Credit Risk Signals in CDS Market vs. Agency Ratings

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Abstract

Our research models the relationship between the credit risk signals in the credit default swap market and agency credit ratings, and determines the factors that help explain the variation in such signals. We provide a comprehensive analysis of the differences in the relative credit risk assessments of CDS-based risk signals and agency ratings. We show that the divergence between credit risk signals in the CDS market and agency ratings are explained by factors which the rating agencies may consider differently than credit market participants. The results suggest that agency credit ratings of relative riskiness of a reference entity do not always correspond with assessments by CDS spreads, as the price of risk is a function of additional macro and micro factors that can be explained using statistical analysis. Our research is unique in modeling the relationship between the credit risk assessments of the CDS market and the agency ratings, which to the best of our knowledge has not been analyzed before in terms of their agreement and the level of discrepancy between them. Our model can be used by investors in debt instruments that are not explicitly credit default swaps or which have illiquid CDS contracts, to replicate market-based, point-in-time credit risk signals. Based on both market-based and firm-specific factors in our model, the results can be used to augment through-the-cycle credit risk assessments, analyze issues surrounding the pricing of credit default swaps, and examine the policies of credit rating agencies.

Keywords: Credit risk, Credit default swap, CDS, Credit ratings, Credit rating agencies

JEL Classification: G10, G20, G24, G28, G32

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1. Introduction

Credit default swaps (CDSs) began trading in the late 1990s, and since then, the CDS market has grown at an extremely rapid pace [1]. The primary purpose of a CDS contract is to provide protection to the purchaser of a debt instrument in case of default or a related credit event, serving as a form of insurance. A CDS contract can also be used on the short side to bet against the credit quality, or to hedge a long position in the debt or equity of a reference entity. An investor in a CDS contract pays an annual premium to the seller of the contract. If a credit event such as default of the underlying reference entity occurs, the seller buys the underlying debt instrument from the investor at par. The annual premium, or CDS spread, ultimately reflects the market price of the credit risk with respect to the underlying instrument.

Credit risk makes up perhaps the largest risk an investor bears when buying a defaultable fixed income instrument. Credit risk may be broadly defined as the uncertainty associated with potential loss of value on a fixed income obligation—either principle or interest —in the event of default, downgrade, or widening of credit spreads.

Prior to the beginning of CDS trading, ratings assigned by agencies were the only signal of the credit risk of fixed income instruments. Credit ratings are, in theory, an independent assessment of the relative credit risk of a firm. There is a natural expectation that the CDS spread on a specific debt instrument will be correlated to the credit rating of the underlying reference entity. The primary difference lies in the timeliness of the information: credit ratings are updated periodically, whereas CDS spreads are continuously updated through ongoing trading, providing a current measure of the market's interpretation of the risk of the debt instruments.

According to the policy and guidelines issued by the nationally recognized statistical rating organizations (NRSROs) [2], at any given time the credit rating on an issue of debt reflects its relative credit quality over some horizon. This has the interpretation that a credit rating embodies information on the obligor's probability of default (PD) relative to a cohort, potentially allowing for a standard comparison of default risks. Therefore, ratings represent an opinion regarding potential loss, a firm's capacity to pay back all its sources of financing, as well as the recovery of a particular instrument in the event of default (Micu *et al.*, 2006). Historically, S&P has primarily issued a senior unsecured debt rating, presumably a ranking of pure default risk; in cases where there is subordinated debt, a separate rating is issued that may be lower than that issued to the senior unsecured debt, to reflect the greater recovery risk.

The agencies claim that they modify a firm's relative credit rating only if a change occurs in a borrower's fundamental creditworthiness, implying that they do not react to systematic events, which affect all firms equally but do not impact relative credit quality [3]. In addition to issuing credit ratings, rating agencies issue rating reviews and outlooks; these announcements follow the occurrence of material events that potentially could have an impact on a firm's fundamental credit quality and signal a possible rating change. Furthermore, rating agencies base their rating assignments on many different factors, some public, as in financial statements or capital markets information, and some private, as in an assessment of management quality or industry position (Hull *et al.*, 2004).

Following the subprime debacle starting in the summer of 2007, rating agencies have come under much scrutiny mainly because the market began to question the validity of the ratings that were issued (Hull, 2009; Stephens, 2012). A key regulation relevant to this research is The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd-Frank, 2010), perhaps the most ambitious and far-reaching overhaul of financial regulation since the 1930s. The main purposes of this legislation include identifying and regulating systemic risk through a special council that can deem non-bank financial firms as systemically important, regulate them, and as a last resort break them up. Furthermore and salient to this study, Dodd-Frank imposes a new regulatory scheme on rating agencies and tightens existing regulation, with the primary goals of holding rating agencies accountable for the quality of their credit ratings and enhancing the transparency of credit ratings.

More recently, in February of 2013, the U.S. government sued Standard & Poor's Ratings Services over the quality of the actual ratings that were issued during the financial crisis (Eaglesham *et al.*, 2013). Much of the scrutiny on the rating agencies centers on their inability to properly rate structured mortgage and commercial credit, such as collateralized mortgage obligations (CMOs) and collateralized debt and collateralized loan obligations (CDOs and CLOs, respectively).One would expect such a deficiency to also be reflected in the single-name corporate credit market.

We note the significance of the Basel III supervisory guidance (BCBS, 2010) for our study of CDS credit signals and agency credit ratings. A number of measures mitigate the reliance on external ratings in the Basel II (BCBS, 2006) framework. The measures include requirements for banks to perform their own internal assessments of externally rated exposures, the elimination of certain "cliff effects" associated with credit risk mitigation practices, and the incorporation of key elements of the International Organization of Securities Commissions (IOSCO) code of conduct fundamentals for credit rating agencies (IOSCO (2004)) into the eligibility criteria for the use of external ratings in the capital framework. Included in this set of measures are market-related monitoring tools, such as CDS spreads, which provide a source of instantaneous data on potential liquidity difficulties, useful data to monitor asset prices and liquidity (in addition to other institution-specific information related to the ability of an obligor to fund itself in various wholesale funding markets and the price at which it can do so). It is evident that international regulators recognize not only that CDS spreads are a useful complement to risk ratings, but also that CDS spreads may provide qualitatively different information, such as liquidity or other market risk–related dimensions that could influence default risk.

Understanding the relationship between agency credit ratings and CDS spreads credit risk signals can help explain how market participants perceive and price credit risk. Considerable research has analyzed the relationship. As noted by Callen *et al.* (2009), although CDS spreads are related to credit ratings issued by rating agencies, among firms having a given rating there is quite a wide variation in CDS spreads. Cizel (2013) indicates that the CDS spreads bear the closest correspondence to the market assessment of firms' credit risk. Therefore, if CDS spreads reflect a component of pure credit risk (i.e., the risk of loss associated with a deterioration in credit quality or default on the reference entity's debt), and credit ratings quantify the relative likelihood of a corporation defaulting on its debt, then the CDS contracts of reference entities with a given credit rating should be priced similarly. The research in this paper models the relationship between the credit risk signals in the swap market and the agency ratings and determines the factors that help explain the variation in such signals.

Hilscher and Wilson (2013) suggest that agency ratings do not clearly separate firms into categories by their probability of default, especially for the investment-grade issuers. Their conclusion that any single measure cannot accurately reflect all relevant aspects of credit risk provides a strong motivation to analyze the credit risk measures from the swap market and the rating agencies. This paper contributes to the literature by providing empirical results for the relationship between credit risk signals obtained from two measures, CDS-based ratings versus agency ratings risk categories.

There are several studies in the literature that have looked at the relationship between credit spreads, bond yields, and agency ratings. Hull *et al.* (2004) examine the theoretical relationship between bond yields and CDS spreads, including how this is influenced by rating agency announcements. The authors find evidence that the CDS market anticipates all three types of negative credit events— downgrade, negative watch, and negative outlook—on the announcement day[4]. Daniels and Shin-Jensen (2005) study the relationship between CDS spreads, credit spreads of corporate bonds, and credit rating changes. They find that downgrades significantly impact spreads, and that this effect is accentuated for investment-grade issues. Using the Treasury yield curve as a proxy for the risk-free term structure, they also illustrate the dependence of the value of the CDS contract on the risk-free rate [5].

Generally, prior studies identified several of the most common variables found to affect CDS spreads: the leverage of the reference entity and option implied volatility of its equity, the risk-free rate, and liquidity of the CDS contract. Villouta (2006) investigates the pricing effects of liquidity in the corporate bond and CDS markets and finds that highly liquid CDS contracts tended to have lower CDS bases, and illiquid contracts higher bases. Carr and Wu (2010) find that equity option implied volatility and CDS spreads covary positively, with credit markets sometimes showing variation independent of the stock and option markets. Cao *et al.* (2010) argue that CDS contracts are similar to out-of-the-money put options and find that put option implied volatility dominates historical volatility in explaining the time-series variation in CDS spreads. Das and Hanouna (2008) find that variables most correlated with recovery rates (i.e., losses given default, LGDs) are the 1-month risk-free rate, the VIX, the yield curve, and correlation between the levels in the term structure and the equity market volatility.

