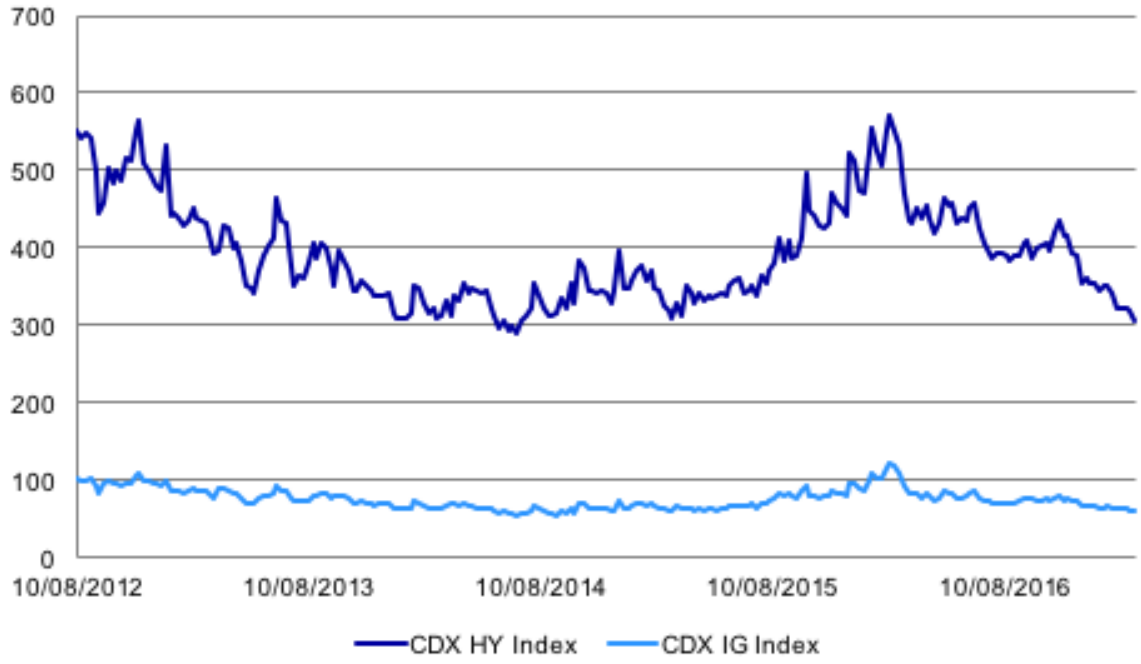

Figure 4. CDS spreads for Markit CDX North American Investment Grade and Markit CDX North American High Yield indices in basis points.

The spread between the two indices stays between 236 and 463 basis points. The peak in CDS spreads at February 2016 was due to worries over bank debt especially in Europe. Investors rushed to buy protection against banks' declining bond prices. The effect seen in the indices shows that CDS spreads do not count only for only idiosyncratic risks but also systemic risks.

Some descriptive statistics from the 748 companies' CDS spreads can be found from Appendix 2. When comparing the average and mean spreads for companies in the risk categories 7 – 10, the category 7 has the lowest average spread and category 10 highest. This means that also by CDS spreads, category 7 companies seem to be bear least credit risk and category 10 most credit risk relative to other categories. On the other hand, the minimum spreads are not as consistent. Company with lowest CDS spreads belongs to category 9 and highest to category 8. This makes using CDS spreads a bit questionable. One reason for this is that CDS trading is mostly conducted when company's credit rating is at the line between belonging to investment grade or high yield. This makes it difficult to separate the companies to credit categories that cover the whole spectrum of different levels of credit risk that credit ratings do. We will do some further testing with the data in the last sub section.

4.2.2 Model Incorporating Credit Default Swap Spreads

We create two new market based credit categories category 4 and category 5. The spread of the company's CDS defines to which category the company belongs. Then the expected loss and return coefficients are determined taken into account the rating based risk category and CDS spread based credit category.