Schneider *et al.* (2007) examine the relationship between LGD and PD as implied by CDS spreads, and use agency ratings as a proxy for PD (i.e., as a crude representation for credit quality). They find evidence that equity market volatility, as measured by the VIX, is positively correlated to long- and short-term default factors that directly influence the valuation of CDS.

A CDS contract allows an investor to trade solely on the credit risk of a firm, especially since an investor does not need to hold the underlying debt contract in order to trade in the CDS market. This fact has led many to conclude that the overall risk in the CDS market is heightened:

there is less of an incentive to monitor borrowers when insurance can easily be acquired (Stulz, 2010), and many investors can purchase a CDS contract on the same underlying asset. Mahfoudhi (2011) examines new market conventions in the CDS market, the so-called CDS "big bang" changes to contracts, meant to reinforce confidence and ensure its long-term growth. Benzschawel and Corlu (2011) also examine this phenomenon, pointing out that conventions for trading CDS have enabled investors to go short with little or no initial investment, contributing to the unprecedented volatility in cash and synthetic credit markets since mid-2007.

Resti and Sironi (2007) indicate that agency ratings are less reactive than CDS spreads to changes in credit risk levels. These facts lead us to hypothesize that variations in CDS-based risk signals for a given agency rating may exist, and a comprehensive analysis of these variations would be useful for both market participants and regulators. Furthermore, the divergence between CDS spreads and agency credit ratings are apt to be explained by factors viewed differently by the rating agencies and credit market participants. Under certain ideal conditions, theoretically the CDS spread should represent pure credit risk. In practice there are many cases in which this does not hold true.

One explanation postulates the effects of systematic, unsystematic, and idiosyncratic factors. That is, both systematic and unsystematic factors independently influence spread levels (e.g., the level of the equity market vs. the implied put volatility on a reference entity's equity. On the hand, idiosyncratic factors should only influence pure measures of credit risk to the extent that they involve fundamental credit quality. For example, worsening macroeconomic conditions may affect the risk aversion of CDS market participants, which may affect spreads above and beyond the detrimental impact of the credit quality of the reference entity (i.e., greater probability of default). Other variables affecting the CDS spread may fall somewhere between systematic and unsystematic factors. A prime example is liquidity: one can think of systematic as well as idiosyncratic notions of liquidity (Dick-Nielsen *et al.*, 2012).

Understanding the relationship between CDS spreads and agency credit ratings can help explain how market participants perceive and price credit risk. Our research examines possible contributing factors that influence this range. While modeling and analyzing the relationship between the credit risk signals in CDS spreads and agency ratings, this study:

- incorporates an overview of different methodologies used to value CDSs;
- addresses the variables considered to influence the value of the CDS; and

- connects the influential variables to the explanation of the range that exists between CDS spreads of reference entities with the same ratings.

This paper analyzes differences in the relative credit risk assessments, identified as the agency credit rating categories (*ACR-c*) versus the credit default swap categories (*CDS-c*). The analysis suggests that the market perceives the average CDS in a given *ACR-c* as riskier than its agency credit rating would dictate. These observations were evident throughout the observed period from February 28, 2003, to December 31, 2010. Two models were used to explain the factors that could lead to this observation, having variables that would either be used to explain the *ACR-c* being equal to the *CDS-c*, or the *CDS-c* being a more severe assessment of credit risk than the *ACR-c*. Results for both of the models are statistically and economically significant, and had signs on (magnitudes of) coefficient estimates that are economically intuitive (significant). The models yield the following results:

- The CBOE volatility index (VIX), term premium, or the put option implied volatility of the associated equity decreases the chances (predicted number of notches) of agreement, and increases relative pessimism on the part of the CDS market.
- Conversely, the level of the S&P 500 index, market capitalization, or the EPS estimate of the reference entity, as well as the seniority of the debt, are always negatively related to the former target variables.
- The crisis and post-crisis dummy variables show that agreement decreases between the credit risk signals from the CDS market and agency ratings during the financial crisis, and risk signals appear to be get closer to each other after market turbulence. When considered with respect to the time periods between agency rating changes, results show that level of agreement decreases and distance between the credit risk categories increases with the length of the duration.

We can highlight a potential use of our model as another element for practitioners in their modeling tool-kit. This element would be especially valuable in the context of portfolios of credit instruments only internally rated, where many practitioners will have access to only through-the-cycle (TTC) credit ratings that may not necessarily incorporate credit market data. Our model bridges the gap between TTC ratings such as what the rating agencies produce, and so-called point-in-time (PIT) ratings. Therefore, if these evaluations can be mapped to the rating agency grades, then the model can be used to augment such credit assessments, thereby producing quasi-PIT ratings that can be used in a variety of contexts such as pricing or trading credit instruments.

The paper is organized as follows. Section 2 discusses our data and variable definitions. Section 3 presents the results of our empirical analysis, and Section 4 concludes the paper.

2. Data and variable definitions

The data used in our study are obtained from Bloomberg. Our CDS sample consists of contracts denominated in U.S. dollars with a 5-year term on reference entities having at least one senior or subordinate issue, in addition to having U.S. equity listings [6]. We exclude contracts with less than 100 days of spread data. Our final dataset contains the daily 5-year CDS spreads on 1,334 contracts on 392 distinct reference firms over the time period from February 28, 2003, to December 31, 2010., We end our sample just after the resolution of the market turmoil in December 2010, as we are interested in analyzing the discrepancies in credit risk signals in CDS market and agency ratings through the global financial crisis [7], and also to avoid a period of new market conventions in the CDS market (the “big bang”) in the years after the financial crisis (Mahfoudhi, 2011)..

In addition to the daily CDS spread data, we collect from Bloomberg these variables:

- following Cizel (2013), the Standard & Poor’s long-term credit rating changes during our data period for all reference entities[8]; and
- put option implied volatility (*POIV*,) which is consistent with previous research that suggests equity market and option market volatilities are key components of CDS valuation, for example Carr and Wu (2010) and Cao *et al.* (2010).

We also obtain the following firm-specific variables for each listed equity:

- market capitalization (*MCAP*);
- leverage (*LEV*), which is measured by the debt-to-equity ratio; and
- earnings per share estimate (*EPSE*) [9].

Our use of equity markets liquidity measure *MCAP* is motivated by Das and Hanouna (2009), while use of the *LEV* and *EPSE* follows from the Merton (1974) basic structural modeling framework for credit risk (i.e., increased *LEV* and decreased *EPSE* imply that firms are nearer to their default points and hence indicate greater credit risk). We use a reference-entity (issue-specific) variable to indicate the seniority of the debt (*SDI*). This is motivated by Das and

Hanouna (2008) who document the existence of a recovery or LGD component of CDS spreads , as well as by Jacobs and Karagozoglu (2011) who show that the LGD of corporate debt decreases with the seniority debt.

We also obtain various market indicators from Bloomberg:

- the S&P 500 Index (*SP500*);
- the CBOE volatility index (*VIX*);
- the 5-year swap yield premium (*SYP*), which is the difference between the 5-year plain vanilla swap rate and the 5-year U.S. Treasury Note rate; and
- the term premium (*TP*) which represents the slope of the yield curve and is the difference between the rates on 5-year Treasury Note and 3-month Treasury Bill.

Zhang *et al.* (2009) demonstrate the significance of the S&P 500 index in explaining CDS spreads as part of a structural model, in which the index proxies for the unobservable state of the economy with a higher index level implying lower level of systematic risk. Schneider *et al.* (2007) find a strong positive relationship between CDS premia and levels of the *VIX* index. Hull *et al.* (2004) suggest that in CDS pricing, the optimal risk-free curve to use lies between the Treasury and the Swap curves; thus we incorporate both measures in our analysis. The rationale for using the *TP* variable comes from the fact that the slope of the yield curve accounts for the risk premia due to investors' time preference, and also for their aversion to interest rate risk, which are expected to enter the pricing kernels of most pricing models applicable to these assets, for example as in Cox *et al.* (1981). On the other hand, following Liu *et al.* (2006), the *SYP* is expected to account for the counterparty risk, which is present between the CDS dealers and which is reflected in the higher borrowing rates than investment counterparties pay, such as clearinghouses or banks, as compared to the U.S. government. An increase in the *SYP*, all else equal, is expected to augment CDS premia.

We create two dummy variables to investigate the CDS and rating relationship during and after the financial crisis. The crisis dummy variable (*CRIS*) takes the value 1 for the period between June 2007 and June 2009, and the post-crisis dummy variable (*POST*) takes the value 1 for the period between July 2009 and December 2010[10].

In order for us to compare credit risk signals from CDS spreads and agency ratings (specifically S&P-assigned long-term ratings), we rescale the ratings to have five agency credit rating categories (*ACR-5c*) [11]:

$$ACR\text{-}5c = \begin{cases} 1 \ldots\ldots\ldots\ldots\ldots\ldots & \text{AAA to A+} \\ 2 \ldots\ldots\ldots\ldots\ldots\ldots & \text{A to A-} \\ 3 \quad \textit{for ratings} & \text{BBB+ to BBB} \\ 4 \ldots\ldots\ldots\ldots\ldots\ldots & \text{BBB- to BB+} \\ 5 \ldots\ldots\ldots\ldots\ldots\ldots & \text{BB to CCC-} \end{cases} \tag{1}$$

Both Huang *et al.* (2012) and Cizel (2013), like others, create CDS categories using the agency-assigned ratings and treat those swaps within each category the same in terms of their risk assessment. However, we show that spreads on swaps with the same rating differ significantly and therefore our goal is to model these observed differences.

Hence, we create a 5-by-5 matrix of independent categories [12]. Based on the quintiles of spread levels, we create 5 credit default swap categories (*CDS-5c*), where *CDS-5c* = 1 is assigned to swap contracts with spread levels within the lowest 20th percentile on a given day, and *CDS-5c* = 5 the highest (which is similar to Das and Hanouna, 2008). As a result of this mapping, we are able to assign *ACR-5c* and *CDS-5c* to each contract for each trading day for which we have the data. We create categories such that both *ACR-5c* = 1 (top alphanumeric scale ratings) and *CDS-5c* = 1 (lowest quintile of spread levels) correspond to the best credit risk signal (i.e., lowest risk). Similarly, *ACR-5c* = 5 (bottom alphanumeric scale ratings) and *CDS-5c* = 5 (highest quintile of spread levels) correspond to the worst credit risk signal (i.e., highest risk). If the CDS market's and rating agency's assessments of the underlying reference entity's credit quality are similar, on average *CDS-5c* and *ACR-5c* should be the same.

In order to check the robustness of the results, and to ensure that they are not biased as a result of our calibration of ACR categories, we also use deciles to create *CDS-10c* and *ACR-10c* variables. The *ACR-10c* variables are defined as rescaled Standard & Poor's long-term credit ratings (i.e., a letter or alphanumeric scale) based upon deciles of the ratings distribution in our dataset. Analogously, the *CDS-10c* variables are based upon deciles of the spread level distribution, where *CDS-10c* = 1 is assigned to swap contracts with spread levels within the lowest 10th percentile on a given day, and *CDS-10c* =10 the highest. Therefore, for the purpose of robustness checking, we create a 10-by-10 matrix of independent categories.

Table 1 presents the credit risk signals cross-tabulated: Panel A by *ACR-5c* and *CDS-5c*, and Panel B by *ACR-10c* and *CDS-10c*. If the CDS market's and rating agency's assessments of the underlying reference entity's credit quality are similar, on average, *CDS-5c* and *ACR-5c* should be the same. If that is the case, most observations would be concentrated on the diagonal cells of Table 1. Our sample contains 394,277 reference entity-days (approximately 8 years of daily data on 1,334 swap contracts with distinct underlying reference entities) and it can be seen that indeed the diagonals are heavily populated relative to the off-diagonals. For example, in Panel A for *CDS-5c* versus *ACR-5-c*, only 8.1% of the sample (32,049 of 394,277 reference entity-days) has credit risk signals in both CDS market and agency ratings that suggest the best credit quality (lowest risk), that is, *CDS-5c* = 1 and *ACR-5c* = 1. Similarly, in Panel B for *CDS-10c* versus *ACR-10-c*, in 3.4% of the sample (13,457 of 394,277 reference entity-days) credit risk signals in both sources suggest the best credit quality, that is, *CDS-10c* = 1 and *ACR-10c* = 1. Overall and by both measures, for the worst credit quality categories, data appears to concentrate below the diagonal, that is, the CDS market's assessment is more severe; and in the case of the better credit quality categories, the rating agency assessment appears to be more severe. A possible explanation for this phenomenon is that the rating agencies may not downgrade these counterparties as fast as their CDS spreads increase as their credit quality worsens, and vice versa for improvements in credit quality.

<Insert Table 1>

The analysis of Table 1 shows a test of robustness: the sample is restricted to the subset where we observe an S&P initial rating or a rating change. Table 2 shows analysis of CDS credit risk signals during two-month periods following either initial or changed S&P ratings and tabulate what percentage of *CDS-5*c and *ACR-5c* provide the same credit risk level. For example, in Panel A of Table 2 for *CDS-5c*, 87.9% of the sample has credit risk signals in both CDS market and agency ratings that suggest the best credit quality (lowest risk), that is, *CDS-5c* = 1 and *ACR-5c* = 1. This high rate of matching holds across categories. Therefore, we observe that in this restricted sample, the credit risk categories as implied by agency credit ratings and CDS spreads match to a significantly higher degree. This finding supports our hypothesis that the factors used in the model can be used to derive a CDS-like PIT credit risk signal, as this is evidence that the level of agreement between credit ratings and CDS spreads is significantly higher for this restricted sample of days following the agency revisions of ratings.

<Insert Table 2>

Table 3 presents the summary statistics in basis points for the daily median swap spreads for each of the CDS categories and agency credit ratings categories: Panel A for *ACR-5c* and *CDS-5c*, and Panel B for *ACR-10c* and *CDS-10c*. As expected, we observe that median swap spreads increase with the worsening credit quality categories in both the CDS market and ACR-based signals. For the best credit quality, the median swap spreads are very close. In the quintiles, *CDS-5c* = 1 is 23.34 bp and *ACR-5c* = 1 is 30.00 bp; for the deciles, *CDS-10c* = 1 is 20.44 bp and *ACR-10c* = 1 is 30.45 bp. For the worst credit risk quality, the median spread level in the quintiles, *ACR-5c* is 1.5 times that of the *CDS-5c*; in the deciles, *ACR-10c* is 1.6 times that of the *CDS-10c*. In addition, the variability of spreads increases noticeably towards the lower credit quality in both *CDS-5c* / *CDS-10c* and *ACR-5c* / *ACR-10c*, while this increase is more severe in agency ratings based signals. Table 3 shows that the standard deviations of swap spreads for the best credit quality are 16.92 bp and 93.94 bp for *CDS-5c* and *ACR-5c*, and 15.51 bp and 81.46 bp for *CDS-10c* and *ACR-10c*, respectively. For the worst credit quality, the standard deviations are 542.96 bp and 591.30 bp for *CDS-5c* and *ACR-5c*, and 685.83 bp and 702.59 bp for *CDS-10c* and *ACR-10c*, respectively. These observations suggest that CDS market and agency ratings credit risk assessments diverge substantially as the credit quality decreases. In the empirical analysis section, we formally model the discrepancies in credit risk signals between *CDS-c* and *ACR-c*.

<Insert Table 3>

Figures 1 and 2 display the evolution of median spread levels during our sample period for each of the *CDS-5c* and *ACR-5c*, respectively. We observe that the cyclicality of median CDS premia varies across the credit cycle for each CDS and ACR category.

<Insert Figures 1 and 2>

To investigate the similarity or divergence of credit risk signals in the swap market and agency ratings, we create two variables for both the quintile and the decile category versions of the variable. The first one is a binary variable that measures the agreement between the credit risk signals and is given by:

$$AGREE = \begin{cases} 1 & \text{if } CDS\text{-}c = ACR\text{-}c \\ 0 & otherwise \end{cases} \tag{2}$$

where *CDS-c* and *ACR-c* represent the credit default swap and agency credit rating categories, respectively. We are interested in identifying the degree of agreement between the two sources in terms of their assessment of the reference entity's credit quality.

In the cases when credit risk signals in the swap market and agency ratings are not the same, we want to measure how different the signals are from each other. Our second variable measures the distance between the credit risk signals and is given by:

$$DIST = CDS\text{-}c - ACR\text{-}c \tag{3}$$

An example of a *DIST* calculation is *CDS-c* = 5 minus *ACR-c* = 1 equals *DIST* of +4. When *DIST* is positive, the credit risk signal in the swap market is the worst (i.e., highest spreads), and in the agency ratings is the best (i.e., top alphanumeric scale rating like AAA). In this case, the level of disagreement between the two sources of credit signals is the highest and we would like to investigate what factors might be behind it. We may refer to such a case as the CDS spread being "expensive" relative to agencies' assessment of credit quality, the inference being that the cost of insurance against the credit risk of the reference entity is high. On the other hand, when *DIST* is negative (e.g., *CDS-c* = 1 minus *ACR-c* = 5 equals *DIST* = –4), the credit risk signal in the swap market is the best (i.e., lowest spreads) and in the agency ratings is the worst (i.e., bottom alphanumeric scale rating like CCC). This suggests that the CDS spread is "cheap" relative to agencies' assessment of credit quality, the inference being that this suggests modestly priced insurance for an investor short the credit. In other words, *DIST* is the number of categories for which *CDS-c* signals higher credit risk if positive and *ACR-c* signals lower credit risk if negative[13].