The companies are divided into two credit categories by their CDS spreads. To make the division we use the Markit CDX North American Investment Grade and Markit CDX North American High Yield indices as our benchmarks. By calculating the arithmetic mean from the two indices we derive the spread value, which divides the two categories. The arithmetic mean is calculated using the standard formula:

$$A = \frac{1}{n}\sum_{i=1}^{n} a_i, \tag{6}$$

where a_i is the value of the index i in basis points. Now the value that separate the two risk categories vary through time as seen in figure 5.

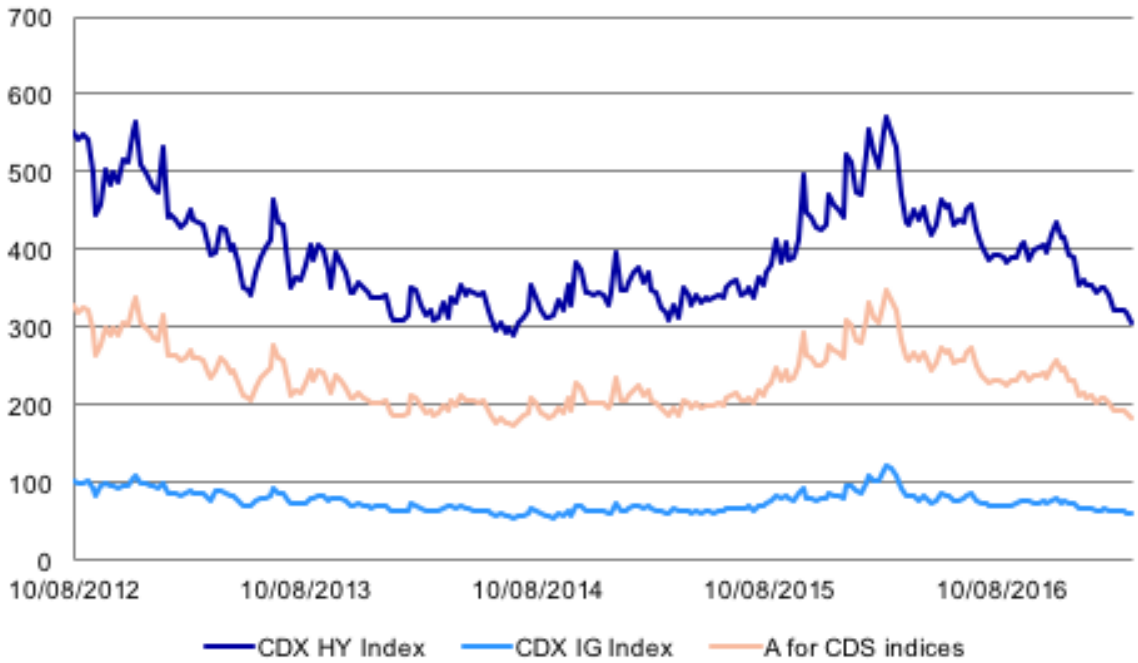

Figure 5. The benchmark indices and their average spread A.

Regulator could also decide on a specific CDS spread that is constant over time. That would be the maximum CDS spread that is accepted for a company belonging to the less risky credit class, which can be referenced as the investment grade. This approach would lead to a situation where during market turmoil more companies would fall to the high yield grade based on their CDS spreads. The effect of the greater systematic risk reflected by CDS market would have greater effect to the capital requirements. We do not consider this desirable feature, thus use the arithmetic mean of the CDS indices.

Risk based models to define the solvency capital requirements have always the undesired feature that they tend to accelerate market trends. For example, if market uncertainty would cause sell-off in certain securities, the decreased value of the securities would increase the risk of these securities and their issuer. The increased risk lead to higher capital requirements for the institutions holding the securities forcing them to sell some of their assets, which would accelerate the sell-off further. Introducing market based variable to the solvency capital requirement formula can potentially enforce this phenomenon.

After defining the mean A, companies can be split to two new credit categories are presented in table 7 by their five-day average closing spreads. The latest closing spread could be used, but using the five-day average reduces the noise and the risk that on exceptional closing level would alone define the needed capital requirement. Five-day average is easy to calculate and easy to get straight from institutional data services like Bloomberg.

Table 7. Market based credit categories.

	CDS spread of a company
Category 4	$0 \leq A$
Category 5	$A <$

Compared to the categories 1 to 3 defined in current legislation, companies in the new category 5 should have around the same credit risk as the companies in category 3, which includes assets with S&P credit rating BB+ (Moody's Ba1) or below. The category 4 should include companies with credit risk equal to the ones in categories 1 and 2. Merging the two

categories was done due to the fact that when comparing the CDS spreads of these two categories, the difference wasn't clear enough to construct two separate categories. Also there was no ready market benchmark, which could have been used. Though defining the highest credit category as a certain quantile of the spread between the two CDS indices is possible. All in all, for the regulatory purpose the two categories seemed sufficient and more efficient to implement in real world situations.

What needs to be noted is that we do not define further risk categories from these credit categories as is done in current legislation. This will diminish the special status public entities currently have in the legislation. If security is defined to belong to the high yield class by the CDS spread, the needed capital requirement will be higher even if it would belong to risk category 7 according to its credit rating. Of course, this kind of situation would be quite rare, but it captures the phenomenon we wish the capital requirements to reflect. If credit ratings are slow to react to new information or are not changed due to for example agent problems the market based indicator would make sure that at least part of the increased risk is reflected in the requirements. For example, if a country with a good credit rating were found to have fake its public accounts the CDS market would probably reflect this risk sooner than the rating. Many studies suggest that CDS markets anticipates rating changes. As there is also evidence that CDS market can reflect non-public information, countries and companies with rigged accounting can have higher spreads before any public scandals.

We modify the original expected loss coefficient S_j and the expected return coefficient m_j so that they take our market based risk measure into account. The new coefficients are presented in the tables 8 and 9.

Table 8. New values for expected loss coefficient S_j

Expected loss S_j	Category 4	Category 5
Category 7: Assets of public entities in credit category 1	0.000	**0.015**
Category 8: Other assets in credit category 1	0.015	**0.020**
Category 9: Assets in credit category 2	0.025	**0.030**
Category 10: Assets in credit category 3	**0.040**	0.050

Table 9. New values for expected return coefficient m_j

Expected profit m_j	Category 4	Category 5
Category 7: Assets of public entities in credit category 1	0.000	**0.005**
Category 8: Other assets in credit category 1	0.005	**0.010**
Category 9: Assets in credit category 2	0.010	**0.015**
Category 10: Assets in credit category 3	**0.015**	0.020

The highlighted cells present the situations where the market based credit category changes the value of the expected loss and return compared to the original coefficient values defined by the Act from the Council of State (447/2015). When plotted against the durations, the new model produces twice the outcomes compared to the original as seen from figure 6.