Since agency credit ratings are typically through-the-cycle credit risk assessments meant to be insensitive to spurious or short-term fluctuations in economic variables not impacting firm fundamentals, it is not surprising that CDS spreads react more quickly to both new information and noise than credit ratings. Thus, the level of agreement between credit ratings and CDS spreads should be inversely related to the amount of time that has passed since the last rating adjustment. Therefore, to test this conjecture we include in our models a variable called time since rating change (*RTCH*) measuring the number of days since the last rating adjustment by the S&P[14].

3. Empirical analysis

In our empirical analysis we model the degree of similarity or divergence between the credit risk signals from *CDS-c* and *ACR-c*, which represent both 5-category and 10-category versions. Similarity is shown by

$$
\begin{aligned}
AGREE = \beta_0 + \beta_1 \cdot SP500 + \beta_2 \cdot VIX + \beta_3 \cdot TP + \beta_4 \cdot SYP + \beta_5 \cdot SDI \\
+ \beta_6 \cdot POIV + \beta_7 \cdot MCAP + \beta_8 \cdot LEV + \beta_9 \cdot EPSE + \beta_{10} \cdot CRIS \\
+ \beta_{11} \cdot POST + \beta_{12} \cdot RTCH + \epsilon
\end{aligned}
\tag{4}
$$

where *AGREE* indicates the agreement between the credit risk signals in CDS categories and in ACR categories, as in Equation (2). Divergence is shown by

$$
\begin{aligned}
DIST = \beta_0 + \beta_1 \cdot SP500 + \beta_2 \cdot VIX + \beta_3 \cdot TP + \beta_4 \cdot SYP + \beta_5 \cdot SDI \\
+ \beta_6 \cdot POIV + \beta_7 \cdot MCAP + \beta_8 \cdot LEV + \beta_9 \cdot EPSE + \beta_{10} \cdot CRIS \\
+ \beta_{11} \cdot POST + \beta_{12} \cdot RTCH + \eta
\end{aligned}
\tag{5}
$$

where *DIST* measures the level of disagreement between the credit risk signals in CDS and ACR, i.e., measures the cardinal difference between the *CDS-c* and *ACR-c*, as in Equation (3). Additionally, *SP500* is the S&P 500 Index; *VIX* is the CBOE Volatility Index; *SYP* is the swap yield premium; *TP* is the term premium; *SDI* represents the seniority of the debt; *POIV* is the put option implied volatility; *MCAP* is the market capitalization; *LEV* is the leverage; *EPSE* is the earnings per share estimate; *CRIS* and *POST* are dummy variables identifying the financial crisis and the post crisis periods, respectively; and *RTCH* represents the time since rating change, as described in Section 3[15].

We estimate the models in Equations (4) and (5) using multinomial logit with fixed effects, and the maintained hypothesis is that the respective error terms ϵ and η satisfy the requisite statistical assumptions necessary for the validity of the econometric model (4) and (5)[16]. Table 4 presents the estimation results [17]. We observe that, in our models for *AGREE* and *DIST*, the coefficient estimates are all statistically significant, signs are all economically intuitive, and partial effects are generally all economically meaningful.

<Insert Table 4>

Considering the coefficient estimates presented in Table 4, a rising stock market (*SP500*) increases the estimated chances of agreement and decreases the distance between the *CDS-c* and *ACR-c*. We interpret this as reflective of an increased flow of information during down markets which could augment the differences between agency and market-based assessments of credit risk—either the agencies are maintaining a through-the-cycle assessment of credit risk or are reluctant to “keep up.” Alternatively, during declining markets, factors that tend to drive this wedge, such as liquidity or investor risk aversion, are more prominent and are more likely to be reflected to a greater degree in the CDS market–based versus the agency-based assessment of credit risk. The magnitudes of the coefficient estimates suggest that comparing the models, a 10% increase in the S&P 500 index is associated with about a 40 bp increase for the estimated probability of agreement and a 30 bp decrease in the probability of a one-notch distance between *CDS-c* and *ACR-c*; and in the case of the in the *CDS-10c* versus *ACR-10c* model, the corresponding increase is 50 bp and decrease is 30 bp, which is close.

We observe that an increase in the *VIX* (the so-called fear index) is associated with either lower odds of agreement or greater odds of a more severe credit assessment in the CDS market as compared to the rating agencies. It is possible that in more volatile environments, investor risk aversion is heightened, and therefore not only is it more likely that the CDS market does not agree with the agencies due to a more severe measure of credit risk, but also that the "tail-risk" component of credit risk is reflected in the *CDS-c* and not in the *ACR-c*. Magnitudes of coefficient estimates indicate that in the *CDS-5c* versus the *ACR-5c* model, for every one point increase in the *VIX*, either the probability of agreement is expected to decline by roughly 1.6%, or the probability of an additional one-notch discrepancy between *CDS-c* and *ACR-c* is expected to increase by about 1.2%; and in the case of the in the *CDS-10c* versus *ACR-10c* model, the corresponding increase is 3% and decrease is 1.8%, which is close.

An increasing term premium, *TP*, is associated with a lower predicted likelihood of agreement between *CDS-c* and *ACR-c*. Interestingly the coefficient estimate of *TP* in the *DIST* model is not statistically significant, while it is highly significant in *AGREE* model. We hypothesize that as the yield curve becomes more upwardly sloping, investors could be extracting a higher premium for investing at the long end of the curve (i.e., a greater time preference for immediacy). This would be directly reflected in richer CDS pricing and higher odds that either *CDS-c* and *ACR-c* do not agree or that *CDS-c* are signaling more credit risk. It is possible that rating agencies would be looking ahead through the cycle to better economic conditions, while the CDS market would tend to maintain a shorter-term view, which would lead to a greater probability that there is a disagreement between *CDS-c* versus *ACR-c*. However, *TP* is not able to differentiate the exact distance between signals. The size of the coefficient estimate suggests in the *CDS-5c* model substantial economic significance of the *TP* in explaining disagreement in absolute terms relative to the other covariates, as a 1% widening in *TP* implies about a 2.4% decline in the chances of agreement; and in the case of the *ACR-10c* model, the corresponding decrease is 1.8%, which is close.

The results for the swap yield premium, *SYP*¸ show that as the yield difference between the plain interest rate swaps and the Treasuries increases, *AGREE* is increasing and *DIST* is decreasing. Based on our variable construction, increased values of *CDS-c* and *ACR-c* imply higher credit risk. Prior research found increases in *SYP* causes CDS spreads to increase. Therefore, we hypothesize that increased credit risk among the inter-bank market participants is indicative of a worse credit market environment and riskier issues; as a result, one possibility is that the rating agencies behave differently in such environments, and are in greater harmony with the CDS market (i.e., agency signals are more likely to agree with CDS signals). The results are robust in terms of economic impact, in the *CDS-5c* versus *ACR-5c* model, with a 1% rise in the *SYP* associated with about a 0.9% greater probability of agreement and approximately 1.8% decreased chances of the CDS market-based credit risk category moving one additional notch worse than the agency-based one. In the case of the *CDS-10c* versus *ACR-10c* model, the corresponding increase is 1.8% and decrease is 3.2%, which is close.

More senior issues are associated with either higher probabilities of agreement, or a shorter distance, between the *CDS-c* and *ACR-c*. This result is readily explainable, in that less senior debt is likely to be evaluated with greater skepticism among risk-averse investors in the CDS market than analysts at rating agencies. The size of the estimates in the *CDS-5c* versus *ACR-5c* model implies that senior issues have a 2% lower probability of a divergence in the credit risk signal between the agencies and the CDS market, as well as a 1.2% higher probability of the CDS market-based credit risk category exceeding the ACR-based one by an additional category; and in the case of the *CDS-10c* versus *ACR-10c* model, the corresponding decrease is 0.8% and increase is 1.6%, which is close.