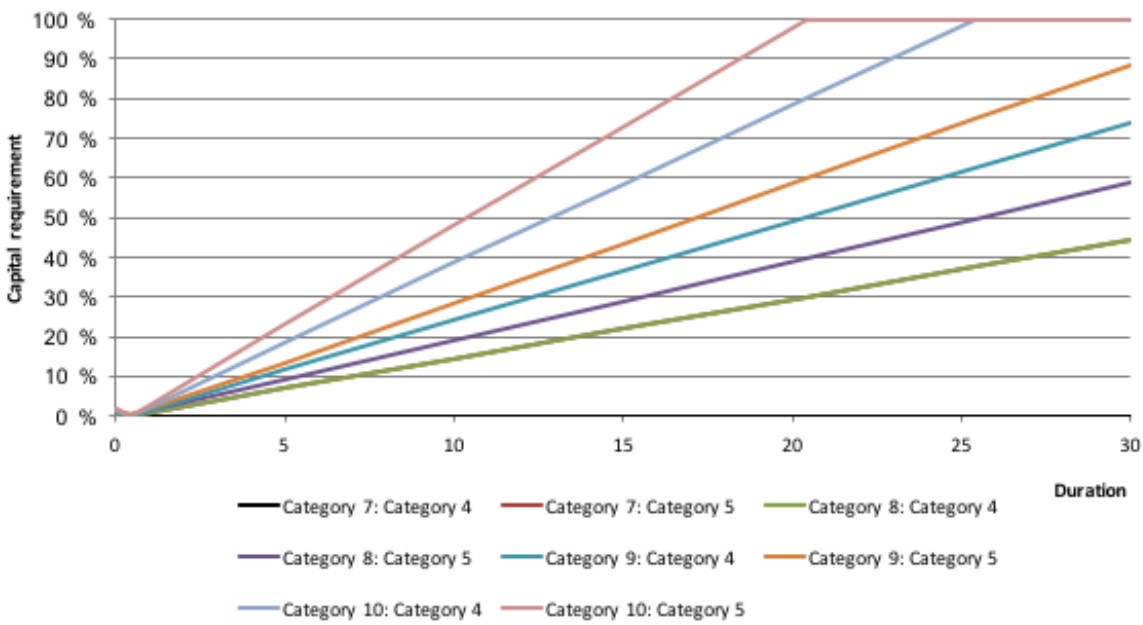

Figure 6. Capital requirements for debt securities in different risk categories against their durations in the new model.

Though not visible from the picture, the line for "Category 7: Category 5" is exactly same as the line for category "Category 8: Category 4". For high grade public issuer bonds, which also markets value to belong to investment grade the capital requirement is still zero. We saw no need to make the capital requirements for the riskiest bonds greater, so we kept the upper bound unchanged.

The presented model represents only one possible solution to incorporate CDS spreads to solvency capital requirements. For example, Creal et al. (2014, pp. 430-444) use CDS spreads to derive default probabilities and then cluster the companies into marked based rating categories using a functional clustering algorithm. The problem of the approach is that the defined rating categories should be updated from time to time, so that they would stay valid as the overall spread levels at the CDS markets will vary. Our solution is simple enough to be implemented in regulatory purpose and it doesn't require frequent revisions.

4.2.3 Testing the Model

We use the data from 748 companies and public entities to see how many of them would have different credit category according to their CDS spreads than what they have according to their credit ratings. We use the average CDS spreads between the time period 27.2.2017-3.3.2017 and current ratings of the companies. Then we examine how the capital requirement for two example company's debt securities would have changed over time with the new model. Making historical comparison for all the 748 companies would have been difficult as their credit ratings might have changed over time and defining their credit category by the credit rating in each day during our example period would have been challenging.

First we define the value A from the two Markit indices, which is 183.53 basis points. Then we sort all the companies by their credit rating to credit categories 1 to 3 and further to risk categories 7 to 10 depending if they are public entities or not. Then we use the companies CDS spreads to sort them to market-based credit categories 4 and 5. The result is summarized in the table 10 below.

Table 10. Number of companies grouped by the original risk categories 7-10 and new credit categories 4 and 5.

	Category 4	Category 5
Category 7	6	
Category 8	34	
Category 9	505	**13**
Category 10	**88**	102
Total	633	115

It seems that by market-based risk category, the companies at the data are less risky than what their credit ratings suggest they are. About 46 per cent of the Category 10 companies are defined to belong to the investment grade Category 4 by their CDS spreads. When looking into the raw data, the companies which belong to different risk category by their credit rating and CDS spread are companies that mostly have S&P ratings from BBB- to BB (Moody's Baa3 to Ba2). Almost all have rating from more than one credit agency and especially for the companies in category 10 the ratings can vary depending on the agency. For the 13 companies which belong to group "Category 9: Category 5" eight had negative outlook by at least one major CRA. It would be interesting to see what has happened to the credit ratings of the five companies, which was defined as high yield by the market-based indicator, but did not yet have negative outlook. The time will show if the CDS markets are reflecting information that's not visible from the credit ratings yet.

All other governments for the chosen six countries belong to category 7, but Japan which has been rated A1 by Moody's and A+ by S&P belongs to category 8. This is probably due to the slow economic growth the country has witnessed over decades, persistent deflation, aging population and the staggeringly large public debts the country holds. Still the credit spread for Japan is the second lowest (23.97 basis points) just after Germany with 21.38 basis points. If we would have had three credit categories instead of two, it is possible that Japanese government bonds would have had lower capital requirements than what they currently have.

The first example company used is Volkswagen AG. The company has been in risk category 9 for the whole example period. The emission scandal that started at September 2015 made the company's five-year CDS spread increase near to the level where it would have been categorised as high yield by the market-based credit rating, but barely stayed under the limit as the figure 7 shows.

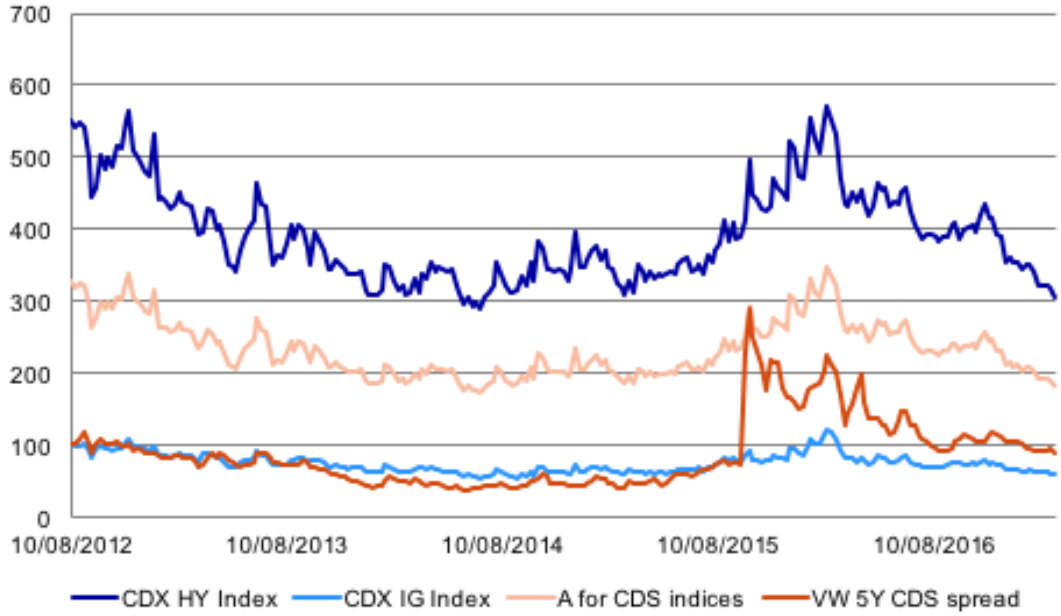

Figure 7. Volkswagen five-year CDS spread compared to the two benchmark indices and their average A.

At the time of the scandal, there was also increase to the CDS indices spreads which kept Volkswagens spread at the investment grade category. As Volkswagen has been in group "Category 9: Category 4" during the example period, the capital requirements for its debt securities have kept steady. The capital requirement for Volkswagen's debt securities having different durations can be seen at the figure 8.