We observe in Table 4 that higher levels of put option implied volatility (*POIV*) of the issuer's equity decreases the estimated probability of an agreement, and increases the odds of a positive increment in distance, between the *CDS-c* and *ACR-c*. The intuition is that to the extent that *POIV* is associated with increasing distress of the issuer, we would expect this to be impounded to a greater extent into the CDS market's assessment of credit risk, as it accounts for factors like investor risk aversion and liquidity that the rating agencies may not incorporate to the same extent into their rating assessments. This variable is economically significant. In the *CDS-5c* versus *ACR-5c* model, a 1 percentage increase in *POIV* gives rise to a 0.17% decline in the chances that the CDS market and ACR agree upon the relative credit quality of the issue, as well as a 1.0% rise in the estimated probability that the CDS market-based credit risk category becomes one notch worse than the ACR-based one. In the case of the *CDS-10c* versus *ACR-10c* model, the corresponding increase is 0.74% and decrease is 1.4%, which is close.

Our results suggest that the debt of larger issuers (i.e., with higher *MCAP*) are more likely to have ACR-based credit risk assessments that are in harmony with the CDS market–based ones, as well as that the latter tend to be closer to the former according to our *DIST* measure. We hypothesize that for such larger firms, better quality and volume of information mitigates factors that likely drive a wedge between the credit risk assessments of the CDS market and that of the rating agencies—for example, credit risk premia or liquidity effects. As an alternative and complementary explanation of the higher observed agreement for these firms, rating agencies more intensely monitor larger companies, and may hence adjust these companies' ratings more frequently. Furthermore, this effect is robust in magnitude, implying in the *CDS-5c* versus *ACR-5c* model that roughly for every doubling in market capitalization of the issuer, it is 4.1% more probable that *ACR-c* agrees with the *CDS-c*, and 9.2% more likely that there is a reduction in the distance between the respective categories of credit quality. In the case of the in the *CDS-10c* versus *ACR-10c* model, the corresponding increase is 2.3% and decrease is 12.2%, which is close.

Our results suggest that more levered issuers are less likely to have debt whose credit risk is assessed similarly by CDS market signals and rating agencies; and it is more likely that the divergence between *CDS-c* and *ACR-c* will widen. This supports the hypothesis that greater leverage is associated with an increase in the default boundary and therefore an elevated risk of default, which in turn increases risk premia demanded in the CDS market above and beyond risk of credit loss that is the focus of the ratings agencies. Our estimates are economically meaningful, as we see in the *CDS-5c* versus *ACR-5c* model that every 1% increase in leverage (*LEV*) results in a 1.2% reduction in the likelihood that the CDS market and ACR agree upon the relative credit quality, as well as an 0.4% increase in the estimated probability that the discrepancy between *CDS-c* and *ACR-c* widens by one notch in the direction of a worse CDS-based credit risk signal relative to agency-based one. In the case of the *CDS-10c* versus *ACR-10c* model, the corresponding increase is 1.8% and decrease is 6.2%, which is close (of a similar order of magnitude).

An improving earnings per share estimate (*EPSE*) among analysts is associated with a greater probability of agreement, as well as a lesser probability of a one notch difference, between *CDS-c* and *ACR-c*. We interpret this result as correlated to analysts' better EPS estimates of the issuer: the implied diminished credit risk leads to a decline in the factors that would drive a wedge between the *CDS-c* and the *ACR-c*, such as investor risk aversion. The magnitudes of the coefficient estimates are such that in the *CDS-5c* versus *ACR-5c* model, every 1% increase in *EPSE* results in a 0.3% greater estimated probability of agreement, or a 0.3% lesser chance of a one notch disagreement, in the CDS-market and ACR-based credit risk assessments. In the case of the *CDS-10c* versus *ACR-10c* model, the corresponding increase is 0.8% and decrease is 0.2%, which is close.

Focusing on the financial crisis and post-crisis dummy variables, we observe that during crisis there has been a decrease in the probability of agreement and an increase in the discrepancy between the credit risk signals in the CDS market and agency ratings. This makes sense: during financial crisis and economic downturn periods, issuers are generally in a state of worse credit quality, wherein factors such as investor risk aversion or liquidity give rise to more severe credit assessments in the CDS market vis-a-vis the rating agencies. The magnitudes of the coefficient estimates suggest that in the *CDS-5c* versus *ACR-5c* model, a 10% increase in the financial crisis period experienced about a 1.2% decrease in the estimated probability of agreement and a 4.5% increase in the probability of a one-notch distance between *CDS-c* and *ACR-c*. In the case of the *CDS-10c* versus *ACR-10c* model, the corresponding decrease is 6.4% and increase is 8.4%, which is close.

Finally, considering the *RTCH* (time since rating change) variable, our new empirical results show that level of agreement decreases and distance between the credit risk categories increases as more time has passed since the last rating adjustment. That is, the level of agreement between credit ratings and CDS spreads is inversely related to the amount of time that has passed since the last rating adjustment. The magnitudes of the coefficient estimates suggest that in the *CDS-5c* versus *ACR-5c* model, an additional quarter since a rating change equates to about a 6% decrease in the estimated probability of agreement and a 6% increase in the probability of a one-notch distance between *CDS-c* and *ACR-c*. In the case of the *CDS-10c* versus *ACR-10c* model, the corresponding decrease is 8% and increase is 9%, which is close.

In order to verify the robustness of our results regarding the relationship between credit risk signals from the two sources in our analysis, we directly regress CDS spread categories (*CDS-c*) on credit rating categories (*ACR-c*), as well as on the other factors from their respective models (4) and (5) as independent variables using the following model [18]:

$$\begin{aligned} CDS\text{-}c = \beta_0 + \beta_1 \cdot ACR\text{-}c + \beta_2 \cdot SP500 + \beta_3 \cdot VIX + \beta_4 \cdot TP + \beta_5 \cdot SYP \\ + \beta_6 \cdot SDI + \beta_7 \cdot POIV + \beta_8 \cdot MCAP + \beta_9 \cdot LEV + \beta_{10} \cdot EPSE \\ + \beta_{11} \cdot CRIS + \beta_{12} \cdot POST + \beta_{13} \cdot RTCH + \xi \end{aligned} \quad (6)$$

where *CDS-c* and *ACR-c* represent the credit default swap and agency credit rating categories, respectively. The first column in Table 5 presents the estimated coefficients in Equation (6) using the five-category classifications, *CDS-5c* based on quintiles of spread levels and *ACR-5c* based on the S&P-assigned long-term ratings rescaled into 5 categories. The second column in Table 6 presents the results when we use the 10-category classifications, *CDS-10c* based on deciles of spread levels and *ACR-10c* based on the deciles of distribution of agency ratings in our dataset. Other variables in Equation (6) are identical to those defined in our Equations (4) and (5).

<Insert Table 5>

We observe that our empirical results hold and that the coefficient estimate of *ACR-5c* on *CDS-5c* is 0.8735 (*ACR-10c* on *CDS-10c* is 0.7912), both highly statistically significant, indicating a very high degree of correspondence between the credit signals from two sources. Furthermore, not only are the signs of the parameter estimates on the explanatory variables economically intuitive and statistically significant, they are of similar magnitudes (and in some cases very close) across *CDS-5c* and *CDS-10c* models.

Our empirical tests confirm our hypothesis that the differences between agency credit ratings and credit market–based assessments can be explained by variables in line with accepted economic theory. We have built two alternative models of this differential and have shown that both challengers have the same qualitative features in terms of the statistical and economic significance of this set of variables. Then we have directly modeled our two measures (the agreement indicator and the notch difference) and this robustness exercise has supported our results. In the process we have provided a potential tool for practitioners who wish to bridge the divide between PIT and TTC credit risk measures, but who may be dealing with non-tradable instruments.

4. Conclusion

Credit risk makes up perhaps the largest risk an investor bears when buying a defaultable fixed income instrument. Credit risk may be broadly defined as the uncertainty associated with potential loss of value on a fixed income obligation, either principle or interest, in the event of default, downgrade, or widening of credit spreads. Before the inception of CDS trading, ratings assigned by agencies were the only signal of credit risk of fixed income instruments. In that credit ratings rank order the relative credit risk of an entity, these assessments should be closely related to the CDS spreads on the corresponding defaultable instruments with respect to the obligors.

However, these measures differ in a fundamental sense: CDS spreads are a real-time market signal regarding immediate creditworthiness, whereas credit ratings are a discrete assessment of credit risk over a longer horizon. Callen *et al.* (2009) observe that while credit ratings may in fact have a close relation to CDS spreads, nevertheless with respect to obligors sharing a common credit rating we observe much variation in the latter. In this vein, Cizel (2013) argues that the CDS spreads represent a more market-based measure of a firm's credit risk relative to credit risk ratings. If on the one hand CDS spreads represent an element of pure credit risk (i.e., the danger of obligor degradation in credit quality or default), and if on the other hand credit ratings are a relative default risk metric, then there should be a correlation between the market price of credit risk and the credit rating assigned an obligor. Herein our research agenda has the objective to build models of the link between CDS spreads and credit ratings, through defining alternative agreement measures between these, as well as identifying economically intuitive covariates that explain such differences.