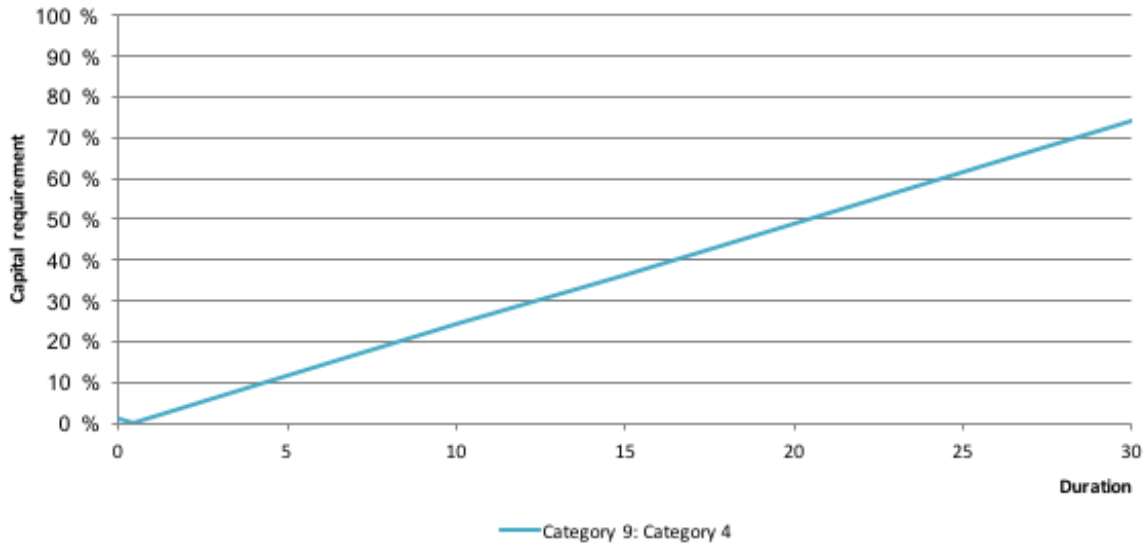

Figure 8. Capital requirements for Volkswagen AG's debt securities against their duration.

After the scandal Volkswagen's ratings have decreased steadily from S&P's A to BBB+. The CDS spreads have declined from the peak after the scandal. Before the scandal the CDS spreads were mostly at or below the Markit CDX North American Investment Grade Index. After the scandal the spreads have stayed above the index, but still clearly on the investment grade area.

The second company we use as example is Nokia OYJ. Nokia belonged to credit category 9 until Moody's downgraded its rating from Baa3 to Ba1 15.6.2012. During our example period Nokia stayed at the risk category 10. Company's credit ratings were downgraded steadily from the beginning of our example period until September 2013, when Microsoft announced that it buys Nokia's line-up of smart phones and a portfolio of patents and services. After the announcement, Nokia's credit ratings got better but the company stayed in category 10. Nokia's CDS spread reacted to the news by a clear drop as seen from figure 9.

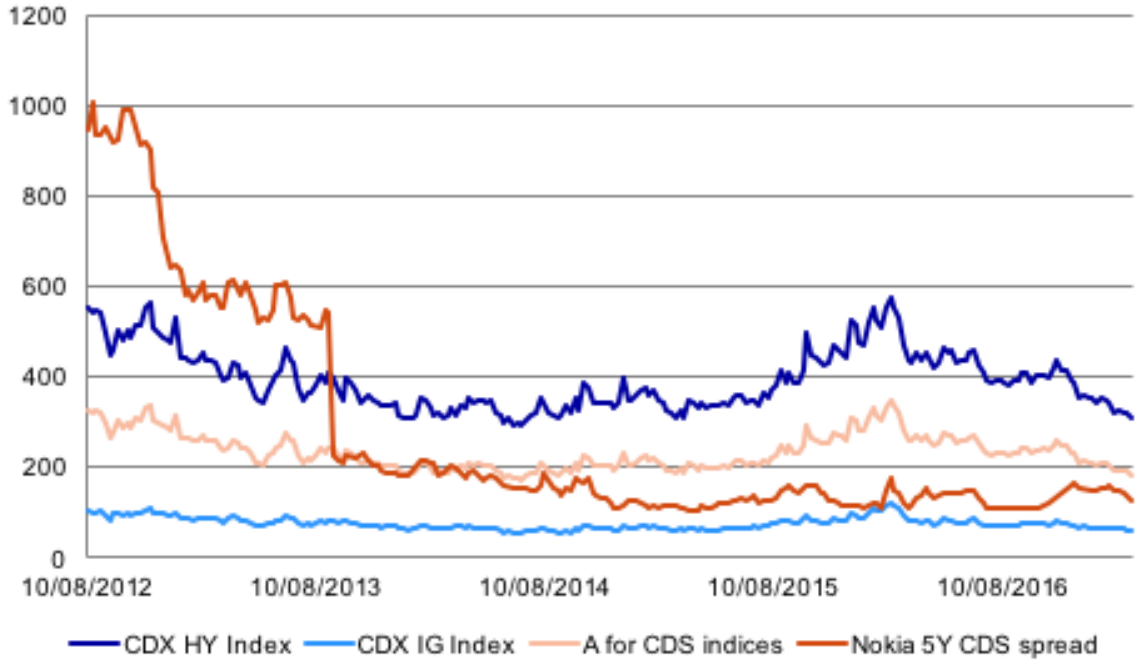

Figure 9. Nokia OYJ five-year CDS spread compared to the two benchmark indices and their average A.