Our model can be used by investors in debt instruments which do not have CDS written on them or which have illiquid CDS contracts. The findings replicate market-based, point-in-time (PIT) credit risk signals based on the factors (both market-based and firm-specific) in our model, and can be used to augment through-the-cycle (TTC) credit risk assessments [19].

We analyze the differences in the relative credit risk assessment from CDS-based and agency ratings–based measures, in part motivated by Hilscher and Wilson (2013). We present evidence that the divergence between the credit risk signals from CDS spreads and credit ratings can be explained by factors which the rating agencies may consider differently than credit market participants.

We provide a comprehensive analysis of the differences in the relative credit risk assessment as implied by the *ACR-c* versus the *CDS-c*, using two models to better explain the *ACR-c* being equal to the *CDS-c*, or the *CDS-c* being a more severe assessment of credit risk than the *ACR-c*. The results are statistically and economically significant, and had signs on (magnitudes of) coefficient estimates that are economically intuitive (significant). The VIX, term premium, or the put option implied volatility of the associated equity decrease the chances of agreement and increase the relative pessimism on the part of the CDS market. Conversely, the level of the S&P 500 index, market capitalization, or the EPS estimate of the reference entity, as well as the seniority of the debt, are always negatively related to agreement and disagreement of CDS-market and agency ratings credit risk signals.

Therefore, our analysis suggests that for investors and other stakeholders in the credit markets having a more PIT rather than TTC orientation, modifications be made to the method of determining relative credit risk that incorporate market-based signals such as the information contained in CDS spreads. Moreover, if the credit in question is not traded in the CDS market (or is an illiquid debt issue), there are factors available to augment TTC measures like agency rating assessments [20] that will mimic the information in the CDS-based signals. Said differently, these results suggest that agency credit ratings of relative riskiness of a reference entity do not always correspond with assessments by CDS spreads, as the price of risk is a function of additional macro and micro factors that can be explained using statistical analysis. Finally, the models we developed and their empirical findings could be used to analyze issues surrounding the pricing of credit default swaps and examine the policies of credit rating agencies [21]. For example, in cases of a rated pool of credits or a structured vehicle rated by an agency which have a market offering price but is not actively traded, our model could be used as a benchmark to provide an alternative rating that could be used to judge if the agencies are pricing aggressively or not with respect to the market.

Endnotes

1. The size of the CDS market more than doubled each year from $3.7 trillion in 2003 to a peak notional value of $62.2 trillion by the end of 2007. The notional amount fell during 2008–2009 as a result of dealer "portfolio compression" efforts (i.e., replacing offsetting redundant contracts), so that by the end of 2009 it had fallen nearly 50% to $30.4 trillion. However, this is still a nearly 10-fold increase in size of the market from the beginning of the decade (ISDA, 2010). Childs (2014) reports that the size of the CDS market further declined to $13.2 trillion by June 2013.
2. The three most prominent NRSROs are Standard & Poor's, Moody's Investors Services, and Fitch.
3. Ratings designed to reflect borrowers' fundamental creditworthiness are sometimes termed the through-the-cycle (TTC) philosophy of ratings, as compared to the point-in-time (PIT) orientation of market-based rating schemes. The TTC ratings are generally favored by risk managers and prudential supervisors for capital management purposes because they result in less cyclicality in capital measures. However, as PIT ratings give more reactive signals, these parties sometimes prefer PIT ratings for account management purposes (Resti and Sironi, 2007).
4. Hull *et al.* (2004) use Moody's ratings and separate the data into three categories: Aaa-Aa, A, and Baa; however, they do not consider high-yield names.
5. Hull *et al.* (2004) argue the best risk-free curve to use when pricing CDSs lies somewhere between the Treasury and the swap curve. However, many practitioners prefer to use the swap curve, as this is the curve used most often in derivative pricing.
6. Cizel (2013) suggests that these instruments represent the most liquid and traded category of CDS contracts.
7. See A. Ross, "JP Morgan Pays $2 a Share for Bear Stearns", *The New York Times*, March 17, 2008.
8. One of the reasons for choosing S&P ratings as compared to alternatives such as Moody's ratings, is that they have certain advantages: Güttler (2011) presents evidence that S&P assigns ratings in a timelier manner than Moody's, as the tendency toward rating convergence is found to be stronger for S&P than for Moody's. Among the three rating agencies of S&P,

Moody's, and Fitch, Cizel (2013) finds statistically and economically significant responses only to S&P announcements.

9. The estimate of the earnings per share is the average of Bloomberg's collection of analysts' EPS forecasts.
10. Construction of our crisis and post-crisis dummy variables are based on Huang *et al.* (2012). Their analysis suggests that by mid-2009 market conditions had returned to normalcy.
11. Norden and Weber (2004) in their study of the effect of agency "watch list" entries on credit risk assessments use Bloomberg rating changes in a similar scale. As credit ratings change overtime, the number of names in each category also changes over time.
12. Huang *et al.* (2012) use two groups: investment-grade AAA to BBB– and noninvestment-grade BB+ and below. Cizel (2013) uses five broad rating categories: AAA/AA (Aaa, Aa), A, BBB (Baa), BB (Ba), and B or below.
13. Hornik *et al.* (2010) study all three aspects of proximity—association, agreement, and bias—in the context of rating systems, concluding that all of these are of relevance. Furthermore, they argue that although these aspects are not necessarily independent, it is evident that none of the three aspects is redundant.
14. We thank an anonymous referee for recommending this variable in our analysis.
15. In our empirical analysis we use the natural log of firm-specific variables and market indicators.
16. This method is similar to the calibration modeling in Das and Hanouna (2008).
17. Our estimation methodology uses heteroscedasticity and autocorrelation consistent (HAC) robust standard errors, which are derived from either bootstrap or jackknife methods. We employ customary post-estimation tests to verify that our model specifications do not suffer from autocorrelation, non-stationarity, heteroscedasticity, and multicollinearity. Results are available upon request.
18. We thank an anonymous referee for suggesting this model for robustness checks.
19. For example, consider bank evaluating the sale or securitization of middle market obligors, which do not have CDS quotes for their debt, but the bank has its internal ratings for those that map to the agency credit ratings. In such a case, our calibrated model could be used to produce a proxy CDS / market-based credit signal that would be used as a benchmark or baseline for pricing this deal.

20. Note that this could also apply to bank loans having internal TTC ratings, where the CDS is illiquid or nonexistent, but the some of the variables in our model are available.
21. We thank an anonymous referee for pointing out such potential uses of our models and empirical results.

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Table 1
Categories of Credit Risk Signals
Credit Default Swap (*CDS-c*) vs. Agency Credit Ratings (*ACR-c*)
Feb. 28, 2003, to Dec. 31, 2010

Panel A:
CDS-5c Based on Quintiles vs. *ACR-5c*

	Contract Days	*ACR-5c* 1	2	3	4	5		
CDS-5c	1	32,049	23,698	20,122	4,172	2,295	**82,336**	20.88%
	2	19,387	34,818	22,939	5,823	2,790	**85,757**	21.75%
	3	13,411	20,239	34,630	8,632	3,254	**80,166**	20.33%
	4	9,247	13,176	18,970	29,884	7,298	**78,575**	19.93%
	5	2,954	3,782	4,091	23,504	32,112	**66,443**	16.85%
		77,048	**95,713**	**100,752**	**72,015**	**47,749**	394,277	
		19.54%	24.28%	25.55%	18.27%	12.11%		

Note. Agency credit ratings categories (*ACR-5c*) are defined as rescaled Standard & Poor's long-term credit (i.e., alphanumeric scale) ratings, given by Equation (1):

$$ACR\text{-}5c = \begin{cases} 1 \ \ldots\ldots\ldots\ldots\ldots\ldots & \text{AAA to A+} \\ 2 \ \ldots\ldots\ldots\ldots\ldots\ldots & \text{A to A-} \\ 3 \quad \textit{for ratings} & \text{BBB+ to BBB} \\ 4 \ \ldots\ldots\ldots\ldots\ldots\ldots & \text{BBB- to BB+} \\ 5 \ \ldots\ldots\ldots\ldots\ldots\ldots & \text{BB to CCC-} \end{cases}$$

Credit default swap categories (*CDS-5c*) are based on the quintiles of spread levels, where *CDS-5c* = 1 is assigned to swap contracts with spread levels within the lowest 20th percentile on a given day, and *CDS-5c* = 5 the highest 20th percentile. As a result of this mapping, we are able to assign *ACR-5c* and *CDS-5c* to each contract for each trading day for which we have the data. We create categories such that both *ACR-5c* = 1 (top letter ratings) and *CDS-5c* = 1 (lowest quintile of spread levels) correspond to the best credit risk signal (i.e., lowest risk). Similarly, *ACR-5c* = 5 (bottom letter ratings) and *CDS-5c* = 5 (highest quintile of spread levels) correspond to the worst credit risk signal (i.e., highest risk). If the CDS market's and rating agency's assessments of the underlying reference entity's credit quality are similar, on average, *CDS-5c* and *ACR-5c* should be the same. If that is the case, most observations would be contained in the diagonal cells of this table.

Panel B:
CDS-10c vs. *ACR-10c* Based on Deciles

	Contract Days	ACR-10c 1	2	3	4	5	6	7	8	9	10		
CDS-10c	1	13,457	5,051	4,018	3,305	2,818	1,316	143	219	2	0	**30,329**	7.69%
	2	6,402	13,594	5,688	4,903	1,731	1,500	331	331	42	0	**34,522**	8.76%
	3	2,834	4,343	14,374	5,083	3,526	2,015	999	449	216	41	**33,880**	8.59%
	4	2,891	5,811	5,694	7,889	7,304	5,510	3,680	2,069	660	512	**42,020**	10.66%
	5	2,951	6,721	6,419	7,495	9,426	5,701	4,303	3,102	1,134	474	**47,726**	12.10%
	6	2,708	4,380	5,775	5,993	9,453	12,965	4025	2729	1101	237	**49,366**	12.52%
	7	2,334	2,224	4,633	4,199	8,382	10,599	9,291	3,754	1,145	96	**46,657**	11.83%
	8	850	1,494	2,839	3,402	5,035	7,686	7,135	8,582	2,506	336	**39,865**	10.11%
	9	165	416	967	1,836	2,463	8,814	5,281	7,997	7,396	1,950	**37,285**	9.46%
	10	48	374	420	781	1,123	2,734	4,812	6,935	12,170	3,230	**32,627**	8.28%
		34,640	**44,408**	**50,827**	**44,886**	**51,261**	**58,840**	**40,000**	**36,167**	**26,372**	**6,876**	394,277	
		8.79%	11.26%	12.89%	11.38%	13.00%	14.92%	10.15%	9.17%	6.69%	1.74%		

Note. Agency credit ratings categories (*ACR-10c*) are defined as rescaled Standard & Poor's long-term credit (i.e., alphanumeric scale) ratings based on the deciles of distribution of ratings in our dataset. Credit default swap categories (*CDS-10c*) are based on the deciles of spread levels, where *CDS-10c* = 1 is assigned to swap contracts with spread levels within the lowest 10th percentile on a given day, and *CDS-10c* =10 to the highest 10th percentile.

Table 2
Relationship between Credit Risk Signals
Following Rating Changes

Credit Default Swap (*CDS-5c*) vs. Agency Credit Ratings (*ACR-5c*)
Feb. 28, 2003, to Dec. 31, 2010

CDS-5c \ *ACR-5c*	1	2	3	4	5
1	87.9%	1.5%	0.0%	0.0%	0.0%
2	6.7%	90.3%	2.9%	0.0%	0.0%
3	5.4%	6.2%	87.2%	1.9%	1.0%
4	0.0%	2.0%	8.5%	84.3%	17.0%
5	0.0%	0.0%	1.0%	13.8%	82.0%
	100%	100%	100%	100%	100%

Note. In this table we consider the credit risk signals from the CDS market during the two-month period following S&P rating changes and tabulate what percentage of *CDS-5c* and *ACR-5c* provide the same credit risk level. We observe that credit risk categories from agency credit ratings and CDS spreads are matching significantly higher for this restricted sample. This finding supports our hypothesis that the factors used in the model can be used to derive CDS-like point-in-time credit risk signal holds. The level of agreement between agency credit ratings and CDS spreads should be significantly higher for this restricted sample of days following agency revisions of ratings.

Table 3
Summary Statistics: Credit Default Swap Spreads*
Credit Default Swap (CDS) Categories vs. Agency Credit Ratings (ACR) Categories
Feb. 28, 2003, to Dec. 31, 2010

Panel A:
CDS-5c Based on Quintiles vs. *ACR-5c*

CDS Categories	Min	Mean	Median	Max	St.dev.	Kurtosis	Skewness
1	4.83	28.91	23.34	180.00	16.92	7.86	1.90
2	14.46	50.79	40.00	357.50	32.46	6.83	1.74
3	15.75	73.75	41.83	568.64	65.96	7.05	1.92
4	19.18	118.02	58.75	1048.43	126.86	9.97	2.46
5	36.39	388.91	220.00	9183.38	542.96	49.58	5.39

ACR Categories	Min	Mean	Median	Max	St.dev.	Kurtosis	Skewness
1	4.83	52.31	30.00	3349.11	93.94	52.27	11.73
2	7.84	65.70	34.00	9003.03	174.24	64.75	22.74
3	8.37	73.87	46.75	3443.68	106.25	94.25	10.40
4	15.51	160.32	105.00	6407.20	229.95	45.36	9.08
5	15.51	463.39	320.00	9183.38	591.30	39.80	4.83

Panel B:
CDS-10c* Based on Deciles vs. *ACR-10c

CDS Categories	Min	Mean	Median	Max	St.dev.	Kurtosis	Skewness
1	4.83	25.50	20.44	161.44	15.51	5.74	1.50
2	10.33	37.39	29.87	180.00	21.21	4.99	1.32
3	14.34	52.14	46.00	240.00	29.29	4.36	1.10
4	15.51	45.06	25.67	357.50	37.70	6.36	1.85
5	15.74	53.59	32.24	420.11	49.31	8.21	2.21
6	15.87	69.52	40.00	568.64	68.16	8.51	2.30
7	18.53	94.33	48.50	602.46	94.98	8.20	2.24
8	22.43	131.51	62.50	1048.43	144.28	8.93	2.37
9	36.30	212.40	103.18	1636.97	219.24	8.08	2.14
10	26.81	545.69	331.67	9183.38	685.83	33.02	4.47

ACR Categories	Min	Mean	Median	Max	St.dev.	Kurtosis	Skewness
1	4.83	49.11	30.45	2413.54	81.46	21.00	8.11
2	6.16	53.49	29.75	3349.11	98.10	68.49	12.36
3	7.84	50.41	31.00	1120.38	74.83	56.74	6.39
4	8.90	82.56	38.41	9003.03	239.03	57.86	18.12
5	8.37	60.29	40.67	1543.82	72.86	79.35	6.71
6	9.10	85.83	53.09	3443.68	127.48	65.48	10.03
7	15.51	130.01	87.75	2531.19	146.15	36.90	4.45
8	15.51	238.29	153.94	6407.20	378.77	81.47	7.59
9	15.51	515.38	368.35	9183.38	600.63	37.53	4.65
10	15.92	651.40	522.50	8599.63	702.59	34.03	4.29

* Median credit default swap spreads are in basis points.

Table 4

Modeling Similarity and Divergence in Credit Risk Signals

Credit Default Swap (CDS) Categories vs. Agency Credit Ratings (ACR) Categories

Feb. 28, 2003, to Dec. 31, 2010

	CDS-5c* vs *ACR-5c		***CDS-10c* vs *ACR-10c***	
Variables	***AGREE***	***DIST***	***AGREE***	***DIST***
S&P 500 Index (***SP500***)	0.0402	-0.0322	0.0513	-0.0299
	(13.57)**	(-11.61)**	(9.93)**	(-10.26)**
CBOE Volatility Index (***VIX***)	-0.0158	0.0118	-0.0298	0.0175
	(-24.81)**	(12.64)**	(-7.26)**	(6.78)**
Term Premium (***TP***)	-0.0242	0.0100	-0.0117	0.0093
	(-12.37)**	(0.95)	(-6.75)**	(0.79)
Swap Yield Premium (***SYP***)	0.0091	-0.0278	0.0184	-0.0321
	(6.24)**	(-7.33)**	(4.67)**	(-6.91)**
Senior Debt Indicator (***SDI***)	0.0196	-0.0117	0.0030	-0.0161
	(2.69)*	(-2.47)**	(2.54)*	(-3.46)**
Put Option Implied Volatility (***POIV***)	-0.0017	0.0102	-0.0074	0.0141
	(-22.83)**	(16.06)**	(-12.65)**	(12.35)**
Market Capitalization (***MCAP***)	0.0407	-0.0920	0.0232	-0.1224
	(13.97)**	(-22.87)**	(9.57)**	(-14.77)**
Leverage (***LEV***)	-0.0120	0.0036	-0.0175	0.0618
	(-2.85)**	(10.17)**	(-2.53)*	(9.43)**
EPS Estimate (***EPSE***)	0.0028	-0.0030	0.0084	-0.0024
	(7.94)**	(-11.87)**	(4.69)**	(-8.16)**
Crisis Dummy (***CRIS***)	-0.0291	0.0454	-0.0642	0.0835
	(-11.1)**	(6.54)**	(-3.42)**	(6.68)**
Post Crisis Dummy (***POST***)	0.0124	-0.0103	0.0143	-0.0164
	(2.37)*	(-8.23)**	(4.33)**	(-7.21)**
Time Since Rating Change (***RTCH***)	-0.0009	0.0010	-0.0006	0.0012
	(-2.81)*	(2.63)*	(-2.93)*	(2.22)*
Constant	-0.2929	1.9174	-0.3749	1.7037
	(-2.47)*	(2.21)*	(-2.85)*	(2.28)*
Number of observations	379,625	379,625	379,625	379,625
R^2 between	0.6715	0.5886	0.4487	0.3924
R^2 overall	0.5978	0.4906	0.3561	0.3187
Wald Chi^2	576.5	350.2	247.7	183.9
Prob > Chi^2	0.000	0.000	0.000	0.000