Again even if the company's credit rating was downgraded at the beginning of our example period the CDS spread was decreasing. Not shown in the figure, but Nokia's CDS spread had shot up at the end of February 2012. It seems that the CDS market had a big reaction to

negative news on Nokia and were gradually evening out the shock at the beginning of our example period. After the September 2013 announcement Nokia stayed mostly at group "Category 10: Category 4" when before the announcement it was at "Category 10: Category 5". Figure 10 illustrates the change to capital requirements for Nokia's debt securities.

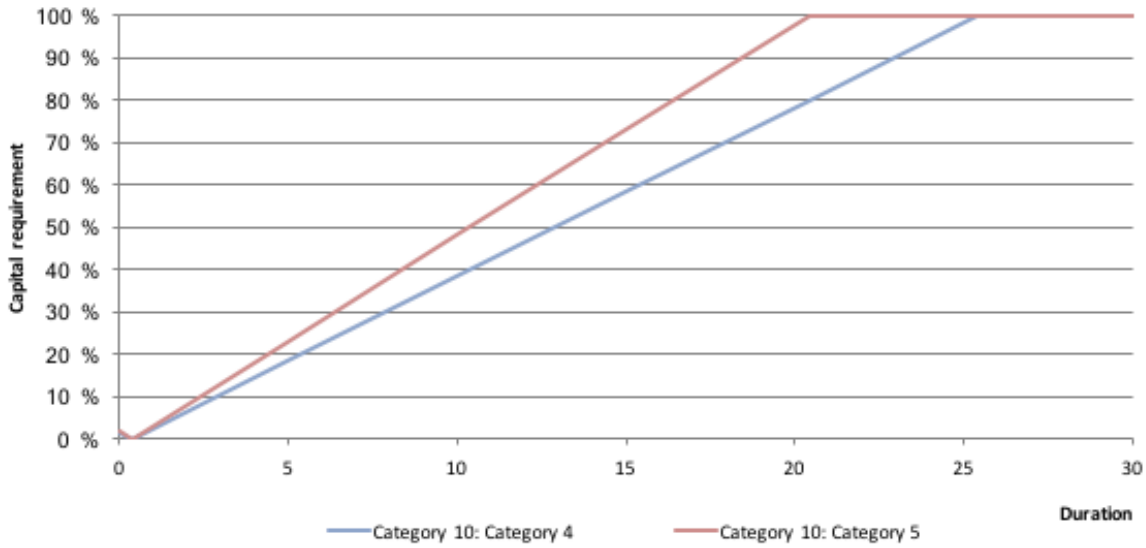

Figure 10. Capital requirements for Nokia OYJ's debt securities before and after the September 2013 announcement.

With the original model using only credit ratings Nokia's capital requirements would have been at the level of the upper line in the figure the whole example period. By introducing the market-based indicator of credit risk to the requirement calculation, the capital requirements for Nokia's debt securities were decreased adjusting to the positive expectations of the company's future.

As seen from these examples, introducing market-based indicator of credit risk to solvency capital requirements seems to adjust the requirements to the correct direction. The aim of the regulation is to protect important institutions like pension funds, but regulation should not become excessive burden neither distort the markets.

5 CONCLUSIONS

There is a real need to diminish regulatory reliance to CRA produced credit ratings as there is clear evidence that the business model of CRA's pose many conflicts of interest. The lack of transparency on how ratings are truly constructed is also a problem. As no measure is perfect reflection of company's credit risk, complementing the current solvency capital requirements with market based measure can produce an outcome that fits better the real credit risk related to the investment.

Even if in theory CDS spread should reflect only the credit risk of the underlying security or company, factors like liquidity also affect the spread. CDS market is largely invisible to the people outside the relatively small circle of direct participants and the prices can be affected by speculation and markets over reaction to surprising information. CDSs aren't considered to affect the fundamentals of the underlying assets. Still, CDS trading can affect decision makers' incentives and induce suboptimal real decisions.