Note. First dependent variable is *AGREE* which is a binary variable looking at the agreement between the credit risk signals and is given by Equation (2):

$$AGREE = \begin{cases} 1 & \text{if } CDS\text{-}c = ACR\text{-}c \\ 0 & o/w \end{cases}$$

where *CDS-c* and *ACR-c* represent the credit default swap and agency credit rating categories, respectively. We are interested in identifying the degree of agreement between the two sources in terms of their assessment of the reference entity's credit quality. The second dependent variable is *DIST* which measures the distance between the credit risk signals and is given by Equation (3): *DIST* = *CDS-c* – *ACR-c*. When DIST is positive (e.g., *CDS-c* = 5, *ACR-c* = 1, and *DIST* = +4), the credit risk signal in the swap market is the worst (i.e., highest spreads) and in the agency ratings is the best possible (i.e., top alphanumeric scale, rating like AAA), respectively. We estimate the models in Equations (4) and (5), for *AGREE* and *DIST*, respectively, using multinomial logit with fixed effects, and the maintained hypothesis is that the respective error terms ϵ and η satisfy the requisite statistical assumptions necessary for the validity of the econometric models (4) and (5).

** and * denote statistical significance at the 1% and 5% levels, respectively. The z-scores are presented within parenthesis.

Table 5
Modeling the Relationship between Credit Risk Signals
CDS Categories as a function of ACR Categories as well as firm-specific and market variables
Feb. 28, 2003, to Dec. 31, 2010

	CDS Category	
Variables [a]	**(*CDS-5c*)** [b]	**(*CDS-10c*)** [c]
Agency Rating Category (***ACR-5c***)	0.8735	
	(16.55)**	
Agency Rating Category (***ACR-10c***)		0.7912
		(8.49)**
S&P 500 Index (***SP500***)	-0.2246	-0.1915
	(-9.17)**	(-8.72)**
CBOE Volatility Index (***VIX***)	0.0641	0.0756
	(11.25)**	(12.82)**
Term Premium (***TP***)	0.0830	0.0848
	(3.56)**	(2.94)*
Swap Yield Premium (***SYP***)	0.0638	0.0552
	(5.82)**	(4.85)**
Senior Debt Indicator (***SDI***)	-0.0118	-0.0158
	(-7.47)**	(-6.13)**
Put Option Implied Volatility (***POIV***)	0.0092	0.0134
	(12.77)**	(14.25)**
Market Capitalization (***MCAP***)	-0.0871	-0.0713
	(-4.74)**	(-3.62)**
Leverage (***LEV***)	0.0138	0.0167
	(8.68)**	(7.56)**
EPS Estimate (***EPSE***)	-0.0032	-0.0037
	(-3.85)**	(-4.29)**
Crisis Dummy (***CRIS***)	0.3720	0.3748
	(5.53)**	(5.91)**
Post Crisis Dummy (***POST***)	-0.8232	-0.8336
	(-6.96)*	(-6.36)**
Time Since Rating Change (***RTCH***)	-0.0001	-0.0001
	(-2.34)*	(-2.96)*
Constant	0.6670	0.4408
	(0.45)	(0.32)
Number of observations	379,625	379,625
R^2 between	0.5973	0.4365
R^2 overall	0.4850	0.3496
Wald Chi^2	306.7	245.2
Prob > Chi^2	0.000	0.000

Note. In this table we model the relationship between credit risk signals from the two sources in our analysis by directly regressing CDS spread categories (*CDS-c*) on credit rating categories (*ACR-c*), as well as on the other firm-specific and market variables.

[a] Variables from Equation (6) are similarly defined in Equations (4) and (5).

[b] 5-category classifications (i.e., *CDS-5c*), which are based on quintiles of spread levels and ACR-5c which are based on the S&P assigned long term ratings rescaled into five categories.

[c] 10-category classifications (i.e., *CDS-10c*), which are based on deciles of spread levels and *ACR-10c* which are based on the deciles of distribution of agency ratings in our dataset.

** and * denote statistical significance at the 1% and 5% levels, respectively. The z-scores are presented within parenthesis.

Figure 1
Credit Default Swap Categories (*CDS-5c*)
Daily Median CDS Spreads
Feb. 28, 2003, to Dec. 31, 2010

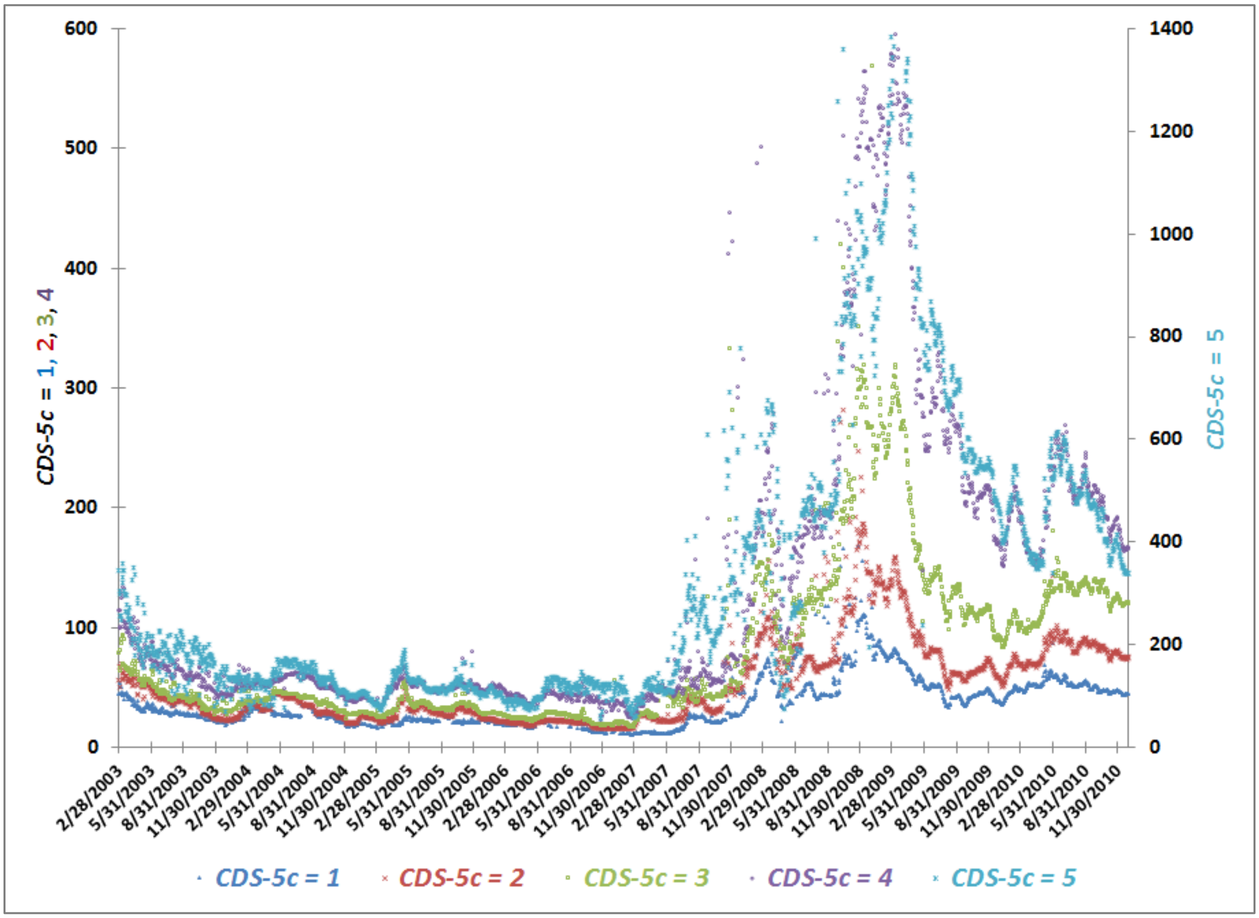

Figure 2
Agency Credit Rating Categories (*ACR-5c*)
Daily Median CDS Spreads
Feb. 28, 2003 to Dec. 31, 2010