Biggest challenge in using CDS spreads in regulation is that not all companies are under CDS trading. Not all companies have credit ratings either, but the amount of companies without official rating is remarkably smaller. CDS market is already big and CDSs account for most of the traded credit derivatives. Still, if trading with CDS becomes more common, using CDS spreads in regulation would be more convenient. As CDS trading is mostly conducted when company's credit rating is at the line between belonging to investment grade and high yield, separating companies to credit categories that cover the whole spectrum of different levels of credit risk is difficult.

CDS spreads do not reflect only idiosyncratic risk, but also overall market risk. Creating market-based credit categories with fixed limits to CDS spreads is likely to perform badly over time. Our model uses two CDS indices, Markit CDX North American Investment Grade and Markit CDX North American High Yield, as a benchmark when separating companies to different rating categories by their CDS spread. This approach enables the categories to adjust to CDS market's overall spread levels, which means that regulator don't have to adjust the category limits over time.

The new model is built on the current legislation. Even if an additional component is introduced, the model stays simple enough to be implemented in regulation. The capital requirements it produces should also be sufficient to protect the financial system and ensure pension funds' solvency at a time of crisis. Risk based models to define the solvency capital requirements have always the undesired feature that they tend to accelerate market trends. Introducing market based variable to the solvency capital requirement formula can potentially enforce this phenomenon. The possible effects, what using a market-based variable in regulation can cause in financial markets, should be further studied.

There is a lot of space for further research among the regulatory use of market-based variables. Instead of using CDS spreads the model could be tested with for example credit spreads. When using bond data, determining the credit component from the spread is likely more challenging. Still, there are more companies who have issued bonds than there are companies under CDS trading. Also developing the model presented in this thesis further, and completely new models, could help regulators move away from relaying only to CRA credit ratings. Testing the model further with more extensive data and different methods would also be important and interesting way to extend this research.

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APPENDICES

Appendix 1.

Total solvency capital requirement.

$$V_{total} = -\sum_i \mu_i + \sqrt{\sum_i \sum_j p_{ij}\,(V_i + \mu_i)(V_j + \mu_j) + \sum_j \beta_j^2\, B_j^2} + \sum_k K_k.$$

Where V_j is the risk value of the risk category j, and μ_j is its expected return. ρ_{ij} is the correlation between the risk classes j and i, B_j is the smaller value, from risk class j, of the sum of the long positions and the sum of the short positions. Finally, K_k is the amount the counterparty risk k limit is exceeded (315/2015 8 §). The constant β_j, representing the risk exposure due to the difference of long and short positions, and the correlation among the risk classes ρ_{ij} are both regulated by an Act from the Council of State (315/2015).

Solvency capital requirement for a single credit investment.

$$V_{total} = -\mu_i + \sqrt{p_{jj}(V_j + \mu_j)(V_j + \mu_j) + 0} + 0$$

$$= -\mu_i + \sqrt{(V_j + \mu_j)^2}$$

$$= -\mu_i + |V_j + \mu_j|$$

$$= |V_j| \qquad (\mu_j \geq 0\ \forall\, j)$$

By the (315/2015 12 §):

$$= \left|\sum_i A_i\, min[(1 + L_i)S_j; 1]\right|$$

$$= |\textstyle\sum_i A_i\, min[S_j; 1]| \qquad (L_i = 0) \text{ no leverage}$$

$$= |min[S_j; 1]|$$

By the (315/2015 14 §) for risk categories (j) 7,8,9, and 10:

$$= |min[(DUR_i S_j - m_j); 1]| \qquad \forall\, j = 7,8,9,10$$

Appendix 2. Descriptive statistics from the 748 companies CDS spreads (1 week averages from 27.2.2017-3.3.2017)

	Category 7	**Category 8**	**Category 9**	**Category 10**
Mean	29.06	37.06	70.02	295.54
Standard Error	6.29	2.93	1.96	24.51
Median	25.11	32.68	60.00	201.27
Standard Deviation	15.42	17.08	44.62	337.86
Kurtosis	4.24	-0.54	4.36	57.95
Skewness	1.91	0.79	1.76	6.33
Range	44.10	60.79	283.81	3724.70
Minimum	14.89	15.40	11.78	12.00
Maximum	58.99	76.19	295.59	3736.70
Count	6	34	518	190